Using discrete choice experiments to explore generics substitution, brand premiums and consumer choice in pharmaceutical policy in Australia

by Elena Meshcheriakova

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University of Technology Sydney
Business School
Centre for Health Economics Research and Evaluation

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I, Elena Meshcheriakova declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the *Business School* at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Impact of the COVID-19 pandemic

The COVID-19 global epidemic had a major impact on my PhD studies. The interruptions caused by lockdowns and working from home during the past two years have taken both a physical and emotional toll.

My ability to continue working on this thesis was significantly impaired. Over the past two years, my schedule to submit the thesis was interrupted by the changes to the work environment. Working from home caused a number of new technical challenges (unstable internet connection, home computer, access to server with data storage), an inadequate workspace, the need to share a close space with another person who had different work needs and the absence of other PhD colleagues and the ability to have casual interactions with my supervisors. Adjusting to video-conferencing was a steep learning curve, as it is very different from the usual face-to-face supervisor meetings.

However, the biggest impact was the lockdowns restrictions, which were designed to reduce the spread of COVID-19, but limited time spent outside and restricted my usual activities significantly. Other impacts were felt in my social life, such as panic buying and a new dependency on finding out the updated daily cases (infections and deaths). There was also an emotional impact due to worrying for family members in other states and those in other countries.

Abstract

Generic medicines play an important role in ensuring sustainable access to affordable medicines under the Australian Pharmaceutical Benefits Scheme, since they cost less while being as safe and effective as the original branded medicine. However, in Australia, allowing branded medicines to charge a 'brand premium' an additional fee above the co-payment, may inadvertently reduce the uptake of generic medicines.

This thesis investigated factors determining consumer choice on demand for branded and generic medicines, focusing on the role of brands and the brand premium policy. In the first instance, the study focused on exploring whether the brand premium label may act as a signal of quality to consumers, given other factors that influence decision making in a pharmaceutical market setting, such as the doctor's prescription, the pharmacist's recommendation, and the availability and cost of the medicine.

The second objective was to evaluate the impact on preferences for branded and generic medicines in a hypothetical scenario in which a consumer choice was limited to a single subsidised brand.

Four discrete choice experiments (DCEs) were developed and implemented using an online survey. Respondents were randomised into three groups (DCE1, DCE2 or DCE3), , with each DCE containing different information regarding the cost attribute, and the presence of a brand premium. All respondents completed DCE4, which asked respondents to make decisions in the context of the government changing the reimbursement policy and consumers being reimbursed for only one of the two presented medicines.

The results demonstrated that Australian respondents have a high preference for pharmacists' recommendation about the brand of the medicine, irrespective of the doctor's script. Considering the prior DCE, those who were not exposed to explicit brand premium information showed a strong positive preference for the branded medicine, compared to the negative preference of the remainder who were aware of the premium.

On average, under a scenario that limits consumer choice, the vast majority of respondents favoured the government-subsidised drug, regardless of the brand, with only a small percentage opting for the more expensive branded option. Thus, generic pricing policies that encourage greater price competition may be acceptable to consumers.

New policies can be designed to engage pharmacists and provide them with a greater capacity to inform the consumer of different options. This may encourage consumers to choose brands that cost the government less.

Abbreviations

ABS	Australian Bureau of Statistics
AIC	Akaike Information Criterion
AIHW	Australian Institute of Health and Welfare
BIC	Bayesian Information Criterion
BP	Brand premium
BWS	Best-Worst Scaling
CHERE	Centre for Health Economics Research and Evaluation
CI	Confidence Interval
CPI	Consumer price index
CV	Contingent valuation
DCE	Discrete choice experiment
DPMQ	Dispensed price for maximum quantity
DTC	Direct-to-consumer
DVA	Department of Veteran Affairs
GDP	Gross domestic product
GP	General practice
HCL	Heteroskedastic conditional logit
IIA	Independence of irrelevant alternatives
IID	Independent and identically distributed
INN	International non-proprietary names
LCA	Latent class analysis
LL	Log Likelihood
LR	Likelihood Ratio
MBS	Medicare Benefits Schedule
MNL	Multinomial Logit Model
MSL	Maximum simulated likelihood
MXL	Mixed logit

NMP	National Medicines Policy
OTC	Over-the-counter
PBAC	Pharmaceutical Benefit Advisory Committee
PBS	Pharmaceutical Benefits Scheme
RP	Revealed preference
RPBS	Repatriation Pharmaceutical Benefits Scheme
SAS	Statistical Analytical System
SD	Standard Deviation
SG	Standard gamble
SP	Stated preference
TC	Total cost
TGA	Therapeutic Goods Administration
TTO	Time trade-off
WTP	Willingness to pay

CHAPTER 1. Introduction

1.1 The use of generic brands to control the rising cost of the medicines in Australia

Access to affordable and safe medicines is a key element of a universal health care system. Medicines need to be affordable for patients and sustainable for governments to fund. Developments in health technology[1] (including new medicines) have had a positive impact, improving both quality and length of life. However, with improvements in treatments and the increasing number of people receiving treatment costs have increased, which places pressure on government budgets to ensure sustainable access to new technologies for the population. Thus, a key element of government policy in relation to health care is managing growth in expenditure while ensuring timely access. One aspect of this is managing prices for existing and off-patent pharmaceuticals on the Pharmaceutical Benefits Scheme (PBS)[2] by controlling overall expenditure to provide more capacity to make new medicines available.

A key policy framework for achieving this in Australia since 1999 has been the National Medicines Policy (NMP),[3] which aims, among other things, to improve health outcomes for all Australians through access to and appropriate use of medicines. The four central objectives of NMP provide the basis of the framework and these are:[4]

- timely access to the medicines that Australians need, at a cost an individual and the community can afford;
- medicines meeting appropriate standards of quality, safety and efficacy;
- quality use of medicines; and
- maintaining a responsible and viable medicines industry.

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[1] The Australian Productivity Commission terms of reference define medical technology in broad terms to encompass physical equipment, instruments and pharmaceuticals, clinical procedures, knowledge and support systems within which healthcare is provided.

[2] PBS is an Australian Government program that benefits all Australians by subsidising medicines to make them more affordable. PBS is governed by the *National Health Act 1953*.

[3] NMP is a framework based on partnerships between Governments (- Commonwealth, States and Territories -) health educators, health practitioners, and other healthcare providers and suppliers, the medicines industry, healthcare consumers, and the media working together to promote:

- quality care responsive to people's needs;
- incentives for preventive health and cost effective care;
- better value for taxpayers' dollars;
- more clearly defined roles and responsibilities; and
- continued universal access to basic health services through Medicare.

(Department of Health, NMP, 29 April 2019; website: https://www1.health.gov.au/internet/main/publishing.nsf/Content/National+Medicines+Policy-1).

[4] Australian Government Department of Health: accessed at https://www.health.gov.au/about-us/the-australian-health-system

Australians can access medicines that are subsidised by the government via the PBS as part of Medicare, a key component of Australia's universal health system.[5]

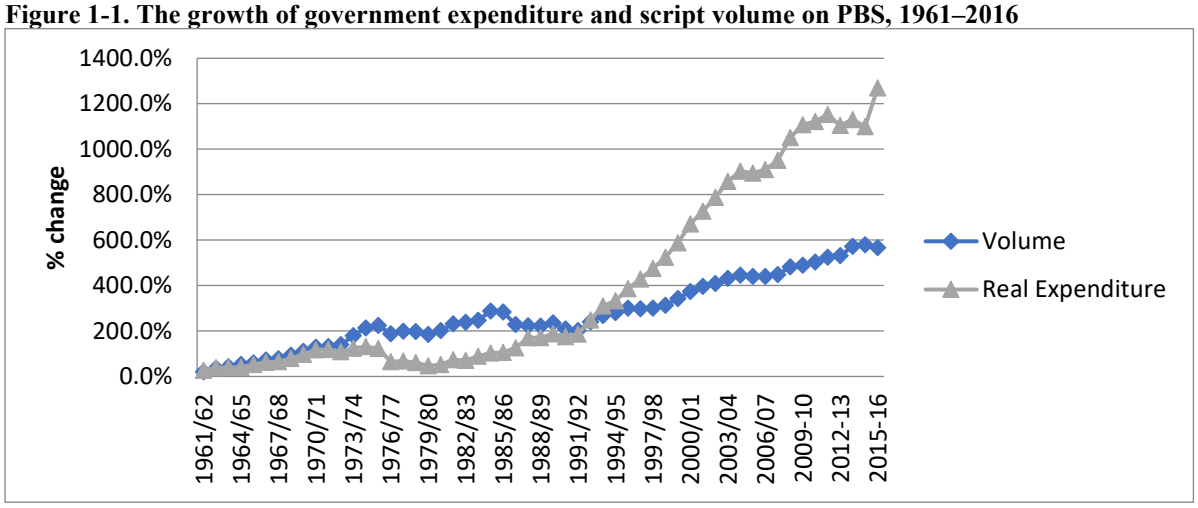
The Australian Government subsidises prescription medicines by allowing the consumer to pay only a fraction (co-payment[6]) of the actual price. The price of prescription medicines is negotiated between the Australian Government and the pharmaceutical companies.

1.2 Increase in cost of medicines

Access to medicines to treat illness for the Australian population is expanding, and the cost to the Australian Government has also been increasing over the years (Duckett et al. (2013)).

The growth in the expenditure has increased very rapidly since 1990 (Clarke & Fitzgerald, 2010). A change in real government expenditure from 1961 to 2016 (Figure 1-1) shows that, compared to when the PBS began in its current form, the cost to the government has increased significantly (by percentages in the hundreds), with a steep increase commencing in the 1990s. In part this growth was due to the increase in number of medicines available to consumers, as well as an increase in prices of the newly developed and listed medicines.

Figure 1-1. The growth of government expenditure and script volume on PBS, 1961–2016



Source: Professor Rosalie Viney (presentation slide).
Abbreviations: PBS: Pharmaceutical Benefits Scheme.

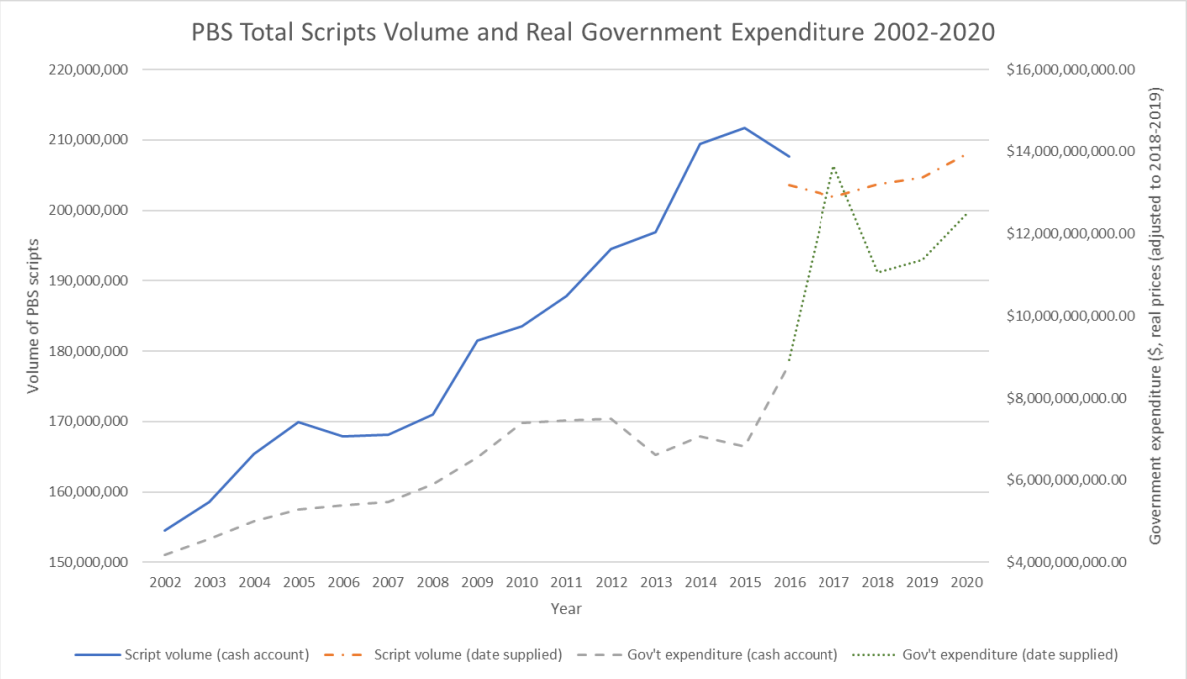
The trend continues today, with the data in Figure 1-2 showing that real government expenditure on

[5] The PBS – an Overview, by Amanda Biggs (2 January 2003). Website: https://www.aph.gov.au/About_Parliament/Parliamentary_Departments/Parliamentary_Library/Publications_Archive/archive/pbs

[6] Patient co-payment for medicines is the cost to the patient for a prescription medicine. There are General Patients and Concessional Patients co-payment. In 2021, the General Patient co-payment is AUD41.30, and Concessional Patients pay AUD6.60. If the price of the medicine is above the co-payment the government pays the rest of the cost, excluding any delivery or after-hours fee, brand or therapeutic group premium, or special patient contribution that may be applicable. These latter are also paid by the patient.

prescription pharmaceutical medicines is on an upward trending slope that has grown to three times the 2002 levels. Although the number of scripts has also grown, with new medicine listed on the PBS, the growth in script volume is only around forty per cent from 2002 levels.

Figure 1-2. PBS Total Scripts Volume and Real Government Expenditure 2002–2020[a]



Source: Combined data from PBS Expenditure and Prescription Reports (from 2002 to 2020).
Note: a=between 2002 and 2017 the expenditure was reported on cash basis, from 2017 the expenditure was reported on data of supply basis. The data for 2015-16 is shown in both cash accounting and date of supply lines. The Australian Institute of Health and Welfare (AIHW) deflator for PBS pharmaceuticals was applied to the expenditure values.
Abbreviations: PBS: Pharmaceutical Benefits Scheme.

The trend of increased cost to the government is seen in the growth in total average cost per script (which includes cost to government and cost to patient for above co-payment prescription medicines and excluding brand or therapeutic premium cost) and average government cost per script is presented in Figure 1-3. There are several factors affecting the cost of new medicines listed on the PBS, including the increase in the price when the sponsor of the medicine knows that the return on investment in the medicine needs to be recovered in a shortened timeframe, largely due to the high development costs of new drugs. Some of these increases in price are also due to PBS reforms that have led to different levels of price decrease after the medicine has been listed on PBS for a certain number of years, as well as large decreases in prices when generic brands enter the market.

Figure 1-3. Average dispensed cost of PBS prescriptions (real) and changes in patient co-payments (nominal) 2002–2020

Source: Combined data from PBS Expenditure and Prescription Reports (from 2002 to 2020).
Abbreviations: PBS: Pharmaceutical Benefits Scheme.

1.2.1 Generic medicines as key method of control

One mechanism available to government to control the costs of medicines is to take advantage of competition once a medicine is off-patent, through approval of generic medicines[7] that can substitute for a branded medicine and provide an additional brand on the market. Producers of generic medicines do not have the protection of a patent, and they do not have to recoup the high investment costs, so generic medicines are typically priced lower than the original medicine. The introduction of generic medicines not only allows for greater patient choice but also, importantly, creates competition between companies for market share. This, in turn, can help reduce the price of the medicine to the government and result in lower expenditure on medicines.

To facilitate such competition, in 1990 a 'reference price' policy was introduced whereby the Government only subsidised up to the cost of the cheapest brand (minus patient co-payment). Additionally, this resulted in the introduction of the 'brand premium' policy that allowed the holders of the original patent to charge the patient an amount higher than the 'reference price'. Therefore, if a doctor prescribed the branded medicine (original brand) that had a brand premium attached the patient would pay a higher price compared with the price of an equivalent generic medicine brand. A 'brand substitution' policy introduced in 1994 allowed the pharmacists to substitute the brand of the medicine

[7] Generic medicines refers to brands of medicine that can be produced by other companies after the patent on the originator brand medicine expires.

for an equivalent brand and allowed the patient to choose the brand of the drug[8] at the point of purchase (the pharmacy).

These policies were aimed at increasing demand for generic medicines. However, more transformation of the Australian prescription market was necessary (Hasan et al., 2019; Vitry et al., 2015). Research showed that in 2000 the prices of generic medicines in Australia were lower than or similar to those in other countries, indicating that the 'reference price' policy at the time was effective (Willis et al., 2019). However, a decade later the prices of generic brands in Australia were high compared to other countries (Duckett et al., 2013). This suggests that the listing of generic medicines resulted in limited savings for the Australian Government, with companies selling generic medicines not offering larger discounts to the government (thus maintaining higher 'reference' prices for all brands). Instead, these companies were competing for market share by offering discounts to the pharmacists, with the latter profiting by charging the government the 'reference' price (Vitry et al., 2015; Willis et al., 2019).

From the early 2000s, a series of major medicine price reforms have been introduced to manage expenditure when generic medicines enter the Australian market: reclassification of medicines into two groups (one brand only and multiple brands), mandatory price reduction, mandatory price disclosure, and more recent policies involving mandatory prescription based on the active ingredient name of the medicine rather than brand name.

The Australian policy approach with respect to generic medicines has aimed not to mandate the use of a generic (i.e., replacement of the branded medicine) but to provide for choice for consumers and providers by having multiple brands available on the PBS.[9]

Although Australian policies allowed substitution between generic and branded medicines, they also allowed the price for the branded medicine to be above the agreed PBS price (benchmark or reference price), thereby charging the consumer a brand premium. A brand premium exists when the government and the drug manufacturer of the original branded medicine do not agree on the price of a particular drug. This results in an additional cost to the consumer. The government can use the brand premium in an attempt to encourage consumers to use a cheaper (generic) medicine (McManus et al., 2001). Two official statements of the reasons for the 1990 brand premium policy are presented in Table 1-1. Each statement describes the way the brand premium policy would affect the consumer's purchasing decision, with both implying that consumers would not choose the brand with a brand premium.

[8] There were three key conditions for the brand substitution to occur: 1) the brands are therapeutically equivalent and can be interchanged; 2) patient agrees to the substitution; and 3) the prescriber had not prohibited the substitution.

[9] The Pharmaceutical Benefits Scheme is a program of the Australian Government that subsidises prescription medication for Australian citizens and permanent residents, as well as international visitors covered by a reciprocal health care agreement.

Table 1-1. Examples of reasons for the introduction of brand premium

Pharmaceutical Benefits Scheme[10]	Australian parliament Brief on Cost control of PBS 2001-02[11]
"The policy does this by increasing prescribers' and patients' consciousness about the price of drugs. In effect, it makes both groups question whether it is necessary for the patient to pay more for the drugs when a cheaper brand is available. The policy also allows companies to establish prices taking into account competition and consumer acceptance"	"… patients may pay more. This may occur where the Commonwealth has set the PBS subsidy at, for example, the cost of a generic drug and if a brand name equivalent is prescribed, there may be an additional charge for the patient. In other cases the government and the drug manufacturer may not agree on the price of a particular drug. In these cases the patient would be required to pay the difference between the Commonwealth subsidy and the price of the drug"

The exclusion of brand premium (for branded medicines) from subsidisation is aimed at stimulating price competitiveness and encouraging the development of the generic pharmaceutical industry in Australia. However, it can also diminish the impact of price competition between brands, and potentially increase confusion among consumers regarding the quality of different brands, since the higher-priced branded medicine may be perceived to be of higher quality (Willis et al., 2019).

More recent evidence from Australian and international studies shows that the expiry of patents of original branded medicines triggers an entry of the generic alternatives into the market, with a large decrease in profit for the manufacturer of the original brand due to the increase in competition, decrease in prices and loss of market share (Clarke & Fitzgerald, 2010; Dylst & Simoens, 2010, 2011; Lines, 2012; Simoens, 2007; Van Der Schans et al., 2021; Vondeling et al., 2018). Although the entry of generic alternatives into the market can result in a sharp decrease in the overall price of the medicine, this largely depends on the medicine pricing policy of the country. In Australia there have been a number of pricing policies adopted to mandate the price decrease of the medicines that have generic brand alternatives on the marker, or those single brands that have been in Australia for many years.

To date, there is a lack of research on how consumers respond to the different specific policies related

[10] https://www.pbs.gov.au/info/healthpro/explanatory-notes/section2/section-2-symbols

[11] https://www.aph.gov.au/About_Parliament/Parliamentary_Departments/Parliamentary_Library/Publications_Archive/CIB/cib0102/02CIB12

to prescription pharmaceutical medicines, and whether there is need to change some of these policies.

The research reported in this thesis aims to investigate the effect of pricing policy in relation to generic and branded medicines on the demand for prescription medicines in Australia. This research explores how consumer preferences for different attributes of a medicine, including brand, can drive demand for different brands of prescription medicines, and to identify whether it is possible to use policy levers around prescribing and dispensing of medicines, including in relation to brand premiums, to more effectively manage government expenditure on medicines.

This chapter provides an introduction to the Australian health system and the role of the consumer, followed by the research problem, aim and objectives.

1.3 Background: Overview of the Australian Health Care System

A key feature of the Australian health care system is that it is underpinned by a universal health care coverage model, with patients[12] having subsidised or free access to health services through public insurance and provision (Willis et al., 2019).

The three pillars of the universal health care system in Australia are free public hospital treatment, subsidised access to medical services provided in the community and private hospitals, and subsidised access to medicines. The funding of the system falls under a hybrid health care model, described as a mix between a welfare state and market model (Dixit & Sambasivan, 2018). The hybrid model comprises funding from taxpayers, private health care insurance and the individual consumer. The consumer thus can decide on the level of health care to seek.

The Australian health system is a complex multi-entity system, comprising public provision of health care, primary health care, specialist services and hospitals, with both public and private providers and with public and private sources of funding. The services are delivered, operated and funded by all levels of government (national, state/territory and local) and the private sector (including for-profit and not-for-profit organisations) (AIHW, Health Expenditure Australia, 2017-2018).

The publicly funded health care system includes access to treatment in public hospitals, general practice (GP), prescription medicines, specialist care (such as mental health, chronic conditions care, palliative care), preventative health services (such as immunisation, cancer screening), pathology, allied health and indigenous health care. These are supported by the Australian Medicare public health insurance scheme, which covers the cost of necessary health care. Attending a publicly subsidised health care

[12] Currently available to Australian and New Zealand citizens, permanent residents in Australia, and people from countries with reciprocal agreements (Department of Health, 2019). Most people outside these categories have to pay full fees for health services or take out private health insurance (PrivateHealth 2019) (AIHW, Health System Overview, 23 July 2020, web site: https://www.aihw.gov.au/reports/australias-health/health-system-overview).

facility for a health service is free or incurs only a low out-of-pocket charge to the patient. However, attending a private health care service typically incurs a higher out-of-pocket cost to the patient.

Private health care in Australia typically operates on a fee-for-service basis, with the fees set by the private businesses that provide the services. These include private hospitals, private specialists, general practice, allied health and others. The service fees provided by the private health care sector are usually set higher than the level Medicare covers, with some services (e.g. allied health) have only limited cover.

The Australian Government funds medicines through the PBS, providing subsidised access to approved[13] prescription medicines. The medicines listed on the PBS have been recommended by the Pharmaceutical Benefit Advisory Committee[14] (PBAC). The price of the prescription medicines is negotiated between the government and the private pharmaceutical company (sponsor) that produces the medicine. The Australian Government agrees on the price of the approved medicine on behalf of all Australians,[15] appearing as a single buyer of the medicine. This medicine cannot be priced higher than the agreed price.[16]

In contrast to the Medicare Benefits Schedule (MBS), where the government covers a proportion of the Schedule fee and the cost of service is set by the provider, the PBS subsidises the medicine with the consumer paying a fixed co-payment per prescription and the remainder of the agreed cost of the medicine being subsidised by the government. Any medicine that has a price below the set co-payment is paid in full by the consumer.

The cost of medicines can be very high, and unaffordable for many Australians. The PBS funding system helps ensure that Australians can access affordable medicine when necessary. In 2019–20, government expenditure for the supply of medicines covered 68% of all PBS prescriptions at a cost of AUD12.5 billion, which covered 89.2% of the total cost of PBS prescriptions (PBS Expenditure and Prescriptions Report 1 July 2019 to 30 June 2020). This means the majority of medicines cost more than the co-payment (general or concession patients), and the PBS covered that cost. Total government

[13] The approval of the medicine is conducted through a two-stage process that includes the assessment of the medicine by the Therapeutic Goods Administration (TGA), and the assessment of the cost-effectiveness of the medicine by the Pharmaceutical Benefits Advisory Committee (PBAC).
[14] PBAC, an independent expert body, advises the Australian Government which new medicines should be listed on the PBS and receive public funding in the community and public hospitals. Other countries use similar advisory groups, such as the Pharmaceutical Management Agency (PHARMAC) in New Zealand, and National Institute for Health and Care Excellence (NICE) in the England, United Kingdom.
[15] This only relates to PBS items and does not include medicines administered in hospital where prices are determined via private negotiations between the state/territory and the manufacturer.
[16] A number of discretionary charges to patients can be applied or deducted by the pharmacist at the point of medicine purchase (i.e. discount the co-payment by up to AUD1.00; charge the Safety Net Recording Fee of AUD1.29 or charge up to AUD4.42 to General Patients (up to the general co-payment amount of AUD41.30 in 2021)).

expenditure on health care in 2019-2020 was over AUD81.8 billion, with the cost of the PBS accounting for 15.5% of total health spending (Australian Government, Budget strategy and outlook, 2019-2020).

1.3.1 Rising expenditure on health care: Australian and world

Health expenditure in Australia is increasing each year. This is due to a number of factors, such as a growing population, improved quality of life and increase in expected length of life, growth in demand for health care, new technologies, and increasing prices in the health sector (Productivity, 2005b).

Expenditure on health care has been rising at a faster pace than economic growth across OECD countries, doubling as a share of the gross domestic product (GDP) since 1970 (Marino & Lorenzoni, 2019). The forecast of government health expenditures by 2044–45, based on population ageing in Australia, showed that health expenditure would more than double from current levels (Productivity, 2005a).

Health care expenditure data from 1990 to 2013 show that the average growth in pharmaceutical expenditures across OECD countries has been decreasing from early 2000s (OECD, 2015)[17]. This is in part the result of government policies aimed at reducing the growth of public spending on medicines. Some of the methods included achieving price cuts via negotiations with pharmaceutical manufacturers, introduction of reference prices across the same medicines with multiple brands, promotion of prescribing and dispensing of generics, and increase in co-payments by consumers (OECD, 2015).

1.3.2 The pharmaceutical market

In general economics terms, the Australian PBS market structure may appear as a single buyer market, a monopsony. The government acts as a single buyer with significant market power in the market of prescription drugs. The government negotiates the price with the supplier of the product on behalf of the consumers, to reduce health care costs. However, there are cases when the bargaining power of the pharmaceutical companies is stronger, the drug differentiation is small, and the level of competition is not high. This leads to situations where some pharmaceutical companies choose to charge higher prices for their medicines.

In addition to the wholesale market, there is a consumer market for prescription medicines that generates the demand for the medicine. In a general consumer demand theory, the quantity of the good that the consumer is willing to purchase at a given price depends on such factors as consumer preferences, consumer's income, and the price of substitute goods. However, in the prescription medicines market, the demand for drugs is driven by the need to cure a health condition. This makes the prescription medicine a good that the consumer may purchase even at a higher price. The benefits of taking the

[17] OECD (2015), Health at a Glance 2015: OECD Indicators, OECD Publishing, Paris, https://doi-org.ezproxy.lib.uts.edu.au/10.1787/health_glance-2015-en

medicine outweigh the high cost. However, as consumers in Australia only pay up to the co-payment amount, the demand does not depend on the price of the medicine charged by the sponsor. The government covers the difference between the agreed price and the co-payment.

Figure 1-4 shows a simplified version of a market relationship between the demand and supply of medicines listed on the PBS. The demand curve (D) represents the quantity demanded in the market for each possible price of the medicine. The demand curve is downward sloping, as the concept of demand theory in microeconomics, stipulates that people buy less at higher prices. The responsiveness of the demand curve to changes in price is measured by the elasticity, that measures factors that affect the demand for the product, such as income, price of substitute product and individual tastes. The supply curve (S) represents the quantity supplied by the producer for each level of price. The supply curve is upward slopping, as companies would be willing to supply more product as the price increases (Folland et al., 2007). The supply curve can shift left or right, which can result in the increase or decrease of price. For example, if the production costs rise, the supply curve would shift to the left, but if more firms with the same product enter the market, the supply curve would shift to the right.

The price at which the product is sold on the market is derived by the intersection of the supply and demand curves.

The price that the government faces results in the PBS expenditure on medicine; the higher the quantity demanded the higher the expenditure. This is particularly the case when the medicine is under patent and there is only one supplier on the market. Government expenditure goes down if the price of the medicine decreases, such as when generic brands enter the market (more suppliers shift the demand curve to the right).

A simplified representation of a demand curve (D) and a single supplier curve (S_{patent}) for a hypothetical Figure 1-4 medicine indicate the equilibrium point for the price under the patent conditions. After the patent expires, more suppliers enter the market, offering lower prices for the same supply, and a new equilibrium would be reached with lower price. However, since the demand for medicine is for the population (and depends on the proportion of population experiencing the relevant medical condition), the quantity demanded is not affected by the decrease or increase in price.

The fixed maximum cost to the consumer (the co-payment) determines the demand for the listed medicine irrespective of the actual agreed price for that medicine. The agreed price is the price that was negotiated between the government and the pharmaceutical company that supplies the medicine. Since the cost to the consumer is relatively low and constant, it can be assumed that the demand for the prescription medicine is price inelastic (represented by the $P_{Co\text{-}pay}$ line) and consumers are insensitive to the real changes in the price of the medicine. The consumer demand is not affected by the price, only by the necessity for treatment. In the case of generic and branded medicines, these products cannot be considered ordinary goods, as demand for prescription medicine does not rise with the rise of income,

and consumer do not start buying more of the medicine. These medicine also cannot be considered perfect substitutes, at least in the real-life examples, where consumers are indifferent to either, and would choose the product with lowest price (Parkin and Bade, 2015). There is evidence that given the lower price of the generic brand, some consumers still choose to buy the more expensive branded medicine (Australian Government, Budget strategy and outlook, 2019-2020). However, these also cannot be considered a Giffen good, which is the opposite of an ordinary good, as consumers do not only buy the more expensive brand of the medicine, and there is not enough evidence to say that consumers with lower income would purchase the more expensive medicine (He, 2021). There are other factors that drive consumers choice of generic and branded medicines.

The horizontal axis shows the quantity, and the vertical axis represents the price ($) on the market for medicine. The downward sloping line marked 'D' represents the demand for medicine in a competitive market. However, due to the subsidisation of medicines, the quantity of medicine bought (demanded) is determined by price level of the co-payment curve, represented by the 'co-pay' horizontal line. In the absence of the subsidy, consumers would face the market price of the medicine, which is much higher, and is represented by the intersection of the supply curves (S_{patent} and $S_{generic}$) and the downward slopping demand curve (D). The vertical line formed between points K and L, represent the difference the government pays for the medicine at the $P_{patented}$ price. Similarly, the vertical line formed between M and N points on the graph show the difference the government covers at $P_{generic}$ price level. This additional cost of the subsidy represents an opportunity cost to the government, as funds for the subsidy could have been allocated to other programs and activities. The magnitude of this loss depends on the degree of the increase in demand and the size of the subsidy. The government (country) is paying more for the product than they otherwise would, however more people have access to the medicine which improves health outcomes and wellbeing.

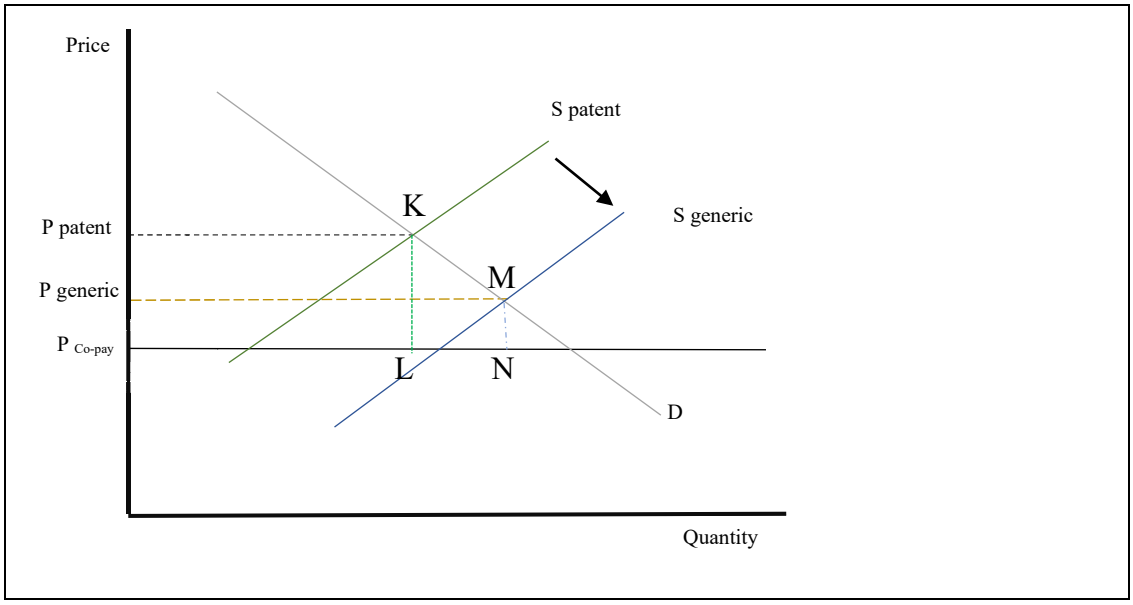
In Australia, when a branded drug comes off-patent and generics enter the market, as described earlier, the drivers for competition do not push the price to government down as quickly as would be expected in a fully competitive market. Hence, the expected fall in government expenditure is not achieved. Although, the government introduced mandatory price drops when the medicine goes off-patent and additional price drop when generic brands are listed on the PBS. This is represented on the graph by the two vertical lines drawn connecting the S_{patent} and $S_{generic}$ with the $P_{Co\text{-}pay}$ line. The manufacturers of the generic medicines also do not have an incentive to offer much lower prices than the originator brands.

The figure simplifies the presentation of the demand curve, by assuming that at the price level of $P_{Co\text{-}pay}$ most consumer will be able to afford the medicine. It is possible to observe, that at that price level, the supplies will not be willing to supply the market, and consumers may not receive their treatment.

The price the government pays for the medicines can be affected by the pricing policy and the size of the medicine's (generics) market. If the agreed price of the medicine is above the patient co-payment,

the consumer does not react to the price changes in the wholesale market. This, in turn, does not affect demand, and thus puts no pressure on the supplying companies to compete on price. This shows the inefficiencies that exist with such a pricing system.

Figure 1-4. The relationship between supply and demand in the market for prescription medicines in Australia.



Abbreviations: D : demand in a regular market; $P_{Co\text{-}pay}$: consumer co-payment (out-of-pocket expense); $P_{generic}$: agreed price (the Government pays) after generic drug(s) enter the market; P_{patent} : agreed price for the branded drug (before generics are available on the market); S_{patent} : supply curve with one brand only; $S_{generic}$: supply curve with multiple brands.

1.4 Background of the prescription pharmaceutical market in Australia

1.4.1 The PBS system

Australia's National Medicines Policy (NMP) is designed to provide Australians with affordable and timely access to safe and efficacious medicines through the PBS. Public funding in the Australian prescription medicine setting began with the establishment of the PBS in 1948 (pbs.com.au). The PBS was preceded by the Repatriation Pharmaceutical Benefits Scheme (RPBS) (est. 1919), which gave free access to medicines to war veterans in Australia (Willis et al., 2019). The RPBS was initially available to a small segment of the population (such as pensioners, widows and veterans) to subsidise a number of very expensive life-saving and disease-preventative medicines. In the second half of the twentieth century the PBS expanded to include all eligible residents of Australia and, at the same time, a co-payment system was introduced (Willis et al., 2019). Under the NMP the cost of the medicine listed on the PBS is shared between the Australian Government and the consumer, with the latter contributing to the cost up to a maximum co-payment. The initial co-payment for PBS medicines was a flat fee of five shillings (AUD7.59 at 2020 rates) (Willis et al., 2019); in 2021, a consumer with a valid prescription pays up to AUD41.30 for most PBS medicines or AUD6.60 if they are a concession card holder (pbs.gov.au).

Medicines on the PBS or RPBS are listed for a particular indication (a condition or population that

meets certain criteria) and with restrictions (which limit who the medicine can be prescribed for). Medicines can be listed on the PBS as 'restricted benefit' or 'unrestricted'. If they are restricted, the medicine is only PBS-subsidised for patients who meet the criteria of the restriction. If the prescription for the medicine is not for the listed conditions and type of treatment, it is not subsidised and the consumer pays 100% of the price.

The PBS has two categories of subsidisation, for general patients and concession patients. Concession patients are eligible consumers who hold a concession card, and pay a lower co-payment for PBS-listed medicines. Additionally, the PBS includes the Safety Net Scheme, which establishes a threshold on total expenditure on PBS per family unit per year to further assist Australians in accessing affordable medicine. After the expenditure threshold (in 2021, AUD1,497.20 for general patients and AUD316.80 for concession patients) is reached, a general patient only pays the concession co-payment for all PBS medicines, and a concession patient receives all PBS medicines for free. Since many health conditions require long-term and multiple medical treatments, the affordability threshold protects consumers from unaffordable medical costs.

In the 1950s, when the PBS was still recently established, there were 139 medicines listed on the scheme; by 2019–20 this had expanded to 902 medicines and 5,371 associated brands (PBS Report, 2019–20). The total cost of the PBS is uncapped; thus, the overall cost of the PBS increases as new medicines are added, as the prices of new medicines increase above the consumer price index, and as the demand for medicines increases. However, this increase in PBS spending is offset somewhat by savings made when drugs lose patent protection.

1.4.2 The PBS-listed medicines

The listing of a medicine on the PBS requires prior approval by the Therapeutic Goods Administration (TGA), which assesses the quality, safety and efficacy of the medicine for the Australian population (Vitry et al., 2015; Willis et al., 2019). As the process of developing the new medicine is very costly, the sponsor[18] of the medicine receives a patent for sole and primary manufacturing of that medicine. After the TGA approves the medicine (the active ingredient), the sponsor of the drug must make a submission to PBAC for PBS listing and provide supporting evidence of the safety, effectiveness, cost-effectiveness and financial impact of the medicine to the Australian population. This submission data is formally assessed by the PBAC.[19] Thus, when a medicine is first listed on the PBS only one brand (that belonging to the sponsor of the patent) of that medicine is available on the Australian market, and this applies until the patent expires.

[18] The sponsor of the drug is the company that holds the patent for the manufacturing of the drug. The sponsor company is not necessarily the one that developed the medicine but may have purchased the patent.
[19] The submissions to the TGA and the PBAC can be done in parallel (simultaneously). However, only if the TGA approves the drug can the PBAC approve the medicine (active ingredient) for PBS listing.

1.4.3 Prices of medicines

Once a medicine has been recommended for listing on the PBS, the price of the medicine on the PBS is negotiated between the government and sponsor of the medicine. Because the single supplier of a new medicine holds a patent, they are a monopoly seller. The prices for new medicines are often very high (Clarke & Fitzgerald, 2010; Willis et al., 2019). Patent lives for new medicines are typically 20 years, a period designed to reflect the costs of investment and to provide incentives to cover the costs of bringing a new medicine to market. The length of the patent often reflects the cost of bringing the new medicine to Australian market, which includes the cost of application for TGA and PBS listing.

The development of the medicines pricing policy in Australia has its roots in the expanded policies around the use of generic alternatives after the expiration of the patent of the original brand (Willis et al., 2019). In most markets, once a patent expires a competitive market is created as multiple producers enter the market, lowering the price until the equilibrium price is reached. This is also generally true for the market for medicines; however, because the initial price for the approved PBS medicine has been agreed by government and the sponsor, the competitive pressures are affected by the policy levers.

1.4.4 PBS generic medicine prices

Typically, new entrants (generic brands) to a market can provide a product at a lower cost than the original patent owner because they do not have to cover research and development costs and they have an incentive to provide at a lower price to create market share. Thus, the cost of off-patent drugs (generic alternatives) is lower than the branded medicine.

In the pharmaceutical market in Australia, for the entry of a new manufacturer of a medicine to create competitive pressure two conditions are required. First, the manufacturer would need to offer a lower price than the original brand; and, second, the new entrant would need to capture market share. Because consumers face the same price for all medicines, the impact of price competition does not directly affect consumer choices, as it would, for example, with the entry of a new smartphone model, where the consumer pays the full cost of the good. The consumer has an incentive to choose the cheaper brand of smartphone device, and thus companies compete for market share through price (for smartphones with similar features).

In Australia a set of policies was mandated to lower the price of generic medicines entering the market. A mandatory price reduction is applied once when a generic enters the market. Subsequent price reductions are applied through mandatory price disclosure reported by pharmacies for the actual prices for each generic medicine (including any discounts) (Willis et al., 2019).

As an example, summarised in Table 1-2, the original brand of the cholesterol-lowering drug atorvastatin (generic compound name) or Lipitor (manufactured by Pfizer) cost (international dollars) $0.87 (AUD1.20) per daily dose in 2006 before generic alternatives entered Australian market, and $0.28 (AUD0.40) in 2014, two years after the first generic was supplied in Australia (Roughead et al.,

2018). Comparatively, in 2006 the price of atorvastatin per daily dose was lowest in New Zealand at $0.10 (generic entered in 2010), but higher in Singapore (generic entered in 2011) at $2.72 and South Korea (generic entered in 2008) at $2.89 per daily dose supply. The data from 2014 show that the price has decreased across all countries; in New Zealand the price was at $0.03, $0.47 in Singapore and $1.15 in South Korea (Roughead et al., 2018).

Table 1-2. Prices of atorvastatin (per daily dose) in four countries pre- and post- generic alternatives

Year	Australia	New Zealand	Singapore	South Korea
Generics entering market	2014	2010	2011	2008
Data from 2006	$0.87	$0.10	$2.72	$2.85
Data from 2014	$0.28	$0.03	$0.47	$1.15

Note: all prices are in international dollars

However, according to the Grattan Institute (Duckett et al., 2013) this was not the case prior to 2011 in the Australian market. The prices of Australian off-patent drugs and their generic alternatives fell much more slowly than expected (Duckett, 2017). The off-patent medicine prices cost more compared to other OECD countries, mainly due to a limited number of suppliers of the off-patent medicine and regulated prices. In 2011–12, prior to the first atorvastatin generic entering the market, Lipitor cost the Australian Government AUD570 million and patient co-payment totalled AUD130 million, with the PBS price per one month supply at AUD51.59. In contrast, in New Zealand a generic atorvastatin, Zarator (also manufactured by Pfizer), cost AUD5.80 per three-month supply.

A major strategy to contain the rising PBS expenditure included generic medicine use, as generic brands are mostly cheaper than the branded. However, before 1990 the use of generic brands in Australia was relatively low (Willis et al., 2019). The government introduced a minimum pricing policy to increase the generic share of the market. This policy set a benchmark (reference price) that allowed the government to subsidise the medicine on the basis of the cheapest brand that is therapeutically equivalent.[20] Under this policy, the sponsors of the original brand were allowed to charge a price above the reference (benchmark) level, but the government subsidy would cover only the cheapest, or 'reference', brand (Willis et al., 2019).

Once the medicine patent expires and multiple off-patent medicines and generic equivalents are available, the reference price applies. The producers of the original brand of the medicine can set their price higher than the benchmark, but the consumers must pay the difference. This is referred to as a price/brand premium, which is the difference between the actual price of the medicine and the benchmark price (Australian Government, Department of Health).

[20] Therapeutic equivalence or bioequivalence indicates brands that may be interchange without differences in clinical effect (PBS).

1.4.5 The brand premium policy

The brand premium policy was introduced to increase price competition by allowing the companies of branded medicines to set their own price for multi-branded items (Sansom, 2004). One of the policy's intended goals was to increase consumer awareness of price differentials between competing brands, to encourage greater use of cheaper generic products (Probyn, 2004). The brand premium was to act as a signal to consumers that would increase demand for the generic brands and put downward pressure on drug prices (McManus et al., 2001). The consumer had a choice between therapeutically equivalent brands based on price.

However, there was an issue with prescription mechanism as the pharmacists were not allowed to substitute different brands from the brand written on the doctor's prescription. This also contributed to the low uptake of generic brands in the early 1990s. As the generic brands had low market share, the impact on PBS expenditure was also low.

Brand substitution policy

In order to further facilitate the uptake of generic medicines, in 1994 a policy was introduced allowing pharmacists to substitute branded products to the lowest priced approved bioequivalent generic product with the permission of the patient, provided the prescribing doctor had not prohibited brand substation on the script (Sansom, 2004; Willis et al., 2019).

In 1994 there were 124 medicines that had a least one brand with a brand premium; by 1999 this had this increased to 240 (McManus et al., 2001). Of the 902 medicines listed on the PBS in 2020, 5,455 brands are available of which 470 (7.7%) have a brand premium. In 2020, the average brand premium amount for PBS-listed pharmaceuticals was AUD5.17 (range AUD0.50–35.30). Since the introduction of the brand substitution policy, the percentage of medicines dispensed at benchmark price (i.e., medicines where one brand has a brand premium) increased from 17% in 1994 to 45% in 1999 (McManus et al., 2001). This number was an average of 79% between 2012 and 2020 reporting periods (PBS Expenditure and Prescription Reports (from 2002 to 2020).

The increased market share of generic medicines shows the success of some policies implemented over the past 30 years. However, demand for medicines with brand premium continues. The demand for branded medicines is allowing the brand premium to remain part of the pricing policy and preventing a faster decrease in prices.

Consumers' preference for brand premium

There could be several reasons consumers buy medicine with a brand premium, including familiarity with a brand consumers have used before; prescribers' preferences; perception of differences between the brands that may be relevant for that consumer; and preferences for presentation or the actual medicine (brands of the same medicine may differ in colour or size). Additionally, consumers may not understand the price signalling that was intended by the policy. It is possible that consumers are unaware

of the pricing mechanism in Australia and treat higher price as an indication of higher 'quality'.

The word 'premium' itself may be a signal of a 'premium product'. The impact of the 'brand premium' attribute on consumer preferences for prescription medicines has not been fully explored in the literature. However, research in other areas (e.g., food, clothes, automobiles) shows that actual or perceived brand quality was a significant determinant of accepted price premium (Anselmsson et al., 2014; Dwivedi et al., 2018; Munir et al., 2017). Finkelman (1993) finds that satisfied customers (i.e., those who receive high quality of service or feel better about a product) have a higher willingness to pay for the product or service. Similarly, (Homburg et al., 2005) report that companies can charge a price premium if they enjoy a high level of customer satisfaction.

Consumers may believe that the original branded drug is better than the 'generic copy' or they may feel loyalty to the brand, even though the quality of the product is the same (as per TGA approval). Therefore, the idea that consumers are willing to buy medicine brands that charge brand premium could be related to a perceived brand quality by the consumer. The perceived quality of branded medicines has been researched; for example, a survey on generic and branded uptake of venlafaxine in New Zealand (Mackrill & Petrie, 2018) found that more than half of surveyed participants (58.1%) preferred branded over generic medicines. Additionally, those respondents who previously took the branded version showed a significantly higher belief that branded was better and safer and that generic medicines had more side effects.

Although direct-to-consumer advertisement of prescription medicines is not allowed in Australia, the consumer can be influenced indirectly, and thus have a certain perception of the brand of the medicine (Mackenzie et al., 2007). This can potentially create demand for the medicine based on the familiar brand name, the fact that the medicine is branded (original brand), or that it has a brand premium attached to it and thus is perceived by some consumers as better than a generic brand.

The impact of prescription reimbursement process on rising prices for generic medicines

In general, the consumer receives a script from the doctor and goes to the pharmacy to fill the prescription. The pharmacist may recommend a cheaper generic brand and sell it to the customer. If the cost of the medicine was above the co-payment, the customer pays the amount of the co-payment and the rest is subsidised by the government. Ten years into the PBS Minimum Pricing, policy the prices of generic medicines were still not substantially lower than the original brands, mainly due to the lack of incentives to prescribe or purchase a generic brand (Lofgren, 2007).

Although the reimbursement data show that generic brands were being sold, the prices were not decreasing (Lofgren, 2007). The changes to the policy to encourage generic uptake were present for more than a decade, but the expected price drops due to competition between brands were not observed. This was partly due to the reimbursement process and lack of transparency in the cost of the medicine to the pharmacist compared to the government price agreement with the sponsor. The competition

between suppliers of generic and branded medicines drove competition in prices to the pharmacist, but not in prices to the government or the consumer because of the structure of the market.

There was a major impact from the private negotiations between the manufacturers and the pharmacies, with the latter being offered discounts for higher sale volume of the brand, and the pharmacies receiving the profits from the lowered prices (Chong et al., 2011); (Vitry et al., 2015). For some brands the discounts received by the pharmacies were as high as 30–50% (Duckett et al., 2013; Lofgren, 2007). As previously mentioned, from the early 2000s the cost of medicines in Australia rose relative to international costs, particularly for generic medicines (Willis et al., 2019).

In 2005 a new policy introduced a mandatory 12.5% price reduction for the first generic brand listed on the PBS, with the reduction increased to 16% in 2010 (Duckett et al., 2013); PBS, Price Reduction). The price reduction was set at 25% from 2018 (PBS, First New Brand Price Reductions 2021). However, the government savings were modest.

1.4.6 Mandatory price disclosure

For these reasons, in 2006 a new PBS reform (price disclosure) disallowed the discount system to the pharmacy and required pharmaceutical companies to disclose to the government the prices at which drugs were sold to the pharmacies. The policy obliges the pharmaceutical companies to report on sales of all eligible medicines, and the disclosed price (the price at which the pharmaceutical companies are supplying the medicine to the pharmacies) across all brands of the medicine. The new price subsidised by the government is then estimated based on these disclosed prices at six-monthly intervals. Since the introduction of the price disclosure policy, the price of medicines has reduced (Chong et al., 2011).

Additionally, to facilitate benchmarking, all medicines listed on the PBS were allocated to one of two formularies, F1 or F2. This distinction also allowed for different price reduction policies to be allocated to the brand depending on the list it was on. Medicines allocated to the F1 formulary were those with a single brand; medicines with multiple brands were allocated to F2.[21] If a medicine is listed in F1 but a new brand enters the market, it is then moved to F2 list.

1.4.7 Mandatory price reduction

In 2008 a mandatory price reduction applied to all F2-listed medicines. Medicines listed in F2 were further categorised by the discount received by the pharmacy (at October 2006), with medicines in F2A being those where the discount was less than 25%, and those in F2T having an associated discount of more than 25%. Under the new policy, F2A medicines underwent mandatory price reduction of 2% per

[21] Medicines listed in F2 were further categorised by the discount received by the pharmacy (at October 2006), with medicine sin F2A were those where the discount was less than 25%, and F2T were those that had an associated discount of more than 25%. The F2A medicines would have mandatory price drop of 2% per year for three years, while F2T medicines would have a one off 25% price drop in August 2008.

year for three years, while F2T medicines were subject to a one-off 25% price drop in August 2008. These reforms reduced medicine prices by an average of 42% (ranging from 10–98%) between 2012 and 2014 (Vitry et al., 2015; Willis et al., 2019).

Since the introduction of the policy, price disclosure is applied to F2-listed medicines twice a year, with the reimbursement price calculated based on the weighted average disclosure price (Lofgren, 2007; Roughead et al., 2018; Vitry et al., 2015; Willis et al., 2019).

In 2015 all F1-listed medicines (including all types of medicine administration) became subject to a policy of a retrospective anniversary price reduction starting in 2018, with a cumulative 5% statutory price reduction for every 5 years of being listed on the PBS (PBS, Fact Sheet – Anniversary Price Reductions). The reduction flow-on effect also affected combination drugs even if the other drugs (in the combination) were listed for less than the anniversary period.

1.4.8 The rising cost of medicines

The government thus has used a range of pricing policies to bring the cost of medicines down, including increasing transparency of the medicine supply, increasing incentives for the dispensing of generic brands, and mandatory decrease of the listed prices. Even with these policy changes, however, compared to some OECD countries the prices the Australian government paid for generic brands were much higher. As an example, the New Zealand government subsidisation program prefers a single provider model; thus, only one brand is subsidised by the government. This helps reduce the price of the medicine (Duckett 2013), as it creates competition among the suppliers to be the single supplier, and more incentive to reveal the true cost at which they are willing to supply, with the government as a monopsony buyer.

International comparison of some medicines in Australia, the United Kingdom, New Zealand and Canada shows that the set prices in Australia were 3.7 times the lowest price across the other three countries (Duckett, 2017).

There are a number of reasons why the availability of generics on the market and the price disclosure policy may not lower the price of medicines as quickly as has been observed in other countries. Consumers do not purchase medicines in a straightforward competitive market in which they have full information or face competitive price signals, and their decisions are mediated by the prescriber and the pharmacist. The co-payment means that the consumer does not observe or respond directly to changes in the prices to the supplier (when the price of the medicine is above the capped co-payment price).

The introduction of the price disclosure policy and substitution of generic brands policy was intended to increase the price competition among manufacturers, and to drive reductions in the prices of off-patent medicines, but the extent of uptake of cheaper brands determines the effect of these policies. If consumers continue to purchase the originator brand, the impact of price disclosure is smaller. This is

particularly relevant where the originator brand maintains a brand premium,[22] as the price reduction is applied only if the difference between the calculated disclosure price and the approved ex-manufacturer price is higher than 10%.

In the 2018–19 financial year, of all prescriptions where at least one brand had a brand premium, 22.9% of prescriptions for which alternative brands are available were dispensed with brand premium (Report on PBS Expenditure and Prescriptions 2018-2019). Although cheaper generic versions of the medicine are available, some consumers continue to choose the more expensive originator brand. As discussed above, this may be because the consumer attaches a value to the brand premium element that impacts positively on their decision to buy branded medicine over the generic – for example, following the doctor's prescription (when brand substitution was allowed), preferences based on the appearance of the medicine (colour, size) or other aspects of the medicine; consumers also may also simply not pay attention to the differences in brands or prices. The demand for brands with brand premiums could also be a result of poorly understood mechanism of substitution of generic medicines by the older members of the population (Bulsara et al., 2010).

1.4.9 Additional government initiatives

As part of the 2018–19 Budget the Australian Government introduced measures to increase the uptake of generic and biosimilar medicines listed on PBS (Australian Commission on Safety and Quality in Health Care). This included the mandating of active ingredient prescribing to begin in 2021.[23]

This mandate is a the most significant policy change in the field of prescribing since 2003, when the Australian Government mandated that default settings of computer-based prescriptions should offer the choice to prescribe generic drugs, as well as having the 'Not for substitution' box unchecked (Burton, 2003; Hassali et al., 2005). The expectation at the time was that through the prescription of generic brands the government would save AUD111 million over four years (Hassali et al., 2005). Further reforms were still needed, however, to increase transparency in the prescribing and dispensing process in Australia.

The initiative to use the active ingredient prescribing incorporates standardised international non-proprietary names (INN) for medicines and would apply for most PBS/RPBS items (Australian Commission on Safety and Quality in Health Care). The reasons cited for this mandate include assisting in conversations between pharmacists and consumers regarding generic and biosimilar alternatives, and

[22] The weighted average disclosed price is calculated based on the cumulative total revenue and volume sold per brand (all strength and forms) Then compared to the approved ex-manufacturer price for the medicines for each form and strength of the medicine.

[23] National Health (Pharmaceutical Benefits) Amendment (Active Ingredient Prescribing) Regulations 2019, and the Veterans' Affairs Pharmaceutical Benefits Schemes (Electronic Prescriptions and Active Ingredient Prescribing) Amendment Instrument 2019.

promoting the appropriate uptake of generic and biosimilar medicines, with a decrease in out-of-pocket expenses for some consumers.[24]

This change in the prescription practice is evidence of a policy shift to increase the use of generic medicine, thus increasing the market share of generics compared to branded medicines. This is also a way to ensure that the competitive market forces associated with the approval of generics are effective in this highly regulated market. To achieve improvement of financial sustainability of the PBS and RPBS, and for the price disclosure policy to work as intended, the majority of medicines need to be dispensed as generics (when available).

1.4.10 International comparison

The mechanisms for generic alternatives entering the national pharmaceutical markets vary around the world (Alrasheedy et al., 2014; Godman et al., 2017). In European countries generic promotion is seen as a contributor to saving for public payers, and different approaches are used to enhance uptake of generic brands (Vogler et al., 2017). These measures, as reported by Vogler et al., (2017) include policies for prescribers (using INN names), financial incentives for pharmacists to dispense cheaper generics and consumer incentives to choose cheaper medicine (e.g., low co-payment for generics, reference price system).

Godman et al., (2017) report a variety of approaches across the European continent, including regulated systems (France), a free pricing market with manufacturers setting prices according to market demand/supply with some regulation from the government (UK, Netherlands and Sweden) and a combination of the two (Austria).

Similarly to Australia, The Netherlands uses a reference pricing for reimbursement; however, the Dutch government only pays for the lowest priced generics, while patients pay the difference for any other brand (Godman et al., 2017). However, as medicines in The Netherlands are covered by the mandatory individual health insurance, the insurer may only reimburse one brand (preferred list of brands), with patients liable for the entire cost of non-preferred brands (Morgan, 2016). This approach led to a drop

[24] Active ingredient prescribing will:

- Increase consumer health literacy around their medicines and make communication clearer and unambiguous
- Improve safe and quality use of medicines with consistent and standardised descriptions of medicines.
- Empower and equip prescribers and consumers to better understand the active ingredients in medicines
- Assist conversations between pharmacists and consumers concerning generic and biosimilar alternatives
- Promote the appropriate uptake of generic and biosimilar medicines, with a decrease of out-of-pocket expenses for some consumers
- Improve financial sustainability of the PBS and RPBS
- Enhance prescribers' stewardship role of the PBS, and encourage more sustainable prescribing practices
- Align Australian prescribing with international practices.

in prices to as low as 2–4% of pre-patent expiry prices (Godman et al., 2017). Similar drops in prices were seen in Sweden, where a compulsory substitution and a review of the prices, which occurs twice a month, have led to increased competition between brands.

The Belgian system resembles that of Australia, with a mandatory price reduction after the patent expiration, as well as a policy that government reimbursement is only up to the reference price (Godman et al., 2017).

An interesting effect was seen in South Korea with a new policy introduced in 2012, where the government set a maximum reimbursement (ceiling) price for the medicine's brands (generic and branded). This, coupled with a lack of incentives to prescribe generics by doctors, or substitute generics by pharmacists, led to a shrinking of the generics market share (Kwon et al., 2015). This may have resulted from a lack of coordination between demand and supply, and has been blamed on the attitude towards generics of the prescribers in South Korea (Godman et al., 2017; Hasan et al., 2019).

1.4.11 The role of the doctor and the pharmacist

Prior to the recent policy change mandating the doctor prescribe based on the active ingredient of the medicine, rather than brand name, an Australian doctor's prescription (prescriber) could be written with an active ingredient (compound name) or with a product name (the original brand or generic brand equivalent). If the doctor chose the brand name (rather than the compound name) they also had the option to select the 'no brand substitution allowed' checkbox. This gives the opportunity for the prescriber to write a prescription to a specific brand. By leaving the box unchecked, the prescriber leaves the opportunity for the pharmacist to offer the consumer a different brand of the medicine (i.e., a generic), provided that the product has the same active ingredients. If a consumer agrees, any available brand of the active ingredient can be dispensed by the pharmacist. Given that there is no direct-to-consumer advertising allowed for prescription medicines in the Australian setting, the Australian consumer may not be aware of the availability of alternative cheaper brands. Further, consumers are likely to have limited understanding of the details of the PBS funding system.

There is some evidence, although limited by the sample size,[25] that consumers do value branded medicines (Hassali et al., 2005). Consumers' perceptions of brands could relate to beliefs about the difference in effectiveness and side effects, quality of the medicine across brands, or use of brands depending on the severity of the medical condition, as well as confusion about the different brand names (Hassali et al., 2005; Nardi & Ferraz, 2016).

The demand for generic medicines may be driven by the cost. In Sweden, where the government reimburses only up to a cost of cheaper generic alternative, consumers tend to buy generic medicines.

[25] Qualitative interviews conducted with 16 respondents (Melbourne, Victoria).

However, if the branded medicines are priced not significantly higher than cheaper alternatives then consumers tend to choose the branded medicine and pay the difference (Hassali et al., 2014).

Additionally, recommendations from prescribers and pharmacists may play a role in the choice of the brand for consumers, and there is some evidence that doctors and pharmacists do recommend branded over generic medicines. In a survey of general practitioners conducted by the AMA (2006), doctors were found to be reluctant to prescribe generic medicines (AMA, 2006) and pharmacists were reluctant to recommend substitution because of concerns about reduced efficacy (Chong et al., 2011). (Mansfield, 2014) show that while 55% of PBS prescriptions were potentially substitutable, actual substitution rates were only 33%, as pharmacists do not always offer to substitute, and patients do not always agree. Overall, there is limited publicly available information on how many scripts are filled with generic medicines.

1.5 Markets for pharmaceuticals

While it is widely accepted that the granting of a patent to a new medicine provides incentives for developers of new medicines, it means that governments pay higher prices for new medicines, and this is a key driver of high and increasing pharmaceutical expenditure. Nevertheless, when the patent expires, the entry of new manufacturers should create competitive pressure to reduce prices and, therefore, expenditure for government, which is important for sustainability of health care expenditure.

The NMP acknowledges that increasing affordability of medicines, and removing or lowering cost as a barrier of access to medicines, may interfere with the 'normal market mechanisms' (NMP, 2000).

The nature of the health care market, and specifically the market for pharmaceuticals, is that the consumer has limited information and relies on the advice of two agents (prescriber and pharmacist) to make choices to maximise utility. This asymmetry of information may result in decisions that do not reflect what the consumers would choose were they fully informed. For example, the doctor may prescribe a specific brand name based on what they usually prescribe, or based on pharmaceutical promotional material, or because the prescribing software they use defaults to a particular brand. In addition, the prescriber may not have enough time during the consultation to discuss the different brands with the patient, or may not feel this is important because the generic alternatives should work as well as the original brand. In a similar manner, the pharmacist may have a number of incentives to dispense a particular brand. They may recommend a product based on availability, or profit, since they are able to receive discounts for some products.

In summary, the consumer does not face the true cost of the medicines at the point of consumption, (only the co-payment), and the government is not involved in the decision at the prescribing and purchasing level.

Under the condition of a wholesale market, the presence of the brand premium results in a market with

imperfect competition. The existence of the brand premium indicates that one brand always costs more and thus has a differentiated product. The consumer market plays a role in the supply of the medicine with brand premium since consumers maintain demand for these brands. The manufacturer of the branded medicines (with brand premiums) can continue making higher profits if the market share (consumer demand) is maintained at a higher level. The manufacturers of generic medicines do not have an incentive to offer much lower prices than the brands with brand premiums. The manufacturers no longer benefit from giving larger discounts to the pharmacies to increase sale volumes, as there is a reduced downward pressure on the generic drugs to compete by lowering prices.

The current market is a response to the existing pricing policies and continues to increase the PBS expenditure to the government (taxpayer). In relation to consumer demand, the challenge for the government is in creating an incentive for the consumer to choose the cheapest brand to generate a competitive pressure among the suppliers.

This research is motivated by the participation of the third party (consumer) in the market and seeks to identify whether active consumer participation and awareness at the population level can influence the demand for generic medicines. Such an increased demand for generic medicines can motivate manufacturers to further decrease prices to gain more market share.

1.6 Research problem

Given the policy settings and the nature of the market, an increase in utilisation of generic medicines can lead to a decrease in total pharmaceutical expenditure (Dylst, Vulto, & Simoens, 2013; Godman et al., 2017). The cost to the government of medicines in Australia is high, especially when the medicine is new and only one patented brand (the original branded medicine) is available on the market. The price of the medicine is expected to decrease when other brands (generic brands) with the same active compound enter the market. However, this is not always the case. For instance, the Grattan Institute (Duckett et al., 2013) analysed fifty-four different drugs on one of the 'top lists' of PBS – either from the top 50 drug-dose combinations by prescription volume or from the top 50 by total expenditure – and concluded that the estimated opportunity cost for Australians is AUD3.5 million a day.

Several studies have demonstrated that the prices for medicines in Australia remained high even after generic copies entered the market. Clarke and Fitzgerald (2010), after analysing the prices of statins in Australia and England between 2002 and 2009, report that four years after patent expiry the Australian price was four times that paid in England. Mansfield (2014) analysed reimbursement prices for 15 medicines with generic substitutes and find that there was on average a seven-fold higher price for medicine in Australia than in England. The latest reports by (Duckett, 2017; Duckett & Breadon, 2015) indicate that prices of generic medicines in Australia are much higher than those in other OECD countries.

A focus on demand-side policies involving prescriber, pharmacist and consumer has the potential to

increase demand for generic brands and increase their market share, which could increase competition between the producers of the medicine (generic and branded) and create downward pressure on the price to government (Dylst, Vulto, Godman, et al., 2013). The emphasis of consumer-centred policies may stimulate the demand for generic products, by increasing health literacy, awareness and understanding of the prescription medicine market in Australia. This is particularly useful in the Australian setting where the consumer does not have a price signal (maximum cost to patient is the co-payment) and increasing understanding of generic medicines is one of the pathways to increase demand.

The existing research on the demand for the generic medicine in the Australian prescription pharmaceutical market is limited. On the one hand, investigators focus on the increasing PBS costs and policies affecting the use of generic medicines (Hassali et al., 2014; Lofgren, 2004, 2009; Mansfield, 2014); on the other hand, there are a number of studies of doctors and pharmacists' behaviour regarding prescription of generic medicines (Beecroft, 2007; Chong et al., 2011; Dylst, Vulto, & Simoens, 2013), but few of consumers' acceptance of generic medicines (Bulsara et al., 2010; Chong et al., 2011; Hassali et al., 2005). The research in this field is interdependent, as the attitude towards the generic medicines among providers and consumers can influence the demand for generic medicines. The attitudes of the Australian consumers have been the least explored.

The research undertaken for this PhD addresses whether and how consumer preferences can drive demand for generic medicine brands and whether it is possible to use policy levers around prescribing and dispensing of medicines, as well as policy on brand premiums, to more effectively manage government expenditure on medicines. As the consumer is to an extent a passive participant in the current policy context, this research aims to identify any triggers that would impact active consumer participation.

This research focuses on determining the factors that may affect consumer preference for medicine brands. These factors include the doctor's script, the pharmacist's recommendation, the price to the consumer, the brand of the medicine, consumer awareness and understanding of the medicine market, consumer personal preferences and convictions, among others. The research involves a series of inter-related studies to explore the impact of information about prices and brand premiums within this broader context of factors influencing demand.

1.7 Research framework

1.7.1 Health economics

The field of health economics studies how resources are allocated to and within the health economy, including the production and distribution of health care across population (Folland et al., 2007). Economic evaluations are used to compare the costs and benefits of different policies, programs, or interventions, and are often used in health economics to determine the most cost-effective ways of providing healthcare services.

Health economics uses both positive and normative frameworks to analyse and evaluate health-related phenomena (Graafland, 2021). Normative economics provides a framework for evaluating the ethical, moral, and social considerations involved in healthcare policies and interventions, and for making recommendations on what should be done (Hurley, 2000). The normative foundations of economic evaluation are based on the idea that economic evaluations should be used to inform decisions that maximise social welfare. These principles reflect values that are important to society, such as fairness, efficiency and equity (Hausman, 2021).

Positive economics aims to describe and explain the behaviour of healthcare providers and consumers, and how they respond to changes in incentives and regulations (Hausman, 2021). For example, positive health economics may use supply and demand analysis to explain how changes in the availability of healthcare services affect the behaviour of consumers and providers, or it may use econometric models to test the impact of policies on health outcomes.

Health economics uses microeconomic concepts such as supply and demand, consumer choice and market structure to analyse the behaviour of health care providers and consumers, and to understand the effects of health care policies and interventions on wellbeing of individuals.

Overall, health economics provides a rich and diverse field for the application of microeconomic theory, and the use of positive and normative theories allows for a comprehensive understanding of the complex interactions between healthcare providers, consumers, and policies.

The scope of this thesis involves the problem of consumer choice and examines the effect of changing consumer preferences on demand for regulated good (prescription medicine). In particular, the thesis explores the factors that impact consumer preferences for the medicine, and studies how changes in preferences between generic and branded medicines can impact the demand for a new hypothetical government policy. This research problem is relevant and important because it has implications for health care professionals, government health care funding organisations and policymakers who want to understand consumer behaviour and make informed decisions to provide best care to individuals that align with consumer preferences and values.

1.7.2 Rational choice theory

The rational choice theory that explains consumer behaviour by assuming that consumers are rational and make choices that maximise their utility, given the individual's limitations of budget and prices of goods available to them (Folland et al., 2007). The utility of each individual is explained by the satisfaction derived by the consumer from their consumption of the good. The more utility the consumer receives form a good, the more that good is in demand, and thus directs their choice. The theory also assumes that consumers have a well-defined preference order over goods, and they choose the combination of goods that gives them the greatest total utility.

Rational choice theory plays a crucial role in the analysis of decision-making behaviour and is used to

study the impact of various factors on consumer decisions, such as change on income, prices and consumer preferences. It is also used to evaluate government policies, such as subsidies, or tax, that aim to influence consumer behaviour and improve economic efficiency. Principles of rational choice theory can help policymakers make informed decisions that better align with consumer preferences and improve consumer welfare.

1.7.3 Demand theory

The study of consumer decision making associated with the branch of economics, called microeconomics. Microeconomic theory is concerned with individual behaviour and interactions between individuals and markets and is capable to modelling consumer choices (Kreps, 2013). Demand theory is a fundamental concept in microeconomics that explains the relationship between the price of a good and the quantity of that good that consumers are willing and able to purchase (Kreps, 2013). Demand theory, as opposed to the consumer choice theory, is concerned with the overall quantity of a good or service that consumers are willing and able to buy at a given price. It seeks to explain how the price of a good or service affects the quantity demanded by consumers, and how changes in other factors such as income or the price of related goods can influence demand. Demand theory is concerned with the market as a whole and the behaviour of consumers in aggregate.

The demand theory assumes, that the quantity demanded of a particular good or service is a function of several factors, including price, income, preferences and availability, price of substitute goods or services and elasticity. The law of demand, states that as the price of a good increases, the quantity demanded of the good decreases, and vice versa. This inverse relationship between price and quantity demanded is based on the assumptions that consumers are rational and will substitute cheaper goods for more expensive ones.

Demand theory has three basic concepts based on the idea that consumers have wants and needs, and that their demand for goods and services is driven by a variety of factors. In this context, "wants" and "needs" are different from "demand" in that they represent different levels of consumer desire or willingness to purchase. Wants are the desires or aspirations that consumers have for a good or service. Wants are shaped by factors such as culture, social norms, and personal preferences. Needs, on the other hand, are the basic requirements for survival and wellbeing. Needs include things like food, shelter, and clothing. While wants are often discretionary, needs are essential and must be satisfied for consumers to function. Demand is the amount of a good or service that consumers are willing and able to purchase at a given price. When consumers have a high level of demand for a good or service, they are willing to pay a higher price for it.

In summary, demand theory recognises that consumers have both wants and needs, but that their willingness to purchase a good or service depends on their level of demand for it. While wants and needs may influence the consumer's decision to purchase, demand is ultimately what determines the

quantity of a good or service that consumers are willing and able to buy at a given price.

1.7.4 Consumer choice theory

Consumer choice theory is a framework that explains how consumers make decisions about what goods and services to consume when faced with limited resources (Folland et al., 2007). The theory assumes that consumers are rational and aim to maximise their utility or satisfaction from consuming different goods and services, subject to their budget constraints.

Consumer choice theory is concerned with understanding how consumers make choices between different goods and services based on their preferences and constraints. It seeks to explain why consumers make certain choices and how their choices are influenced by factors such as price, income, and product features. Consumer choice theory is concerned with individual consumers and their decision-making processes.

In the field of microeconomics, consumer choice theory is used to model consumer behaviour, predict consumer responses to changes in market conditions, and to understand the factors that influence consumer choices.

Overall, consumer choice theory seeks to explain how consumers make choices based on their preferences, budget constraints, and the trade-offs they must make between different goods and services. Consumers have preferences for certain goods and services over others, based on factors such as taste, quality, and price. Consumers seek to maximise their utility, or satisfaction, from the goods and services they consume. They make choices that increase their overall utility, subject to their budget constraints. Consumers face budget constraints, which means they have limited resources to spend on goods and services. They must allocate their resources in a way that maximises their utility, or satisfaction.

The study of consumer choice is not limited to microeconomics, as it is also studied in a field of behavioural economics which is a subfield of economics that combines insights from psychology, sociology, and neuroscience to explain how individuals make decisions. Behavioural economics studies how people make decisions in the real world and how cognitive biases, emotions, social norms and other psychological factors affect their choices (DiClemente & Hantula., 2003; Foxall, 2017).

Additionally, the study of consumer choice is relevant to other fields such as marketing, psychology, and sociology, which explore various aspects of consumer behaviour, including brand loyalty, social influence, and cultural factors that shape consumer preferences (Casielles & Alvarez, 2007; Dahl, 2013; Shavitt & Cho, 2016).

In addition to the traditional consumer choice theory, Lancaster (1966) presented a new approach to consumer theory by including the properties of the goods themselves, with the approach looking at changes in demand as a result of changes in product attributes, or as a result of a new good entering the

market (Lancaster, 1966; Warshaw and Droge, 1986). This framework allows for the comparison between the branded and generic medicines by presenting the consumers with a choice of two medicines described by a variety of characteristics with the idea that the respondents would choose based on a bundle of characteristics of the medicine.

The choice theory has several research methods that can be used to explain consumer preferences. The different methods analyze consumer behaviour and can estimate consumer preferences.

The most common data collection techniques in research are a survey and observational data (Louviere et al., 2000). These techniques use a variety of methods that can be described as stated preference (SP) methods and revealed preference (RP) methods. The SP methods are a type of survey where participants are asked to state their preferences for different options, such as different level of quality, prices or brands (Johnson et al., 2013). These methods can be used to estimate the value the consumers place on different attributes of goods and service. The RP methods are based on observing actual consumer behaviour, such as sales data. These methods can be used to validate the results of SP methods and to estimate the actual demand for different goods or services. However, the RP methods cannot predict how the demand will change for product if a new brand comes into the market. The exact factors influencing consumer choice are not available in the observational data, or such data does not exist at all.

Therefore, research studies like this thesis, can apply different methods to collect data that can provide information on consumer preferences, in particular on the factors that influence consumer choice, and thus provide data that can help estimate the changes in demand for good or service if some key factors in the available options also change.

One of such research method is a discrete choice experiment (DCE) in which participants are presented with a series of hypothetical choices between different combinations of attributes and asked to choose that option that they prefer (Train, 2009). DCEs can be used to estimate the relative importance of different attributes in shaping consumer preferences and to understand how changes in these attributes might impact consumer behaviour. The use of DCEs as a tool to investigate the impact of health policies has been long established (Viney et al., 2014).

By using available research methods in the context of rational choice theory, researchers can gain a deeper understanding of consumer behaviour and how it is influenced by different factors. This information can be used to inform decisions about pricing, production, and to evaluate government policies that aim to influence consumer behaviour.

1.7.5 DCE within economic framework

DCEs are an economic evaluation tool, that can be used to estimate the value an individual places on different factors of a particular good or service. Economic evaluations aim to compare costs and benefits of different interventions and policies, with DCE used to estimate the benefits. DCEs can also be used

to estimate the willingness-to-pay for different healthcare services, which can be used to inform resource allocation decisions. DCEs can be a useful tool in economic evaluations of healthcare interventions and policies, providing valuable insights into patient preferences and the relative value of different aspects of healthcare services.

The normative foundations in economics evaluation guide the economic decision making via the principles that reflect values that are important to society, such as fairness, efficiency, and equity. These provide a framework for evaluation of decision to allocate resources and their effect on society, with the objective for the decision to be efficient, as well as fair and just (Drummond et al., 2015).

As theoretical basis of DCEs follows the theory of consumer behaviour, DCEs fall under the properties of neoclassical consumer, where it is assumed that individuals are rational decision makers that seek to choose the preferred option from the available alternatives to maximise their utility (Ryan et al., 2008).

The importance of individual choice and preferences in economic decision making allows the use of tools such as cost-benefit analysis to evaluate different policies and interventions. In this framework, DCEs can be used to measure individual preferences and willingness-to-pay for different goods and services.

While DCEs can provide useful information about individual preferences, they may not be able to capture the full range of social goals and decision-making processes that are important for evaluating economic policies and interventions. The DCE work can supplement the analyses which focus on social goals beyond individual preferences and analyses that include impact of cognitive process on individual decision making. Although, these are not within the scope of this thesis.

1.8 Research aims and objectives

The main research objective is to investigate the effect of current and possible alternative medicine pricing policies on the consumer demand for generic and branded medicines in Australia. This research addresses how consumer preferences can drive demand for generic medicine brands and whether it is possible to use policy levers around prescribing and dispensing of medicines, as well as policy on brand premiums, to more effectively manage government expenditure on medicines. This aim is explored in a structured approach by designing and analysing a series of interlinked discrete choice experiments (DCEs). A total of four DCEs were designed to investigate the effect of current and possible alternative medicine pricing policies on the consumer demand for generic and branded medicines in Australia.

For simplification, the DCEs are called DCE 1, DCE 2, DCE 3 and DCE 4. The first three DCEs explore consumers' preferences for branded medicines and the brand premium, and the impact these have on consumer choice for medicines. The following objectives were explored in DCE 1 to DCE 3:

1. Respondents understanding and awareness of the difference between multiple brands of the same medicine;

2. Determining whether respondents attach a value to the original branded medicine;
3. Determining whether the presence of the brand premium is treated as an indicator of quality that respondents attach to the medicine;
4. Assessing responsiveness of consumers to drug prices in the context of brand premiums;
5. Identifying factors that affect consumers' perceived value of the brand premium of the medicine.

The three DCEs were implemented simultaneously with a group of respondents who were randomised to one of the DCEs. The DCE 4 contained all the respondents from DCE1 to DCE 3 and focused on the following objective:

6. Assessing the impact of a new hypothetical government policy with only one subsidised brand listed on the PBS (with other brands available on the market) on consumer preferences for branded and generic medicines.

Currently, there is little research on the impact of prescription medicines policies on consumer choice. This thesis aims to fill this gap by exploring the effect of the medicine pricing policies for different brands on Australians' preferences for branded and generic medicines. The preferences were assessed for each factor that can be important in the choice making under current policies as well as under a hypothetical government policy with only one brand being reimbursed. All the models were controlled for socio-demographic and economic variables that could also impact on preferences for the prescription medicines. Age, gender, education, marital status, work status, health status, medical condition, doctor visits and pharmaceutical prescriptions were all included in the model.

DCEs are used because they provide the opportunity to explore factors that cannot be observed with current market (observational) data. There are no datasets with observational data that include the factors influencing the consumer choice when purchasing prescription medicines. Therefore, a method for quantifying a relative importance of differing characteristics (attributes), trade-offs between these attributes, and consumers' utility regarding the specific collection of attribute levels can be used to analyse consumer's understanding, awareness and preferences for choosing between two options (i.e., generic and branded medicine) (Lancsar & Louviere, 2008). A SP method, DCE has been used in evaluation of health services and goods (Clark et al., 2014; De Bekker-Grob et al., 2012; Soekhai, De Bekker-Grob, et al., 2019; Soekhai, Whichello, et al., 2019). In DCEs, respondents are asked to choose their preferred option from a set of hypothetical (but realistic) alternatives, described by attributes and their respective levels determined using established qualitative methods (Coast et al., 2012).

This PhD provides the first such systematic approach to using DCE method to explore consumer preference in relation to prescription medicines.

1.9 Overview of the thesis components – structural outline

The thesis presents a series of four DCEs to answer the research questions. The next chapter (Chapter 2) provides the overview of the DCE method and the base of the study format. The rationale, structure, development of the four DCEs and assessment of the research are described in the chapter.

Chapters 3, 4 and 5 of the thesis then present the four DCEs in detail, including the results, analysis and interpretation. Together they provide a new body of knowledge by exploring the use of SP methods to investigate decisions about prescription medicines under different policy settings and contexts. The four DCEs build on each other by varying attributes to reflect different policies and information for consumers. The overall policy context is highly relevant to the Australian pharmaceutical market, where consumers have a choice of brands of prescription medicines and may face different prices for different brands. Chapter 6 discusses the findings from the previous three chapters and presents the policy implications of the impact of the medicine policy on the engagement of the consumer and the potential price level.

CHAPTER 2. Using Discrete Choice Experiments to understand pharmaceutical policy in Australia

Chapter Summary

A survey of a sample of the Australian population was conducted to collect consumer preferences in relation to prescription medicine purchases, particularly for medicines with multiple brands. In this chapter, the focus turns to the discrete choice experiment (DCE) method used to obtain consumer preferences and the development of the DCEs used to address the research questions of the thesis. This chapter outlines the process of DCE design and how it is used in the survey; this includes the development of attributes and the choice sets that form each DCE. The statistical framework used to analysis the resulting DCE data is also described. The chapter concludes with the presentation of the demographic and socio-economic characteristics of the respondents who participated in the survey.

2.1 Overview

The core research question relates to consumer preferences for prescription pharmaceuticals, identifying attributes that are important to consumers and influence their purchasing decisions, particularly for medicines with multiple brands. As explained in Chapter 1, the availability of multiple brands should create competition and reduce prices (to government) and therefore reduce government expenditure; however, this has not occurred to the extent that might be expected because of market structures. Government has used various policy levers to influence price – including price disclosure and allowing companies to charge a brand premium – but these have had limited impact. In this research I am interested in investigating how the brand premium policy may influence consumer behaviour, and in testing the impact of a new policy in which only a single brand has PBS subsidy. This analysis cannot be readily undertaken using revealed preference data; therefore, to address this question, a series of DCEs were designed and implemented across a random sample of consumers.

This thesis uses DCE methods to explore the preferences of the Australian population for purchasing prescription medicines. The surveys are implemented in a general population sample, representative of the Australian population in terms of age and gender quotas. The respondents are presented with various pieces of information about the medicines, including information about the cost which is presented in different ways across the experiments. The results are used to measure preferences in relation to purchase of prescription medicines, but also the relative strength of preferences (by demographic characteristics of population), as well as the trade-off the respondents would be willing to make between different characteristics of the choices presented to them. The results of the DCEs developed for this thesis help answer the research questions about consumers' preferences for generic or branded medicines, whether consumers respond to information about the existence of brand premiums for some pharmaceuticals, and whether consumers respond to the brand premium attribute. I also test sensitivity

to price of the brand premium, and estimate the effect of a hypothetical change in policy of government subsidisation of drugs.

This chapter is ordered as follows. Section 2.2 provides an overview of DCEs; Section 2.3 presents the results of the literature search in relation to the research topic, provides an overview of the format of the survey design and describes the development of the survey; Section 2.4 describes the development of the survey and the attributes and levels; Section 2.5 presents the details of the design of the choice sets based on the selected attributes and levels for DCEs 1–4; Section 2.6 presents the statistical framework used in the analysis of the DCE dataset; Section 2.7 describes the implementation the survey and the ethical approval obtained to conduct the study; and Section 2.8 presents the review of data, detailing the data clean-up, and Section 2.9 presents the details of the demographic and socio-economic characteristics of the respondents who completed the survey.

2.2 The use of discrete choice experiments

Consumer engagement in Australian health policy has become an increasingly important component in policy development and program design. The underlying reasons for consumer engagement range from ethical and democratic rights to improved policy outcomes, including informing the consumers about a new policy, and involving the consumer in decision-making process and joint planning (Gregory, 2007). Participation of consumers in research and policy development has been recognised as desirable and as adding value to decision making, planning, policy development and service delivery in health (Lancaster et al., 2017; NHaMR, 2016). Co-design of programs and services with consumers and service providers can lead to solutions that meet their needs (Roper et al., 2018). However, to design effective programs and policies, there is a need for data and evidence about consumer preferences, decision making and values. It is important to understand how certain decisions are made, what choices are made, what is taken into account, and whether there are any defining characteristics of the people who make a particular choice.

One means of engaging with consumers is through surveys – for example, if consumers are buying branded medicines at higher prices when cheaper generic medicines are available, why is that so? If the government only reimbursed the cheapest brand, would that nudge consumers to forgo the medicine with brand premium, or are other approaches needed? Or are there non-price factors that can have a bigger impact on consumer choice of purchase? And, if that is so, which can be prioritised? By collecting and analysing consumer opinions and preferences, the design of programs and policy arrangements can be optimised.

There are a number of methods that can help engage consumers in the development or assessment of a program or policy. Although qualitative[26] methods generate rich data for analysis, some factors that may impact the consumer preferences for generic or branded medicine would be difficult to assess through a qualitative approach using small groups to identify the key factors or priorities, which cannot be ranked. Ranking requires the use of quantitative methods with a structured instrument that can be used to collect data for more precise measurement and analysis of data from a broader population. Quantitative data can be analysed using statistical techniques to make inferences about the population and explore multivariate relationships.

The field of research into the choices of consumer of prescription medicine is relatively young. Existing studies are mainly of qualitative nature, and the field can substantially benefit from a quantitative approach. With careful design, a quantitative approach can assist in determining the motivation behind certain choices, and it can provide inputs to predict how consumers respond to different policy settings and market conditions. The potential contribution of quantitative methods has been recognised previously in the area of demand for and supply of medicines (Srivastava & Wagh, 2020).

There are various quantitative choice-based methods that have been used in health economics to measure stated preferences[27] of respondents (patients, consumers, health care professionals, carers and other stakeholders), including standard gamble (SG), time trade-off (TTO), contingent valuation (CV), best-worst scaling (BWS) and DCEs (Hauber et al., 2016; Miguel et al., 2005; Potoglou et al., 2011).

Although these various methods each have their own advantages, the DCE that is used in this study is the optimal eliciting techniques to answer the research question and test the hypothesis that consumers respond (by adjusting preferences) to key information provided to them, and that there are key factors in the decision making that would be important under a different government policy.

In general, the TTO and SG methods are used when respondents are asked to consider own health state, with the goal of estimating health state utilities or value associated with different health states (Bleichrodt, H., 2002).

TTO is based on the idea that an individual is willing to trade-off a certain amount of time spent in full health for an equivalent amount of time spent in a different (worse) health state (Dolan et al.,1996). The

[26] A qualitative method focuses on collecting data in non-numeric, or text format, that also has a loading on the researcher's time and engagement in the data collection. The analysis of the data also involves interpretation of the recorded answer in order to draw results. Examples of qualitative methods of data collection include surveys (questionnaires), controlled observations, experiments, focus group or individual interviews/discussions, longitudinal studies and polls.

[27] Stated preference methods are methods that have respondents rate, rank or choose from a set of experimentally controlled profiles consisting of multiple attributes with varying levels.

SG method is based on the idea the at the individuals are willing to trade-off a certain amount of health for a probability of full health (Salomon, 2014).

CV asks individuals to value a certain good or service, by asking how much money they are willing to pay to cure a certain health condition. However, the CV method is limited that it may not capture the multi-dimensional nature of the choices presented to the individuals. The CV method can ask for the willingness to pay (WTP) or expected amount of reimbursement (willingness to accept) for a certain product or service, however, it is limited in identifying the importance of the factors that constitute the options. (Klose et al., 1999).

The BWS method is a preference elicitation technique that was developed in 1990, with the tasks asking respondents to choose the 'best' and 'worst' option from the tasks presented to them (Potoglou et al., 2011). The BWS method can be presented as a single option (profile case) to the respondent, or as a multi-profile with two or more options to choose from. In the single profile case, the respondents choose the 'best' and the 'worst' attribute level from the list describing that option (Cheung et al., 2016). In the multi-profile BWS the respondent chooses which option is 'best' and which is 'worst' (Cheung et al., 2016). Using this method to identify the most important attribute by assuming that the option identified as 'best' is preferred because it has the most desirable attribute(s), and the option identifies as 'worst' has the least desirable attribute(s). The BWS is used to obtain a ranking of importance of each attribute. The multi-profile BWS, that is closest to the DCE, and has the advantage of providing additional information on the option that is picked as the 'worst' as well as would require a smaller sample size, has its limitations to that it needs a larger set of options to choose from in each choice task (Cheung et al., 2016)). This would also lead to a different research objective and require a different set of attributes.

This study focused on determining the factors that impact consumer preferences in purchasing generic medicines, compared to branded, therefore the DCE is the optimal method to be used in this research. In comparison to the methods described, the DCE method allows to measure the value of the individual characteristics of each choice (attribute levels) (Bridges, 2003).

A DCE is a quantitative technique that can be used to measure preferences via stated preference (SP) data. The method can be used in situations where there are no suitable available revealed preferences data (Ben-Akiva et al., 1994; Mangham et al., 2009). The DCE is one example of a conjoint analysis task, which is increasingly used in health economics, outcomes research and health service research (Clark et al., 2014; Hauber et al., 2016; Johnson et al., 2013; Miguel et al., 2005; Soekhai, De Bekker-Grob, et al., 2019). The DCE has become a go-to method for measuring preferences for hard-to-observe underlying contexts of choice and trade-offs between attributes of choice made by consumers and can be used to inform health policy-related decisions (van den Broek-Altenburg & Atherly, 2020).

A DCE is a SP choice experiment technique that consists of a set of choice tasks that are presented to the respondents (Street & Burgess, 2007). The DCE method assumes respondents maximise their utility

from the available choices, and their utility function can be estimated by analysing the actual choices made (Street & Viney, 2019). The design of the DCE choice tasks focuses on making sure that a utility function can be estimated from the collected responses and "the impact on the utility of each of the attributes of the items can be determined" ((Street & Viney, 2019), p3).

A recent review of the literature on DCEs in health economics (Soekhai, De Bekker-Grob, et al., 2019) outlined the use of qualitative, quantitative and mixed-methods approaches with examples of interviews, focus groups and SP techniques such as SG or TTO, and emphasised that the use of a particular method should depend on the circumstances and conditions of the research question. The decision to use the SP approach arises when RP data are not available, or would be hard to obtain, or for cases where RP data are inadequate to model a specific context of interest, such as policies that do not yet exist, or testing policy circumstances that have not been implemented or developed.

DCEs were developed from Lancaster's work on the economic theory of value of characteristics of goods in determining consumer utility (Lancaster, 1966) and McFadden's work on the random utility theory modelling framework (McFadden, 1973, 1986). The individual respondent is assumed to maximise their utility, which is assumed to be a function of the attributes of the alternative; in choosing an option from the choice set, the respondent is considered to be choosing the one with characteristics that bring the highest benefit (utility) to them. As presented in Chapter 1, Section 1.7 the theoretical basis of DCEs is rooted in the principles of consumer choice theory, which assumes that consumers make choices to maximise their utility and that their behaviour can be predicted based on the factors describing the good that are presented to them and their preferences. DCEs are based on the idea that consumer preferences can be revealed through hypothetical choice scenarios, where respondents are asked to choose between different combinations of attributes. In order to estimate the preferences of consumers, DCEs rely on mathematical models that use statistical techniques, such as multinomial logit or mixed logit models, to estimate the probability of choosing an option. The statistical framework and these models are presented later in Section 2.6.

Typically, in a DCE, a hypothetical scenario is described and, a choice task is presented to individuals who are asked to choose their most preferred option from the set of options in the choice task. Each choice task consists of two or more hypothetical alternatives. Each respondent is shown a set of choice tasks one at a time and asked to choose one of the alternatives presented. In a DCE, all alternatives in each choice task are described by the same set of characteristics (attributes), and each of these attributes takes one level from a finite set of possible levels, which can be altered in each choice task.

The choice of DCE method for this thesis is supported by the underlying format of the DCE, where the attributes that define the alternatives are developed and selected by the researcher and are assumed to have a bearing on consumer preferences, are adequate to describe the product and to be the ones that are (most likely to) influence consumer choice. The DCE method allows exploration of aspects of

choice that are not observable in RP data, or options that are not available in RP data. For example, in the DCE the researcher knows the other alternative that was not chosen and knows the attributes of that alternative, thus making it possible to estimate the probability the individual would choose an alternative among a set of alternatives. Additionally, in the DCE method, the cost attribute, if included, allows for the estimation of a marginal willingness to pay (WTP) for the specific features of the good or service (Train & Weeks, 2005).

Reviews of the literature focusing on DCEs in health economics (Clark et al., 2014; Kleij et al., 2017; Soekhai, De Bekker-Grob, et al., 2019; Trapero-Bertran et al., 2019) reveals a growth in DCE application and research to collect preference data from consumers, patients, health care providers, government and other stakeholders to address health policy-related concerns since their introduction to the area in 1999. Soekhai, De Bekker-Grob, et al. (2019) also conclude that the use of DCEs continues to increase, with an increased focus on quantifying preferences for healthcare.

Nevertheless, DCEs have limitations. One of the most noticeable is the potential discrepancy between the respondent's stated choice in the DCE and what would be their actual choice in a real situation. It is important to have a thorough preparation of the design of scenarios and choice tasks, including proper development and understanding of the target population, policy settings and collection of primary data (interviews or pilot studies) (Hauber et al., 2016; Johnson et al., 2013; Trapero-Bertran et al., 2019). It is equally important to select the best regression model, based on the dependent variable and type of data set, and the model needs to take account of the fact that there are several choice tasks presented to each individual. Nevertheless, in settings where reliable retrospective data is challenging to obtain, the use of DCEs can support planning decisions.

2.3 The development and application of the DCE

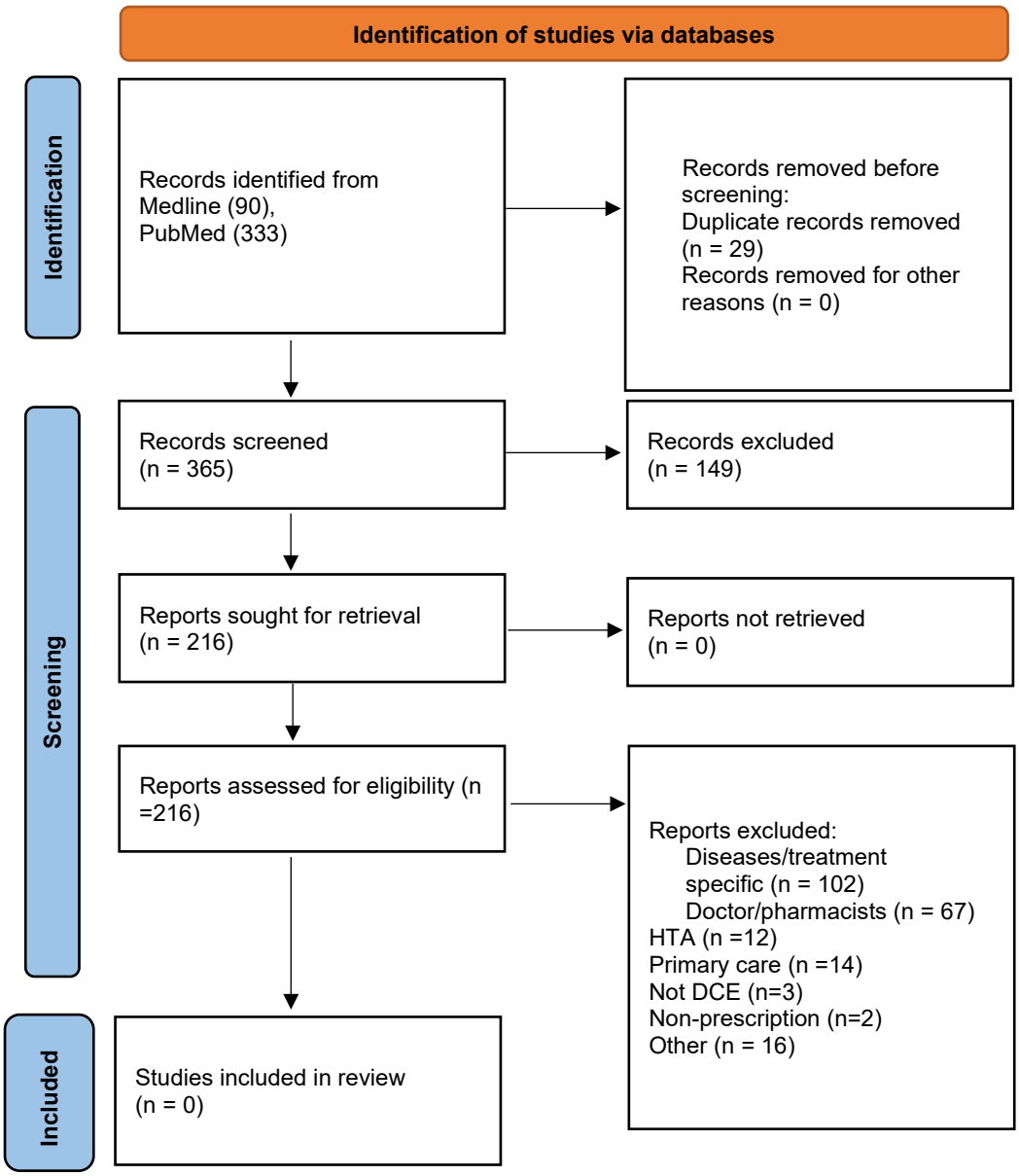
In preparing the DCEs for this study, a literature search was conducted to identify relevant publications on the evaluation of consumer preferences for prescription medicines, branded or generic, as well as consumer (patient) attitudes towards brand premium(s). The search used the PubMed and MEDLINE electronic databases to identify English-language peer-reviewed studies available as full text between 1950 and 28 February 2018. The search terms for the DCE components were sourced from published literature reviews on DCEs in health economics (Clark et al., 2014; De Bekker-Grob et al., 2012). The other search terms were based on an overview of keyword in the published studies on the generic/branded medicines and consumer/doctor/pharmacists topics in Australia. The search terms were as follows: 'discrete choice experiment(s)'discrete choice modelling', 'stated preference', 'prescriptions', 'prescription medicines (drugs)', generic medicines (drugs)', 'branded medicines', 'brand(price) premium', 'patient', 'consumer', 'doctor', 'pharmacists'.

The literature search did not identify any publications that explicitly used discrete choice experiments to elicit consumer preferences for prescription medicines. A Prisma Search flow diagram (Page et al.,

2021) summarising the screening process for the literature review of the two databases is presented below in Figure 2-1. Additionally, a search of results from databases and Google Scholar was conducted to identify quantitative studies in consumer preferences for prescription medicines in Australia and internationally.

Of the total 423 records identified during the search there were 365 screened based on title and keywords, with majority of the publications relating to measuring of health utilities, purchases of non-prescription drugs and other goods in pharmacies, consumption of other products. There were 216 publications retrieved for abstract check, with all excluded at the end of the check. There were reports that focused on a specific disease (i.e. multiple myeloma, kidney dialysis, health promotion, other) with a total of 102 reports excluded. There were reported that focused on surveys of doctors and pharmacists (i.e. community pharmacy services, preferences for younger doctors, other) a total of 67 reports were removed. There were 14 reports that focused on preferences for primary care services, that were also removed. There were 12 reports focusing on economic evaluations, such as cost-utiltiy analysis, cost-effectiveness analysis, which were also removed. There were three reports that explored consumer preferences however using other elicitation techniques (i.e. contingent valuation), and two reports that asked for preferences of non-prescription drugs. There was a total of 16 papers that focused on statistical analysis of DCEs, literature reviews and other various topics. There were no DCE studies identified, however, a total of four studies in the area of consumer references for prescription medicines were identified and are presented in the next section 2.31.

Figure 2-1. PRISMA Search flow diagram for a literature review



From: Page M.J., McKenzie J.E., Bossuyt P.M., Boutron I., Hoffmann T.C., Mulrow C.D., et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71. Webpage: http://www.prisma-statement.org/

Notes: HTA : health technology assessment; Other reasons for exclusion included: food/beverage, nursing homes, etc.

2.3.1 Summary of the existing evidence

The literature search was used to inform the development of the DCE attributes and levels. The most relevant studies reported on consumers' general beliefs about generic/branded medicines, their efficacy and safety. Two studies focusing on the cost of the medicine and the impact of the brand on preferences are highlighted below, with the others summarised.

A study by Denoth et al. (2011) used a contingent valuation method (asking for WTP) to identify preferences of consumers in Switzerland for a brand name drug or a generic name drug for the treatment

of acute and chronic conditions. The questionnaire contained eight scenarios (four acute conditions and four chronic) and in each the respondents were asked to select an additional amount that they would be willing to pay extra for a branded drug. The results showed that the majority (61.1–70.5%) of respondents were not willing to pay an additional amount for a brand name medicine (WTP=0). The study reported that those patients who had self-reported a current acute or chronic condition (51.1%) were on average willing to pay more for branded medicine than were those in good health. Some respondent characteristics affected the WTP results; for example, people of non-Swedish origin were willing to pay more for branded medicines. The study had limitations and was considered exploratory given the unrepresentativeness of the population, as the survey was conducted in a single town, with women comprising three-quarters of respondents.

A study by Lessing et al. (2015) investigated New Zealand patients' understanding of and preferences regarding switching between brands and their opinions on funding options, such as an increase in co-payments, using a survey questionnaire. The questionnaire included general questions on awareness of and rationale for brand substitution, used a five-point Likert scale to elicit patients' preferences for different co-payment options related to substitution between brands, and asked respondents to nominate a dollar value that they would be prepared to pay for their choice of brand. The respondents indicated prescribers and pharmacists as the primary source of information on brand substitution. Half (51%) of the respondents indicated that there should not be a difference in price between a government-funded brand and another brand.[28] Approximately 49% of respondents were unwilling to pay extra for the original brand medicine. Approximately 27% were willing to pay an additional NZ$5 to be able to choose the brand, and 11% were willing to pay NZ$10, with 8% indicating a range of NZ$20–50, while 5% stated that there was no limit of what they would pay. Therefore, it appears consumers did not see a difference between generic and branded drugs, but were willing to pay a small amount to receive the brand of their choice. The paper concluded, however, that based on the preferences that respondents expressed regarding different types of drug payments, there was an apparent lack of understanding of the differences in price between original branded medicines and generic brands, as well as the country's current pricing mechanism.

The literature search also found several papers that reported on aspects of doctors' prescriptions and drug preferences. Specifically, the preference for branded drugs for treating acute and chronic conditions is discussed in Denoth et al. (2011); brand loyalty is discussed in Costa-Font et al. (2014); and the perception of the value of the medicine derived from attributes on safety of the medicine, use

[28] In New Zealand the Pharmaceutical Management Agency (PHARMAC) decides which medicines are funded, by choosing a single manufacturer (sponsor) for drug reimbursement in a bid-like system, with the other brands able to be sold, but the total cost of unsubsidised brand of medicine would fall to the consumer.

in acute and chronic conditions, effectiveness and side effects, and quality of branded medicines vs generic medicines is discussed in Nardi and Ferraz (2016).

The attributes and levels used in these papers were reviewed as potential attributes and levels for use in the DCEs constructed for this thesis are presented in Table 2-1.

Table 2-1. Attributes (language) used in the studies

Denoth et al., 2011	Costa-Font et al., 2014	Nardi et al., 2016
• Acute conditions (7 to 10 days) • Chronic conditions (1 month) • Doctor's prescription	• Acceptability of generics from doctor • Accepting of generic substitution by pharmacists • Subject (not subject) to a co-payment for medicines	• Doctor's prescription • Pharmacist's recommendation • Price comparison across brands

Since the search found limited evidence about preferences for brand premium and the preferences for generic or branded drugs in the field, the development of the DCEs used in this thesis was also based on an analysis of the current prescription dispensing practice in Australia, feedback from presentations of the DCE concept to health economists and health care professionals (doctors, pharmacists), and the results of a pilot study.

2.4 The survey

The main research objective is to investigate the effect of current and possible alternative medicine pricing policies on the consumer demand for generic and branded medicines in Australia. The policy of interest is the presence of 'brand premium' in some brands of the PBS-reimbursed medicines. The brand premium is an additional cost ($) added to the medicine price agreed between the Australian Government and the pharmaceutical company. However, the brand premium is paid by the consumer (additional out-of-pocket cost).

The first three objectives of this thesis focus on

- respondents' understanding and awareness of the difference between multiple brands of the same medicine;
- determining whether respondents attach a value to the original branded medicine; and
- determining whether the presence of the brand premium is treated as an indicator of quality that respondents attach to the medicine.

Lessing et al. (2015) show that the general population may not be aware of government pricing mechanisms in relation to subsidised prescription medicines. Additionally, respondents' preferences can be affected by their understanding of this price mechanism. However, there are limitations on the quantity of information that can be provided to respondents of a survey. Firstly, trying to explain all the components of the policy in a survey would lead to a high cognitive burden for the respondents. Secondly, such information in the setup of the DCE may limit the applicability of research results, as it

would be difficult to evaluate whether the respondents understood the complex policy that leads to different prices of medicines and whether such understanding impacted on their decision, and perhaps limited the applicability of the results to the less knowledgeable general population.

Therefore, to evaluate respondents' preferences, it was decided that a simple, realistic and reliable way to elicit respondent preferences for medicines with original brands or generic brands was to focus on the price component. To evaluate the respondents' preferences based on the information with which they are presented, it was decided that Part 1 of the survey would set up an information framing based on the total cost components of the medicine.

DCEs were developed to explore whether consumers have different preferences depending on the information they receive. There are three DCEs (DCE 1, 2 and 3) focusing on varying the presentation of the cost attribute and exploring whether the changes to the presentation of the cost attribute impacted preferences for the attributes presented to the respondents. The differences across the three DCEs are presented in Table 2-2.

Table 2-2. Differences across the three DCEs focused on the cost of medicine.

	DCE 1	DCE 2	DCE 3
Components the differentiate the three DCE	The respondents are presented with a set of attributes describing the choice, with a cost attribute presented as a single dollar ($) value	An additional attribute of brand premium is added to the list of attributes. This attribute identifies the alternative that has a brand premium added to the medicine (no dollar ($) value of the attribute is given)	The brand premium attribute is given a dollar ($) value that specifies the amount of the brand premium that is a component of the total cost of the medicine

The survey comprises two parts, with all respondents completing both parts. In Part 1, respondents were randomised to DCE 1, 2, or 3. In Part 2, DCE 4 was presented to the respondents after they completed their designated DCEs (DCE 1, 2 or 3). DCE 4 was designed to introduce a hypothetical new government medicine subsidisation mechanism that asked respondents to choose between the two alternatives.

The rationale for such a hypothetical policy is that the government could use its monopolistic purchasing power to lower the price of generics drugs, as well as branded medicines. This could be achieved through some form of tender process, as currently happens in New Zealand (Hasan et al., 2019) and The Netherlands (Godman et al., 2017). Several studies have demonstrated that the prices of generic medicines in New Zealand and Europe are much lower than in Australia (Breadon et al., 2013; Duckett & Breadon, 2015).

Having chosen the form of the survey, the next step was to select the format for presenting the

information so that it could be analysed across all the DCEs. A simplified stepped flow chart of the survey is presented in Table 2-3 below, with a detailed flow chart of the survey shown in Table 2-7 at the end of this section.

Table 2-3. A simplified stepped process of the survey

Step 1	All eligible respondents are randomised to one of the three DCEs		
Step 2	DCE 1	DCE 2	DCE 3
	Respondents answer 12 choice tasks		
Step 3	All respondents are presented with DCE 4 (eight choice tasks)		

The overall design of the survey is aimed at establishing respondents' preferences for prescription medicines under the current policy in Australia (DCE 1, DCE 2, DCE 3) and then exploring how this might be affected by a hypothetical change in policy that changes the form of government reimbursement for medicines (DCE 4). The survey was designed to test for the impact of several information conditions on the preferences of respondents. The analysis of the dataset of DCE 1 is presented in Chapter 3, analyses of the datasets of DCE 2 and DCE 3 are presented in Chapter 4 and the analysis of DCE 4 dataset is presented in Chapter 5 of this thesis. I now explain more broadly the development of the DCE.

The context of the DCE, in which the choices were to be made, included a hypothetical doctor's prescription for an acute health condition. An acute health condition is defined as one requiring treatment for not longer than one month (30 days).

In the survey, the respondents were asked to imagine a hypothetical situation in which they presented to a doctor with an acute health condition for which treatment was required. This was done to help set up the situation within which the respondent would need to make a choice. The choice of an acute condition, rather than a chronic condition, was made because many respondents with a chronic condition expect that the prescribed medication is the one they usually have. This approach was chosen to limit the impact of differences in respondents' experience of a particular health condition.

Using this approach ensures that the focus of the research is on exploring respondent preferences for a brand of the medicine and its cost, rather than preferences for switching between brands (or brand loyalty). For example, in the treatment of chronic diseases, the doctor and the patient may be more likely to choose a medicine brand that has been previously prescribed. The question of the choice between the two medicines with brand premiums for people with chronic conditions is also of interest but beyond the scope of the research presented in this thesis.

2.4.1 Selection of attributes and levels – Part 1

Overview

The design of all DCEs needs to include a well-rounded set of attributes with enough variation in the

factor levels necessary to produce a meaningful response (Ryan et al., 2007). In the design of the DCEs in this thesis, the steps and reasoning for selecting the attributes and levels are described below.

I first explain the selection of the attributes and levels for the DCEs presented in Part 1 of the survey, followed by DCE 4 in Part 2 of the survey.

In Part 1 of the survey each DCE choice task consisted of one context attribute (doctor's script) and five attributes describing the options included in the DCEs of Part 1 of the survey:

- the *product*: branded or generic;
- the availability of the product at the pharmacy – whether the respondent can collect the medicine Now or Later;
- pharmacist's recommendation to purchase the product, the product being mentioned by the pharmacist;
- the *total cost* of the script: total out-of-pocket cost to consumer;
- a *brand premium*; or the amount of the brand premium.

These attributes were developed at the initial stages of the research, using literature reviews and prior experience at pharmacies for purchasing prescription medicines (by visiting local pharmacies). Limiting the total number of attributes to six allowed the creation of a simple DCE that was not too cognitively demanding, and also meant that more choice tasks could be presented to each respondent. Street and Viney (2019) state that the challenge in DCE design is to maintain realistic alternatives but without imposing an undue burden on respondents, either in terms of the number of choice sets or in terms of the number of attributes to be considered, as doing so might impact on accuracy.

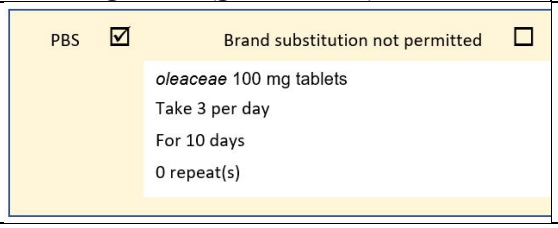
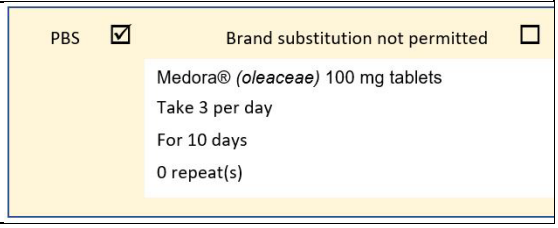
Remembering that the respondents' derived utility is solely defined by the attributes presented, there is a limitation with missing attributes, if the important ones were not included in the choice set. Thus, there is always a balance between including all the possible attributes, and overwhelming the respondent with the complexity of the choice set versus not including enough attributes.

Doctor's prescription

Each of the DCEs in part 1 has two arms and includes an information attribute of the doctor's prescription, which can take one of two forms. The two types of prescription represent the information attribute of the medicine name prescribed by the doctor. The two prescriptions are identical except that one prescription is written with the active ingredient of the medicine (aka generic name of the medicine),

and the other includes the branded medicine name[29,30] The doctor's prescriptions are presented in Figure 2-2.

Figure 2-2. Two types of doctor's prescription presented to the respondents in Part 1 of the survey.

Active ingredient (generic name)	Branded medicine
	

Abbreviation: PBS- Pharmaceutical Benefits Scheme

The doctor's script represents an attribute with two levels (generic medicine (active ingredient) name, and branded product name) presented in a graphical way, rather than a text format like the other attributes in the survey. The information shown to the respondents in the survey was simplified, with only one information line changing between the scripts.

The components of the scripts are the two check boxes at the top of the image, with the description of the medicine in the white area of the script. The box 'checked' PBS indicates that the medicine is listed on the PBS and therefore is reimbursed. The RPBS box, as in the real script, is not in the survey script to reduce complexity and not overwhelm the respondents with text information.

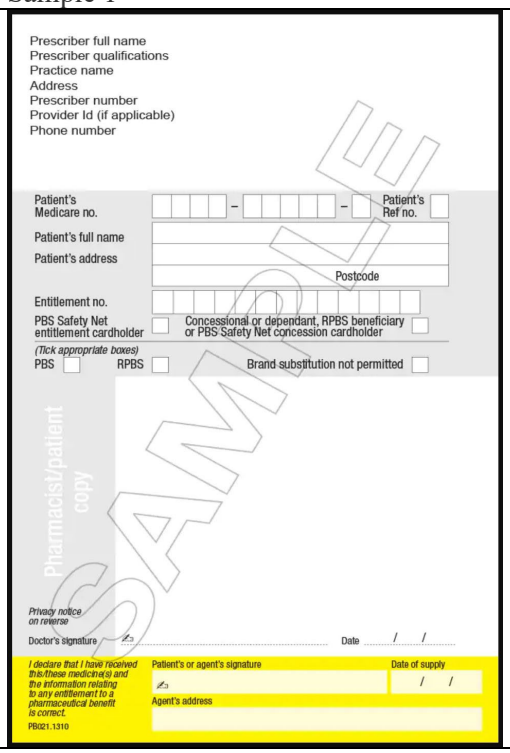
The 'unchecked' box for 'brand substitution not permitted' is always unchecked in the survey to indicate that the doctor did not specify the exact brand of the medicine, and therefore any brand can be dispensed by the pharmacists (although, they may have written the script using the brand with which they were more familiar).

The intention of a DCE is to make the choice task as close to the real situation as feasible to test the hypothesis. In this survey the intention was to replicate the real situation a person experiences when purchasing a prescription medicine by including the information in way similar to the way scripts appear in Australia. Note that in 2017–18, when these DCEs were being developed, there was no official mandate requiring doctors to prescribe the medicine using generic name, thus allowing the prescriber to write a prescription using either a brand name or the active ingredient name. The visual design of the doctor's script used in the survey was based on samples of Australian scripts (Figure 2-3).

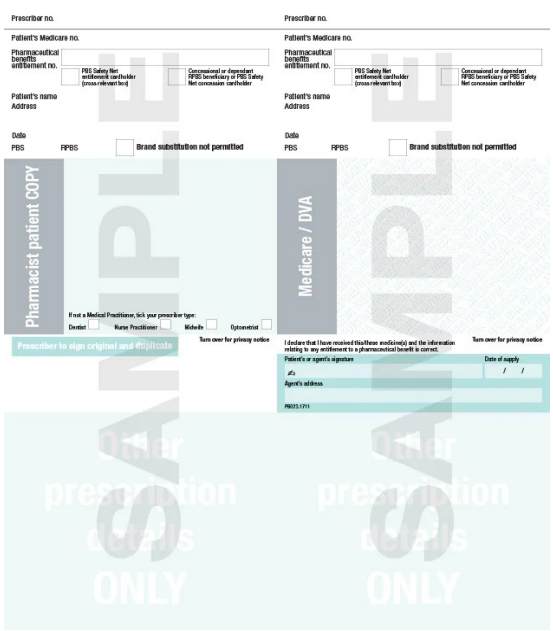
[29] Generic brands of medicines whose patent has expired are called by the name under which the medicine is registered (its generic name). Branded medicine is the name of the original brand, generic medicine. It is important not to confuse the generic name of the medicine with the generic medicine (which is another brand).
[30] From February 2021, Australian prescribers have been required to use the medicine generic name in prescriptions, unless the prescriber recommends the specific brand for clinical reasons.

Figure 2-3. Samples of prescriptions available to Australian prescribers.

Sample 1



Sample 2



Source: Services Australia https://www.servicesaustralia.gov.au/organisations/health-professionals/services/medicare/pbs-and-rpbs-stationery/what-stationery-you-can-order/stationery-medical-practitioners.
Abbreviations: DVA: Department of Veteran Affairs; PBS: Pharmaceutical Benefits Scheme; RPBS: Repatriation Schedule of Pharmaceutical Benefit.

During the experiment, respondents were shown both types of scripts, to see whether what was written on the original script impacted choice of medicine or brand substitution. To test any order effect that may be present in relation to the information presented in the doctor's prescription, respondents were randomised into one of the two arms within each DCE (DCE 1-3).

In the survey, the respondent saw one type of prescription format (either branded or active ingredient) followed by six choice tasks. After the sixth-choice task, the respondent was told that the prescription has changed and then asked to make six further choices based on the prescription with the other format. Respondents randomised to *Arm 1* first saw a doctor's script with active ingredient (generic name). Respondents randomised to *Arm 2* first saw a doctor's script for the branded medicine.

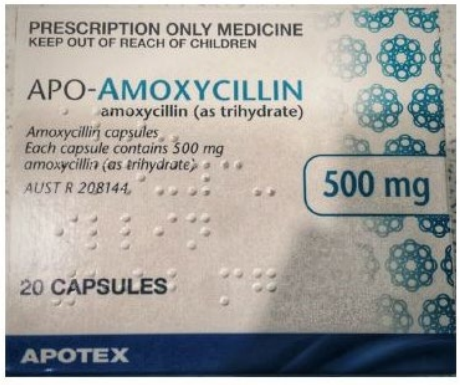
The medicine product attribute

For the product attribute, it was decided to use hypothetical names for the reasons mentioned in the section on doctor's prescription. However, in the early stages of developing attributes and levels, a real drug product was used with its brand and generic names. During a feedback session the advice was that some respondents might be familiar with the product and have preconceived notions, which could impact their preferences. While it may have been possible to account for this by asking the respondents whether they had previously taken or been prescribed this drug, after consideration it was decided that invented names were preferable.

The product attributes used hypothetical names from an existing Latin name of a common plant. This was done to maintain a degree of familiarity for the respondents, as it is common for the generic names of medicine to have Latin roots, as do many names of medical conditions. The attribute levels for the product attribute were based on the plant family Oleaceae (olive family) which includes such members as olive trees and jasmine (Encyclopedia Britannica Online). The levels of the product attribute consisted of two generic products and one branded. The branded name was derived from a genus of jasmine plant, *Menodora*, shortened for simplicity to 'Medora' with a registered sign ® added at the end of the word to make the compatible with other brand names used on product packaging. The first generic attribute level was pharmacy brand, since there are home brand drugs in pharmacies. The name for the second generic – Megorium – was derived from the branded name Medora.

During an analysis of the names of generic drugs listed on the PBS with branded and multiple generic brands, it appeared that the names had some resemblance to each other, although produced by different companies. Often the names also resembled the name of the active ingredient of the drug. For example, a commonly prescribed antibiotic, amoxicillin, is produced by different companies and sold in Australia under the brand name Amoxil®, as well as APO-Amoxycillin® as a generic medicine. A picture of the two products is presented in Figure 2-4.

Figure 2-4. Two products of amoxicillin produced by two companies under a branded ana a generic name.

Branded medicine	Generic medicine
	

Source: Photographed by the researcher for the purpose of survey and this thesis.

The collection of the medicine from the pharmacy attribute

The *collection* attribute was included to provide a measure of 'convenience' of purchasing medicines from the pharmacists. Some pharmacies may not stock all available brands of medicines, and waiting for the specific 'order' to arrive at the pharmacy can take several hours. Alternatively, this attribute can correspond to the consumer having to visit another pharmacy (spend time) to get the brands they prefer. The attribute provides the respondents with a chance to trade-off time against other attributes.

The *collection* attribute was first implemented as a three-level attribute (now, later today, and tomorrow). However, during consultations and internal reviews, the last level was removed as, in an acute setting, it is most likely that drugs is available for the patient on the same day. In discussion with

the pharmacist it emerged that there are drugs that may need to be picked up the next day. However, these are usually drugs with short shelf-life and which are used for chronic conditions.

The pharmacist recommended attribute

The *pharmacist recommended* attribute is both a policy lever available to government and a means by which the pharmacist may direct a consumer to a product that is more profitable for them. Therefore, including this attribute can provide information about the impact on the consumer's choice of branded or generic prescription medicine. At the point of dispensing the pharmacist may suggest several options for the product or suggest a different brand to the one in the doctor's prescription. In each choice task, the assumption was that the doctor permits 'brand substitution', which is indicated on each page of the choice task on the sample script. Under Australian PBS policy, this gives the pharmacist freedom to suggest other brands of the medicine the consumer. The inclusion of this attribute provides an estimate of the level to which pharmacists are able to direct consumers to a product that is more profitable for them (i.e., control demand), which is important in the prescription drug market.

The total cost and the brand premium attributes

The *total cost* attribute was developed based on the review of the PBS data of branded and generic drugs, and brand premiums associated with some branded drugs. In 2020 the brand premium for PBS-listed medicines ranges from AUD0.50 to AUD35.30, with a mean of AUD5.17. The brand premium amount on PBS had a wide range. In the survey the brand premium was set at a realistic range from $0 to $20 to allow for a trade-off between prices in the DCE. The *total cost* attribute was constructed from the combination of the base prices $30, $35 and $40 and the six attribute levels from the *brand premium* attribute ($0; $2; $5; $10; $15; $20).

The DCE design was the same across DCEs 1, 2 and 3. The levels of *total cost* attribute were the same in all DCEs of Part 1. As previously described, the main difference between DCE 1, 2 and 3 was the way in which the total cost attribute was presented. (DCE 1 = the *total cost*, DCE 2 *total cost* with a *brand premium* applied to the product (Yes or No), DCE 3 full information in the *brand premium* attribute included the actual dollar amount).

Based on the selected attributes and levels, a number of predictions could be made regarding the likely results from the DCEs. It is expected that respondents would prefer lower prices to higher ones. However, it is also possible that the outcome is not be significant, since the product is for a one-off treatment of an acute condition. It is also expected that the convenience of immediate collection would be preferred by respondents. Since DCE 2 tests the impact of the presence of *brand premium*, without any information about the amount of *brand premium*, it is hypothesised that some respondents may see the presence of the *brand premium* as a signal of higher quality, or unique information about the product. In DCE 3, it is expected that respondents would prefer options with no *brand premium* (brand premium = $0) if the *total cost* is lower or prefer low/medium *brand premium range of $2–5)* as a trade-off to

collection and *pharmacist recommended*. It is expected that a non-significant proportion of respondents will choose an option with high *brand premium ($15–20)* amount.

The survey has two parts with a total of four DCEs, with different attributes and levels chosen for each DCE. The following section describes the attributes and levels and of each DCE in detail.

In Part 1, respondents chose between two alternatives in each of 12 choice sets (DCE 1-3). The *total cost* attribute ranged from $30 to $60, and the *brand premium* attribute in DCE 3 ranged from $0 (no *brand premium*) to $20. Part 1 of the survey consists of three DCEs, of which each respondent saw only one. The representation of the *total cost* and *brand premium* attributes and levels are shown in Table 2-4.

Table 2-4. Attributes and levels of total cost and brand premium as shown in DCE 1, DCE 2, DCE 3.

Attributes	DCE 1	DCE 2	DCE 3
Cost (Australian dollars)	30; 32; 35; 37; 40; 42;45; 50; 55; 60	30; 32; 35; 37; 40; 42; 45; 50; 55; 60	30; 32; 35; 37; 40; 42; 45; 50; 55; 60
Brand premium	-	Yes/No	$0, $2, $5, $10, $15, $20

In Part 2 of the survey, DCE 4 presented a hypothetical change in government policy for reimbursing medicines that cost above the specified co-payment ($40), such that only one medicine is reimbursed at the amount of co-payment, and the alternative medicines can cost in the range of $35 to $120 with cost entirely borne by the respondent.

At the start of the survey, all respondents saw the same information that describes what a doctor's prescription can look like in Australia, and what its parts signify. They also saw an explanation of the differences between branded medicines and generic medicines. The information presented to the respondents is shown in Figure 2-5 and Figure 2-6.

Figure 2-5. Survey Information on Doctor's prescription

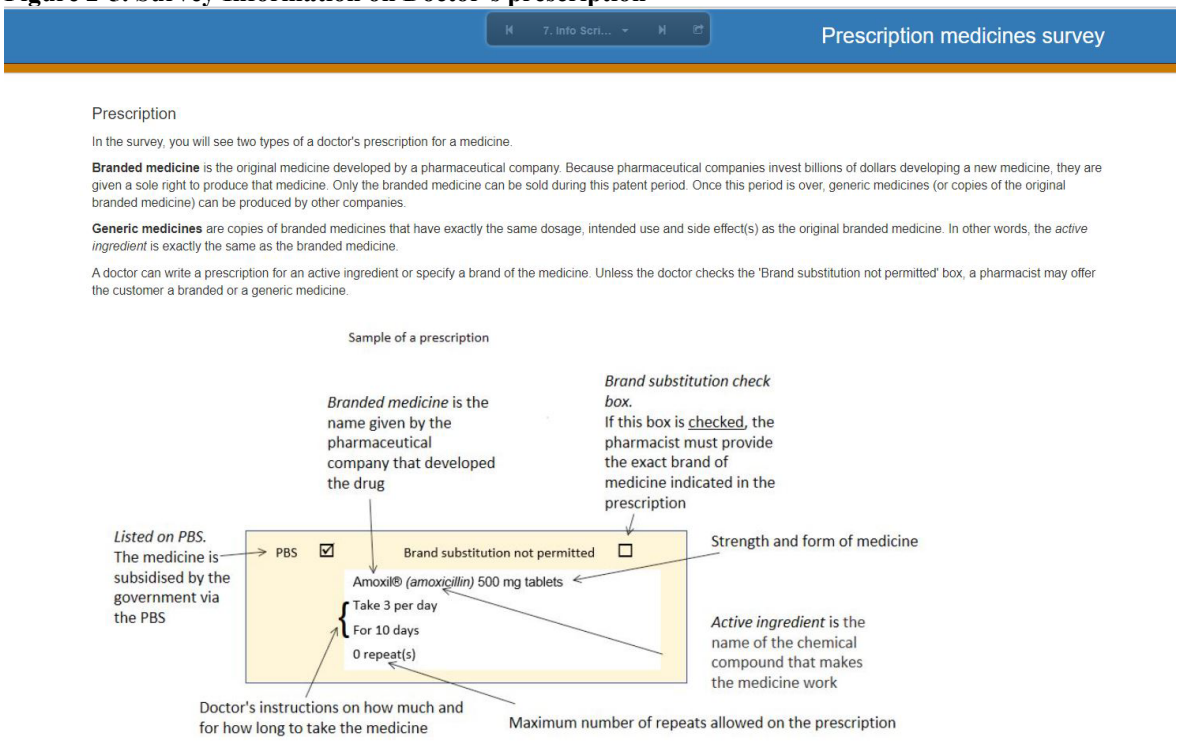
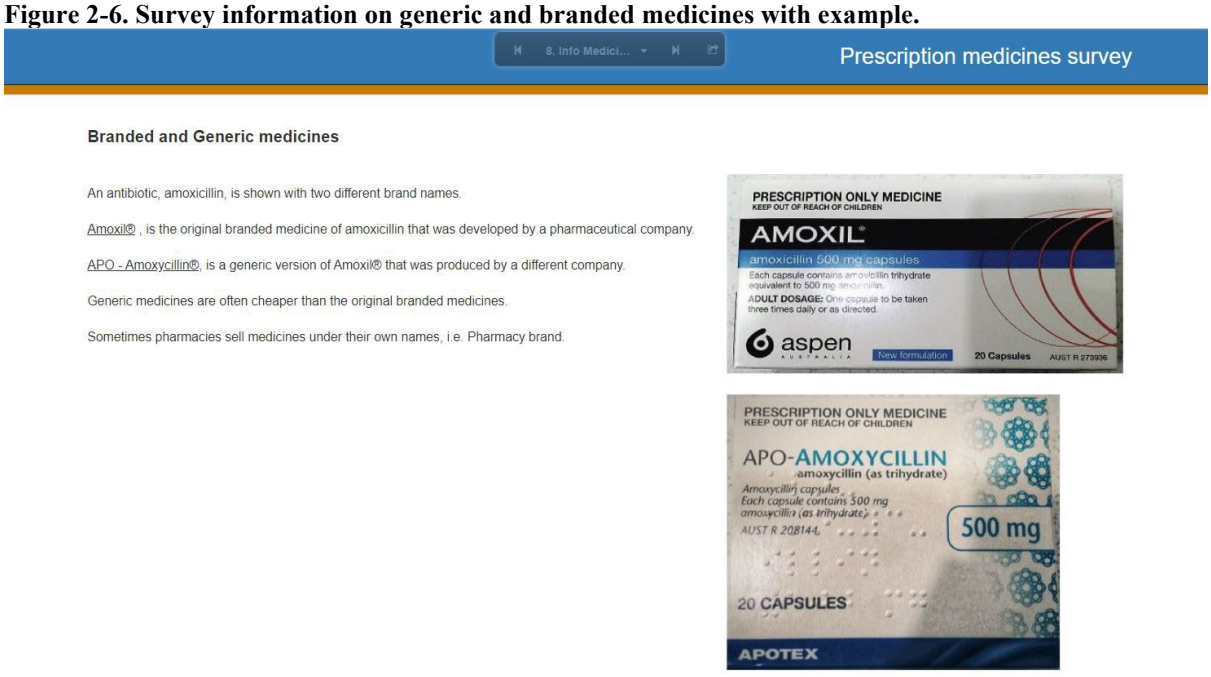


Figure 2-6. Survey information on generic and branded medicines with example.



After the information has been presented, respondents were randomised to one of the three DCEs in part 1 of the survey.

After completing the 12 choice tasks in Part 1 of the survey, respondents from all three DCEs entered a single pool of DCE choice tasks in Part 2. They were presented with additional information on a hypothetical changed government medicine reimbursement policy, including on its implications. Each respondent was randomised into one of the eight blocks of eight choice sets and asked to make their choices in the context of the new policy. In Part 2, under the hypothetical new policy which sees the Government only reimbursing for one brand of the medicine (and the patient paying full cost if another brand is preferred) the doctor would only write a prescription with the active ingredient name of the medicine, since with such a script the name of the medicine brand is irrelevant.

As described above, the selection of attributes and levels was based on a literature search and feedback from Centre for Health Economics and Research Evaluation colleagues.

Household demographic questions are collected at the end of the survey. These are described in detail in Section 2.9 of this chapter.

The design of the DCEs – Part 1

In this section, I describe the setting of the DCE, then explain the attribute and level selection process, and explain the approach to the design of the choice sets for DCEs in part 1 of the survey.

Six attributes were used to describe each option. The attributes and corresponding levels are given in Table 2-5, with attribute level combinations derived from three attributes of two levels, one attribute of three levels and one attribute of ten levels (representing price). The *total cost* attribute was constructed from two attributes, one representing base price and one the price premium, which were used to determine the attribute levels of the *total cost*.

Table 2-5. Description of attributes and levels for DCEs in Part 1

Attributes	Levels	Code	Description
Information condition			
Doctor's prescription	Generic name: Oleaceae Branded: Medora® (oleaceae)	0 1	Each level is allocated six choice tasks seen by the respondent. The order of the scrips is randomised into two arms
DCE attributes			
Product name	GENERIC 1: Pharmacy brand (oleaceae); GENERIC 2: Megorium brand (oleaceae); BRANDED: Medora® (oleaceae) – branded.	0 1 2	Two generic medicines and one branded medicine. GENERIC 1 is a base case in analysis
Total cost you pay	$30; $32; $35; $37; $40; $42; $45; $50; $55; $60	30; 32; 35; 37; 40; 42; 45; 50; 55; 60	A single attribute was constructed from these two attributes by adding the base price levels ($30; $35; $40) to the brand premium levels
Brand premium (DCE 3 only)	$0; $2; $5; $10; $15; $20	0; 2; 5;10; 15; 20	
Brand premium present (DCE 2 only)	No Yes	0 1	Nested within the brand premium attribute. 'No' is for when the brand premium is = $0
Collection time ('collection')	Now Later today	0 1	The medicine could be bought straight away, or it needs to be picked up later (same day) due to preparation time or waiting for a delivery
Pharmacist recommended ('recommended')	'-'(*no recommendation received*); Yes	0 1	The pharmacist may recommend the medicine or say nothing

The DCEs in part 1, DCEs 1, 2 and 3, included four attributes; the product (brand name or generic), the cost (which was further differentiated into two components in DCE 2 and 3: total cost and brand premium), the collection time for the medicine from the pharmacy, and pharmacist's recommendation of the product. A single design for the DCE was created for DCE 1-3.

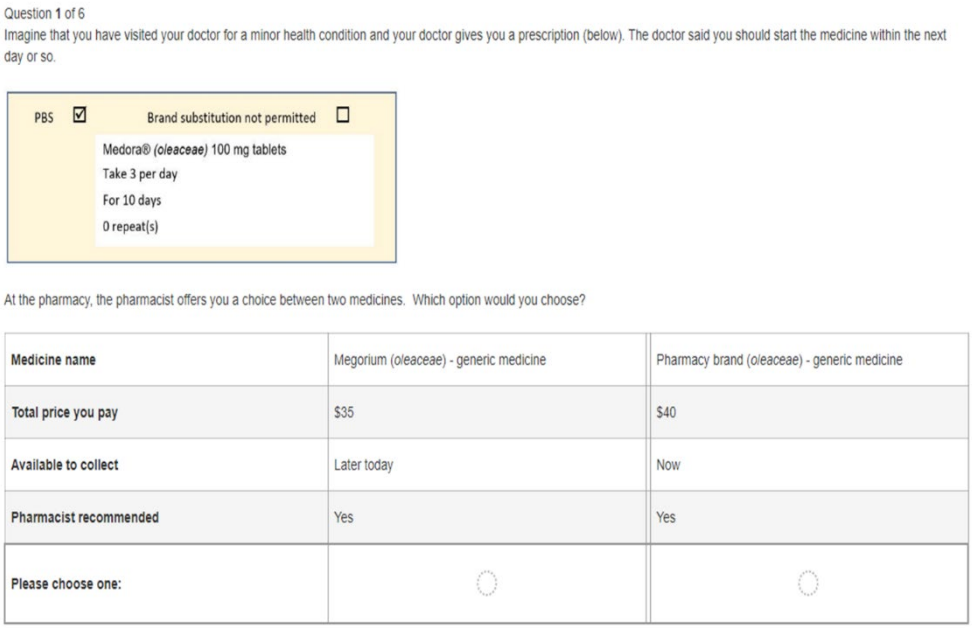
In Part 1 of the survey, attribute framing was used to present the information on the *total cost* of the product using one of the three formats. The *total cost* attribute consists of two components, the base cost and the *brand premium* cost. The level of information presented depended on the DCE to which the respondents were randomised.

DCE 1

The aim was to compare any differences in preferences for the particular attributes based on whether or not the additional information about cost was presented to the respondents. To avoid any confounding with the choice tasks, the DCE designs had identical choice sets in which the only difference was the method of presentation of the *total cost*. DCE 1 presented the least amount of information and acted as a control DCE for the project, while DCEs 2 and 3 included additional information about the cost of the

product. In DCE 1, respondents only saw the total cost attribute, and it was not possible to ascertain if a brand premium amount had been added, or the level of the brand premium. An example of a choice set shown to respondents randomised to DCE 1 is presented in Figure 2-7.

Figure 2-7. Example of a choice task shown in DCE 1 (*total cost* only)



DCE 2

In DCE 2, a binary variable was provided that indicated whether or not the total cost included a brand premium (although the amount of the brand premium was not revealed to the respondent). The objective of DCE 2 was to compare how respondents' preferences changed if they were aware of a brand premium, but unaware of the amount of the brand premium component. DCE 2 can be used to investigate whether respondents would prefer a product with the brand premium if it were one of the alternatives presented to them. An example of a choice set shown to respondents randomised to DCE 2 is presented in Figure 2-8.

Figure 2-8. Example of a choice task shown in DCE 2 (total cost and brand premium (binary) attribute)

Imagine that you have visited your doctor for a minor health condition and your doctor gives you a prescription (below). The doctor said you should start the medicine within the next day or so.

PBS ☑ Brand substitution not permitted ☐

Medora® *(oleaceae)* 100 mg tablets
Take 3 per day
For 10 days
0 repeat(s)

At the pharmacy, the pharmacist offers you a choice between two medicines. Which option would you choose?

Medicine name	Pharmacy brand (*oleaceae*) - generic medicine	Megorium (*oleaceae*) - generic medicine
Total price you pay	$35	$42
Brand Premium	No	Yes
Available to collect	Later today	Now
Pharmacist recommended	Yes	Yes
Please choose one:	○	○

DCE 3

In DCE 3 the amount of the *brand premium* in addition to the *total cost* attribute was provided. The aim of DCE 3 was to investigate if respondents have positive preferences for a product with brand premium, and/or what additional amount of the brand premium the respondents are willing to pay for the product. An example of a choice set shown to respondents randomised to DCE 2 is presented in Figure 2-9.

Figure 2-9. Example of a choice task shown in DCE 3 (*total cost* and *brand premium* ($) attribute)

PBS ☑ Brand substitution not permitted ☐

oleaceae 100 mg tablets
Take 3 per day
For 10 days
0 repeat(s)

At the pharmacy, the pharmacist offers you a choice of two medicines.

Medicine name	Megorium (*oleaceae*) - generic medicine	Pharmacy brand (*oleaceae*) - generic medicine
Total price you pay (including a Brand Premium, if any)	$40 (Price includes a Brand Premium of $5)	$40 (No Brand Premium, $0)
Available to collect	Now	Later today
Pharmacist recommended	Yes	Yes
Please choose one:	○	○

The design of the three DCEs was developed from the same set of choice tasks. The initial DCE design included the *total cost* to the consumer with the amount of the *brand premium* as a component of the *total cost* attribute. This design became DCE 3. To further test the consumer's response to the brand

premium attribute, the dollar ($) of the brand premium was exchanged for a dummy attribute that only indicated if the brand premium was present or absent in the presented alternative. The DCE brand premium was based on the cost amounts of brand premium attribute in DCE 3, where $0 amount would indicate absence of brand premium and any value above $0 would indicate presence of brand premium. This design was labelled DCE 2. Finally, to evaluate the preferences for medicine when the respondent is not told if the brand premium is attached to the medicine a DCE design was created by removing the brand premium attribute from the design of DCE 3. This became the DCE 1. Apart from the changes to the brand premium attribute, all other attribute and attribute levels were identical across the three DCEs.

2.4.2 Selection of attributes and levels – Part 2

DCE 4

After completing the 12 choice tasks in Part 1 of the survey, respondents from all three DCEs entered a single pool of DCE choice tasks in Part 2. DCE 4 is an experiment to investigate the likely impact of a hypothetical government policy in which only one medicine brand is subsidised by the government through the PBS. The format of the survey was such that all of the respondents from Part 1 also saw DCE 4, which would give additional analysis of the impact of the information seen in Part 1 on the responses to the DCE presented in Part 2. In particular this allowed one to test whether the additional information on the brand premium component of the price had an impact on the preferences for the new hypothetical price policy.

The rationale for such a hypothetical policy is that the government could use its monopolistic purchasing power to lower the price of generic drugs, as well as branded medicines. This could be achieved through some form of tender process, that would result in decrease of prices (Duckett & Breadon, 2015; Duckett et al., 2013; Godman et al., 2017; Hasan et al., 2019).

However, Godman et al. (2017) show that a choice of brands of the medicine after the patent expiration is prevalent in the policies of European countries, although medicines may not be fully subsidised by the government if certain price criteria are not followed (e.g., in Belgium). Also, for some consumers, access to choice is important (Lessing et al., 2015); therefore, DCE 4 incorporates an element of restricted choice, although the respondent is able to choose a non-subsidised alternative.

The hypothetical change in government policy is for reimbursing medicines that cost above the specified co-payment ($40), such that only one medicine is reimbursed at the amount of co-payment, and the alternative medicines can cost in the range of $35 to $120 with cost entirely borne by the respondent. The respondent is asked to choose between a subsidised medicine with a flat price of $40 for the prescription or a non-subsidised medicine, usually at higher cost. The development of the attributes and levels for DCE 4 was based on the processes in Part 1, including the *collection time* and *pharmacist recommended* attributes, as well as the product attribute, with two significant changes.

The brand premium attribute was removed and a *listed on the PBS* attribute was included. The product attribute was reduced to two options from three, the *pharmacy brand generic* and *Medora branded*. This was a simplification of choice for generic drugs; however, the choice between a branded and generic remained to identify preferences. In DCE 4 each option consists of five attributes, with four attributes of two levels and one attribute of eight levels (representing price). The attributes and levels used in DCE 4 are presented in Table 2-6.

Table 2-6. Description of attributes and levels for DCE in Part 2

Attributes	Levels	Code	Description
Product	GENERIC: Pharmacy brand BRANDED: Medora®	0 1	One generic and one branded medicine
Total cost you pay	$35; $40; $50; $60; $75; $90; $100; $120	35; 40; 50; 60; 75; 90; 100; 120	The dollar amounts of the total cost
Listed on the PBS	- Yes	 0 1	'Yes' level is nested with $40, however price of $40 does not mean PBS-listed
Collection time ('collection')	Now Later today	0 1	The medicine could be bought straight away, or it needs to be picked up later (same day) due to preparation time or waiting for a delivery
Pharmacist recommended ('recommended')	'-' (no recommendation received) Yes	0 1	The pharmacist may recommend the medicine or say nothing

The *total cost* was based on the analysis of the PBS database of the dispensed price for maximum quantity (DPMQ) for various drugs (such as amoxicillin). In the *listed on PBS* attribute the level response 'Yes' was nested with the *$40* level in the *total cost* attribute. Each choice task always included one alternative that was *listed on PBS*.

In DCE 4, it was expected that the respondents would pick the PBS-listed option each time unless the second option cost less ($35) or maybe slightly more ($50). Since in Part 2 government policy is focused on minimising expenditure, this can make other attributes less relevant, or perhaps a small difference in cost may be tolerated.

The design of DCE 4 in Part 2 was based on the concept of a hypothetical pharmaceutical price policy that may impact the out-of-pocket price the consumer pays for a preferred medicine. The format of the survey was such that all of the respondents from Part 1 also saw DCE 4, that would give additional analysis of the impact of the information seen in Part 1 on the responses to the DCE presented in Part 2. In particular this allows me to test whether the additional information on the brand premium component of the price had an impact on the preferences for the new hypothetical price policy. An example of a choice set shown to respondents in DCE 4 is presented in Figure 2-10.

Figure 2-10. Example of a choice task shown in DCE 4 (new Government policy)

Imagine that you have visited your doctor for a minor health condition and your doctor gives you a prescription (below). The doctor said you should start the medicine within the next day or so.

oleaceae 100 mg tablets
Take 3 per day
For 10 days
0 repeat(s)

At the pharmacy, the pharmacist offers you a choice between two medicines. Which option would you choose?

Product	Medora® (*oleaceae*)	Pharmacy brand (oleaceae) - generic medicine
Total price you pay	$40	$90
Listed on the PBS	Yes	-
Available to collect	Now	Later today
Pharmacist recommends	-	-
Please choose one:		

The survey was administered online to a representative sample of Australians. The final survey consisted of Part 1 (respondents randomised to one of three DCEs) and Part 2 (all respondents answering DCE 4) with 1,233 completed responses. The detailed survey flow diagram is shown in Table 2-7.

As described above, the selection of attributes and levels was based on a literature search, feedback from focus group at the Centre for Health Economics and Research Evaluation colleagues, the pilot survey, and the consultation with a practicing pharmacist (Bridges et al., 2011; Kleij et al., 2017; Vass et al., 2017). After the pilot study of 104 respondents there were no changes to the attributes and attribute levels presented in the DCEs.

A possible limitation in the development of the attributes and levels in this survey could be attributed to the lack of qualitative work with a variety of stakeholder, such as general consumers and doctors (Mangham et al., 2009; Lancsar & Louviere, 2008). The CHERE (UTS) internal focus groups who were asked for comments and feedback on the attributes and levels, as well as to take the survey numbered over 20 people. The lack of focus groups involving health professionals, could be covered by the fact that one of the CHERE (UTS) colleagues is a practicing general practitioner, who was part of the internal focus groups.

There is a number of ways to conduct the qualitative work for any DCE or other methods, and each topic would require adjusting its approach (Coast & Horrocks, 2007). However, as long as there is through understanding of the research question, the target population and available resources, the collected data can be validated and be useful for the study (Bridges et al., 2011; de Bekker-Grob et al., 2012).

Table 2-7. Survey flow diagram.

Survey flow		Introduction to the survey Screening/quota demographic questions TEXT: General Information Randomisation to 1 of 3 DCEs (on quota gender & age)			
PART 1					
Information page: Respondents only see information on *Total cost*		Information page: Respondents see Information on *Total cost* and *Brand premium* (Same Information text for DCEs 2 and 3)			
DCE 1		DCE 2		DCE 3	
Randomisation to 1 of the 144 blocks (72 blocks per arm) Each block consists of 12 choice tasks		Randomisation to 1 of the 144 blocks (72 blocks per arm) Each block consists of 12 choice tasks		Randomisation to 1 of the 144 blocks (72 blocks per arm) Each block consists of 12 choice tasks	
TEXT Page: Respondents see a page with information about Prescription for 'generic name' Respondents answer 6 choice tasks/questions *Total cost*	TEXT Page: Respondents see a page with information about Prescription for 'Brand name' Respondents answer 6 choice tasks/questions *Total cost*	TEXT Page: Respondents see a page with information about Prescription for 'generic name' Respondents answer 6 choice tasks/questions *Total cost + Brand premium* (dummy)	TEXT Page: Respondents see a page with information about Prescription for 'Brand name' Respondents answer 6 choice tasks/questions *Total cost+ Brand premium* (dummy)	TEXT Page: Respondents see a page with information about Prescription for 'generic name' Respondents answer 6 choice tasks/questions *Total cost + Brand premium* ($ amount)	TEXT Page: Respondents see a page with information about Prescription for 'Brand name' Respondents answer 6 choice tasks/questions *Total cost + Brand premium* ($ amount)
TEXT page: Respondents see a page with information about Prescription for 'Brand name' Respondents answer 6 choice tasks/questions *Total cost*	TEXT Page: Respondents see a page with information about Prescription for 'generic name' Respondents answer 6 choice tasks/questions *Total cost*	TEXT page: Respondents see a page with information about Prescription for 'Brand name' Respondents answer 6 choice tasks/questions *Total cost + Brand premium* (dummy)	TEXT Page: Respondents see a page with information about Prescription for 'generic name' Respondents answer 6 choice tasks/questions *Total cost+ Brand premium* (dummy)	TEXT page: Respondents see a page with information about Prescription for 'Brand name' Respondents answer 6 choice tasks/questions *Total cost + Brand premium* ($ amount)	TEXT Page: Respondents see a page with information about Prescription for 'generic name' Respondents answer 6 choice tasks/questions *Total cost + Brand premium* ($ Amount)
PART 2					
		TEXT: All respondents see Information Page on Policy Randomisation to 1 of 8 blocks Respondents answer 8 choice tasks/questions Additional socio-demographic and post-DCE questions Survey Exit			

2.5 Design of DCE

There were several steps in the DCE design process. In this section, I explain the design of the sets of choice tasks for each DCE, that is based on the attributes and levels selected for the DCEs, and presented in the sections above. I then describe the software used to generate the choice sets in Mathematica (Wolfram Research, Inc.) and to carry out the simulation of the data using R (RStudio Team).

The design and selection of choice tasks was considered in line with objectives listed by Bunch et al. (1996):

- minimising the practical difficulty of obtaining the design;
- minimising cognitive difficulties for survey respondents. Also includes minimising the number of choice sets in the survey; minimising the number of alternatives per choice set; and minimising the number of attribute trade-offs required;
- maximising the capability of estimating a variety of model functional forms; and
- maximising the "statistical efficiency" of the design.

The designs of the DCEs were based on a generator-developed approach (Street & Burgess, 2007), using starting designs obtained from the table of orthogonal arrays of strength two maintained by Kuhfeld on the SAS website (Kuhfeld, 2006). This is one of the most common types of theoretical construction of choice sets and has been shown to perform well in simulations and applications (Street & Viney, 2019). Other methods to construct DCE designs are also available and include use of software package Ngene (Choice Metrics, 2012), the statistical packages Stata (StataCorp)[31] or SAS software (SAS Institute Inc. 2015) or various routines written in RStudio (RStudioTeam)[32].

A DCE can allow for repeated observations (DCE scenarios) per individual, which reduces the number of participants required to provide sufficient variation to examine the relationships of interest within the data. The aspects of DCE design include decisions about the number of choice tasks and the number of respondents (sample size) required to ensure adequate statistical power to detect a difference in preferences (De Bekker-Grob et al., 2012). Potentially, as few as 20 respondents per choice task are required to provide estimates for simple relationships between the choice task and the attributes included (Burgess et al., 2011; Lancsar et al., 2007).

Additionally, the choice of statistical model used in the DCE analysis can play a role in the estimation of the number of respondents needed to obtain estimation precision of the parameters (De Bekker-Grob

[31] StataCorp. 2021. Stata Statistical Software: Release 17. College Station, TX: StataCorp LLC.
[32] RStudio Team (2020). RStudio: Integrated Development for R. RStudio, PBC, Boston, MA URL http://www.rstudio.com/.

et al., 2012). The data is analysed using conditional logit model (to account for heterogeneity of individual preferences) and mixed logit model (aka random parameters logit model) that extends the conditional logit model by allowing for random variation in the preference parameter , with the designs in Part 1 constructed to allow for the estimation of main effects. The designs were a forced choice as there was no opt-out option, and I chose to use the mixed logit model as it is frequently used for DCEs (Soekhai, De Bekker-Grob, et al., 2019) and may be associated with better 'goodness of fit' (Clark et al., 2014). The mixed logit model used in the analysis accommodates preference heterogeneity across the respondents.

The section below describes the design of the choice tasks for DCE 1 to DCE 3 and DCE 4.

2.5.1 Size of the choice task

Following the selection of the attributes and levels, other components of the DCE were considered: the number of alternatives per choice task (two or more), the inclusion of an opt-out option, and having labelled or unlabelled alternatives (where unlabelled alternatives do not name a particular good or service but use generic names such as option A, B or C, and labelled alternatives use alternative specific names – for example, one option is always a tablet form of the medicine, and another is an IV form). The decision was made to present two unlabelled alternatives per choice set to minimise the complexity of the task and to focus on the investigation of trade-offs between attributes.

The concept of the research question included two generic medicines and one branded medicine to enhance the comparison of attributes that each product can assume, rather than the product label. In this case, the use of unlabelled alternatives was considered most appropriate.

In addition, the decision to use an unlabelled design was based in part on the merits of such designs as described by De Bekker-Grob et al. (2010): the unlabelled DCE can have a smaller design, since there is no additional restriction of the choice set size that needs to be accounted for in the labelled design; there is no need to identify and use all alternatives within the universal set of alternatives, as the attribute levels can be used to represent all alternatives; unlabelled DCEs are more robust in not violating independent and identically distributed (IID) assumptions (where error terms of each random variable are independent and identically distributed); and they encourage respondents to trade-off attribute levels (De Bekker-Grob et al., 2010; Hensher et al., 2005). The last point is particularly appropriate for this setting since the point of the DCEs is not to have a market valuation of a product but, rather, to understand the factors that may influence respondents when choosing a product they are not familiar with. Additionally, the 'invented' product names devised for this research would not provide any additional information for the analysis if they were used as alternative labels.

Also, in line with choosing an unlabelled design, the DCE did not include an opt-out option, as I wanted to force the respondent pick a product described by a combination of alternative-levels. In addition, the context of the choice task was more realistic with the opt-out excluded, since, in the situation which

involves the patient seeing a doctor, receiving a prescription and going to the pharmacy, there is a high likelihood that the patient is going to purchase the prescribed drug.

2.5.2 Design of DCE1, DCE 2 and DCE 3

As noted above, the DCEs presented in this thesis offer two choice alternatives in each choice task. DCEs design developed for Part 1 were based on fractional factorial designs, with a number of restrictions imposed on the presentation of attribute levels. Half of the design had overlap on collection attribute levels and half on *pharmacist recommended* attribute levels, with no simultaneous overlap in both attributes; the base level of product attribute, pharmacy generic, appeared in every choice task; and the *brand premium* level ($0) is overrepresented in the design to increase the frequency of base prices ($30; $35; $40).

Attributes and levels used in the DCEs in part 1 of the survey are shown in Table 2-7. In DCE 1 there is one three-level, one 10-level and two two-level attributes; in DCE 2 there was an additional two-level attribute compared to DCE 1, and in DCE 3 there was an additional six-level attribute compared to DCE 1.

The full design for DCE 1 includes 120 possible options (3^1 x 10^1 x 2^2); for DCE 2 there are 240 possible options based on (3^1 x 10^1 x 2^3); and for DCE 3 there are 720 possible options based on (3^1 x 10^1 x 2^2 x 6^1). The number of possible choice tasks with two options per choice task in DCE 1 is 7,200 (=120 x 120 /2); similarly, in DCE 2 it is 28,800 and in DCE 3 it is 259,200. It would be impossible to present all choice tasks to the respondents in the survey; therefore, a subset of choice tasks is chosen for the DCEs.

Table 2-8. Attributes and levels for DCEs in Part 1

Attributes	Levels	Code	# levels
Product name	GENERIC 1: Pharmacy brand (Oleaceae); GENERIC 2: Megorium brand (Oleaceae); BRANDED: Medora® (Oleaceae) – branded.	0 1 2	3
Total cost you pay	$30; $32; $35; $37; $40; $42; $45; $50; $55; $60	30; 32; 35; 37; 40; 42; 45; 50; 55; 60	3 base levels ($30; $35: $40) 10* levels overall
Brand premium (DCE 3 only)	$0; $2; $5; $10; $15; $20	0; 2; 5;10; 15; 20	6
Brand premium present (DCE 2 only)	No Yes	0 1	2
Collection time (‘collection’)	Now Later today	0 1	2
Pharmacist recommended (‘recommended’)	‘-‘(*no recommendation received*); Yes	0 1	2

*Note: Total cost has ten levels that were derived from all possible combinations of the total cost base levels ($30, $35, $40) with levels in brand premium attribute ($0, $2, $5, $10, $15, $20).

As the design of all three DCEs is identical, apart from the removal of the *brand premium* attribute for DCE 2 and DCE 1, the overall DCE design was based on the total attributes and levels selected for DCE 3.

In the selection of the number of choice tasks in the DCEs, several conditions were imposed during the construction of the design.

- The *Medora branded* product and the *Megorium generic* product do not appear in the same choice task. This condition was imposed so that there was always an option that did not attract a *brand premium* (*pharmacy brand generic*).
- Following on from the previous point, the *pharmacy brand generic* was only available at one of three prices ($30, $35, $40), since this generic product did not attract a *brand premium*.
- Some *total cost* attribute levels can be constructed from two different combinations (levels) of base price and *brand premium*, i.e. $35 can be formed from the sum of ($35+$0) and ($30+$5); this may lead to more replication of some levels of the *total cost* attribute compared to others.
- To present a more realistic choice to respondents, lower levels of the *total cost* attribute were overrepresented in the design. It would be less common for the alternative (more expensive) product to be offered or sold at the pharmacy.

Using starting designs obtained from the table of orthogonal arrays of strength two maintained by Kuhfeld on the SAS website (Kuhfeld, 2006), for DCE 3 a design with two attributes with two levels, two attributes with three levels and one attribute with six levels was used. I used the 3^9 9^1 (with 27

rows) array and, to get the design I required, I omitted five of the three-level attributes and collapsed (that is, equated some of the levels) two of the three-level attributes to obtain two levels (by equating 2=0). Finally, the nine=level attribute was collapsed to six levels in such way as to increase the frequency of the *brand premium* level of $0. The other columns from the design were chosen arbitrarily; however, several samples were tested to identify the impact on optimality results for the design.

Two columns had to be collapsed from three levels to two to accommodate the two attributes with two levels (*collection* and *pharmacist recommended*). The use of two generators was necessary to create a design in which each of the two-level attributes appear at the same level in half of the choice sets. Thus, recommendation appeared at level 'yes' in both options only when both collection levels appear in the choice set. This was done in an attempt to force respondents to think about these attributes independently of each other. When constructing the design, the following order of the attributes was used: *collection time*, *pharmacist recommended*, *product*, *base price* and *brand premium*. The generators were (0,1,1,2,3) and (1,0,2,1,4). The design approach was a generator-developed design constructed using a Mathematica Notebook developed by Leonie Burgess (Street & Burgess, 2007). The constructed DCE consisted of 54 choice sets and had a D-efficiency of 87.9% compared to the best possible design under the assumption of zero priors. The collapse of the attribute happened after the generation of the choice sets, because I wanted to have an over-replication of the brand premium attribute (level $0).

Additional changes were made to the choice set by first collapsing three of the nine levels to create more $0 *brand premium* attribute levels, resulting in $0 appearing 48 times, while $2, $5, $10, $15 and $20 appeared 12 times each. The efficiency decreased to 75.9% after the levels were collapsed.

The next step in designing the choice sets involved implementing the condition that the branded medicine and the second generic brand medicine would not appear with each other, and that the branded medicine would appear twice as often as the second generic brand medicine. This operation involved changing the level of the *Megorium generic* product to the *pharmacy brand generic* product when it was in combination with the *Medora branded* product. Additionally, the *brand premium* levels were set to zero for all product levels of *pharmacy brand generic*. The D-efficiency decreased to 51.6%.

Blocks combined choice tasks

The 54 choice sets were divided into nine blocks of six choice sets each. The blocks were chosen so that each included a range of price differences between the options as well as several choice sets in which the *pharmacist recommended* levels were the same and several where the *collection time* levels were the same.

Each arm of the DCE required two blocks of six choice sets, one block for each prescription type. To avoid respondents seeing the same block twice, the 72 ordered pairs of distinct blocks were created.

Each arm in each of the three DCEs has the same underlying design but with the representation of the price attribute differing among the designs.

Validating the DCE design

The design of the DCE is important since it impacts on the validity of the estimated respondents' preferences. To test a statistical validity of the design, a simulation of the multinomial logit data results using selected priors was conducted. The priors were selected only to test the choice set design during the simulation, and were not used in the design or any amendments to the choice set.

For the simulation, I assumed prior values for the terms in the mixed logit model for each attribute and these were used to calculate the corresponding probability that each option in each choice set would be chosen. A random sample of size (n=24) was then generated from each choice set, and these were used to estimate the corresponding coefficient for each parameter. For each investigated prior value, this simulation was repeated 1,000 times. The performance of the design was assessed by examining the estimated beta coefficients and comparing them with the assumed priors, as well as analysis the standard deviations for each of the parameter. The simulation of the data was performed in RStudio software, with the code provided by Street (2019).

The priors used in the simulation of the responses to the choice set were selected as follows:

- *collection* of medicine prior was chosen based on the assumption that respondents prefer to get their medicine 'Now' rather than having to come back later;
- *pharmacist recommended* prior reflected the expectation that some respondents would seek pharmacist's advice at the point of purchase;
- product of *Medora branded* prior and *Megorium generic* prior were chosen arbitrarily, but both with a positive sign on the prior; and
- the *total cost* prior reflected the expectation that respondents prefer to pay less for the product (medicine).

Simulations were conducted using orthogonal polynomial contrasts for all price values to test linear order effects. The quadratic and cubic values were also tested but are not reported here.

The estimated coefficients were in line with the assumed priors. The confidence intervals were narrow and standard errors were quite small except for the *total cost* attribute, which is expected with a continuous variable. Overall, the DCE design appears to be performing well. The graphical summary of the simulated betas and associated standard errors are presented in Figure 0-1 in Appendix A.

2.5.3 Design of DCE 4

The derivation of the design of the DCE 4 was different to the DCEs 1,2 and 3.

The design of DCE 4 was based on the selected attribute levels: *product*, *listed on the PBS*, *collection time* and *pharmacist recommended* attributes had two levels and *total cost* had eight attribute levels. The details of the attributes and levels in DCE 4 are shown in Table 2-8.

Table 2-9. Attributes and levels in DCE 4

Attributes	Levels	Code	# levels
Product	GENERIC: Pharmacy brand BRANDED: Medora®	0 1	2
Total cost you pay	$35; $40; $50; $60; $75; $90; $100; $120	35; 40; 50; 60; 75; 90; 100; 120	8
Listed on PBS	- Yes	 0 1	2
Collection time ('collection')	Now Later today	0 1	2
Pharmacist recommended ('recommended')	'-' (no recommendation received) Yes	0 1	2

I decided to present each respondent with eight choice tasks, with each level of the *total cost* presented once. There were several conditions imposed on the design of the choice set of DCE 4. First, there was an even combination of *product* attribute levels with the *listed on PBS* attribute levels. Second, the *listed on PBS* attribute always appeared with the second level of *total cost* attribute "$40". However, the "$40" level in *total cost* attribute was not always paired with the *listed on the PBS* attribute. Third, half of the design had overlap on *collection* and *pharmacist recommended* attributes, with no simultaneous overlap in both attributes; and the combinations of the two attributes (*collection* and *pharmacist recommended*) were combined with all the eight levels of the *total cost* attribute. The combinations of the attribute levels with imposed conditions resulted in a choice set of 64 choice task pairs.

The 64 choice sets were divided into eight blocks of eight choice tasks each. Each block consisted of two alternatives per choice task, of which one alternative was always *listed on PBS*. Four choice tasks were a combination of *branded* product – *listed on the PBS*, and four were a combination of *generic* product with *listed on the PBS*. The alternative option was always *not listed on the PBS*. Additionally, in each block of eight choice tasks there were an even number of the two attribute levels for *collection* and *pharmacist recommended* in each alternative, with different combinations.

For example, in one block a choice task that included $60 *total cost* level, option one was (branded product (Medora), listed on the PBS, $40 (PBS cost), collect later, no pharmacist recommendation); and option 2 was (pharmacy generic product, not listed on the PBS, $60, collect later, pharmacist recommended). This compared to a choice task from another block for a *total cost* level of $60, with option one (pharmacy generic product, listed on PBS, $40 *total cost*, collect later, not pharmacist recommended) and option two (branded product (Medora), not listed on the PBS, $60 *total cost*, collect now, pharmacist recommended). Each respondent was randomised to one of the eight blocks.

2.6 Statistical framework

2.6.1 Random utility theory and discrete choice framework

This section presents an overview of the statistical framework used to analyse discrete choice data and to estimate the respondents' preferences for the different attributes and levels that describe the different options presented in the four DCEs.

The dataset from the survey is the collection of SP from Australian respondents about their choice for branded and generic products in hypothetical situations of purchasing prescription medicines at a pharmacy.

The respondents' utility maximisation of the chosen alternative is a function of the attributes of the alternative (McFadden, 1973). To infer the strength of preference for each attribute and attribute levels that describe each alternative, the analysis is based on random utility theory (Ben-Akiva et al., 1985), which acknowledges the discrete nature of choice as the dependent variable.

In the model, the individuals are the decision-makers and evaluate the attributes of each alternative, then select the better alternative for them. Each person is assumed to get some utility from each option, and it is assumed that the person chooses the alternative that gives the highest utility of all the alternatives on offer in a given choice task.

Using this framework, I would like to understand the components that determine that utility for respondents making choice of prescription medicine. For example, if I, as a researcher, could observe everything in a respondent's decision making, then I would be able to identify what the utility is for each option for each person, and identify which one is the highest, and be able to correctly predict what option each person would choose. However, since this is not yet possible, I can use the information that is available from the choices made to make guesses and probability statements about what the chosen option would be in a new choice task.

The DCE is based on probabilistic choice theory and random utility theory, and is consistent with Lancaster's economic theory of value (Arons & Krabbe, 2013; Green & Gerard, 2009; McFadden, 1973). The basis of probabilistic choice theory is that there is some uncertainty surrounding an individual's choices. Thus, the models can assign the level of probability at which each alternative is chosen.

Since the choice is discrete, the result indicates the trade-off between the two alternatives, with the probability of choosing alternative *j* changing as the levels of the attributes in the alternative change.

The utility can be decomposed into two parts: the components that can be observed (based on variables that we can observe, measure, put into the model) (denoted by V) and the components that cannot be observed (usually denoted by ε).

Random utility theory assumes that the individual acts rationally and chooses the alternative with the highest level of utility. As we cannot observe the individual's true utility function, we can only calculate the probability of an individual making a particular choice, estimated from observed choices (Viney et al., 2005). These models assume that utility that individual *n* derives from choosing alternative *j* is given by the following equation [1]:

$$U_{jn} = V_{nj} + \varepsilon_{nt;\ n=1,\ldots,\ N;\ j=\ 1,\ldots J;} \qquad \text{Equation 1}$$

where there are *N* individuals making the choice among *J* alternatives.

In a situation with two available alternatives, *j* and *i*, the probability (Pr_{nj}) of individual *n* choosing alternative *j* is the probability that the utility of alternative *j* (U_{nj}) is greater than the utility of alternative *i* (U_{ni}), based on the (cumulative) probability that the error term difference is less than the difference of observed quantity of the predictable component of the overall utility of choosing alternative *j*. This is given in Equation 2:

$$Pr_{nj} = Pr\ (U_{nj} > U_{ni}) = Pr\ (V_{nj} + \varepsilon_{nj} > V_{ni} + \varepsilon_{ni}) = Pr\ (V_{nj} - V_{ni} > \varepsilon_{ni} - \varepsilon_{nj}), \qquad \text{Equation 2}$$

where V_{nj} represents the systematic component of the utility and ε_{ij} is the random (unexplained) component. The systematic component of utility V_{nj} depends on attributes of the alternative, *j*, and on attributes of the individual, *n*, making the choice (Viney et al., 2005). This approach shows that each option has a separate utility: each individual choosing between the two alternatives, the choices are aggregated over the individuals with the total observed percent of the sample that chooses alternative *j* (Train & Weeks, 2005).

Equation 1 can be extended by splitting utility into an observable and unobservable parts. The utility an individual *n* derives from choosing alternative *j* in choice task *t* is estimated for U_{njt}:

$$U_{njt} = \beta_n X_{njt} + \varepsilon_{njt,} \qquad \text{Equation 3}$$

where β_n represents the vector of coefficients, and X_{njt} is a vector of explanatory variables The choice of the econometric model to analyse the data depends on the assumptions about the distribution of the random component for the utility function, ε_{nj}, and the function of the observed variable, V_{nj}. It has to be represented by variables comprising the observed attributes of alternative *j* (that vary over alternatives) and variables representing characteristics of the individual *n* (that do not vary over the choice tasks presented to the same individual). The part of the utility that can be captured is presented in Equation 4:

$$U_{nj} = V_{nj} + \varepsilon_{nj} = (\beta_n X_{nj} + \delta_n Z_n) + \varepsilon_{nj,} \qquad \text{Equation 4}$$

where β_n represents the vector of the attribute related variables and δ_n represents the vector of individual-related variables (that define the direction and importance of the effect of an attribute on the utility of an alternative). These variables are collected in vector Z_n for each respondent *n*.

The following sub-sections explain the models used in the analysis of the data collected from the survey. I start with the conditional logit model, then move to a random parameter model (mixed logit), including the estimation of the WTP, possible due to the presence of the cost attribute in the design, and finally present the latent class model as this allows for further identification of heterogeneity within the samples.

2.6.2 Conditional logit model

A conditional logit model is a common model used to analyse DCE results, with a straightforward interpretation of the estimated coefficients as the marginal utility of characteristics of the attribute.

The conditional logit model (McFadden, 1973) is a popular multinomial model among DCE researchers (e.g., (Lancsar et al., 2017; Soekhai, De Bekker-Grob, et al., 2019)). Conditional logit model can be used to confirm the performance of the data before moving to more complex models (i.e. mixed logit model).

From Equation 2, the conditional logit model can be specified ((Train & Weeks, 2005), Chapter 3 (3.1)), assuming that the random terms are IID, where each random variable has the same probability distribution as the others and all are mutually independent – known as independence of irrelevant alternatives (IIA).

The IIA assumption simplifies the conditional logit model; however, it also has an unrealistic aspect in that implies that the odds ratio of two alternatives *j* and *i* are the same, regardless of any other alternatives available (Haan, 2004).

In a situation of two alternatives, the probability of individual *n* choosing alternative *j* over *i* is given by:

$$\Pr(\text{choice} = j) = \frac{P_{\text{nj}}}{P_{\text{ni}}} = \frac{exp(V_{\text{nj}})}{\sum_i \exp(V_{\text{ni}})} \Big/ \frac{exp(V_{\text{ni}})}{\sum_i \exp(V_{\text{nj}})} = \frac{exp(V_{nj})}{\exp(V_{\text{ni}})} \qquad \text{Equation 5}$$

where $V_{\text{nj}} = \beta X_{\text{j}}$, and β represents the constant marginal utility and X varies over the alternative j, and similarly $V_{\text{ni}} = \beta X_{\text{i}}$, represents for alternative i. The conditional logit model assumes that respondents have the same preferences that depend only on observable characteristics of the alternatives presented to them.

This assumption implies that an individual's unobserved preference for a chosen alternative is independent of their unobserved preference for another alternative. However, as the DCE data is panel data, where we observe respondents making several choices, it is not reasonable to expect independent choice outcomes across choice occasions made by the same respondents, as pointed out by (Fiebig & Hall, 2005).

The conditional logit model is estimated in Stata 17 (StataCorp, 2021) statistical package, using 'clogit' command. The model does not account for possible preference heterogeneity among respondents. In

order to account for such heterogeneity, I consider a random parameter model (mixed logit model) that allows for the lack of independence between choice outcomes in the next section.

Different choice models arise from different assumptions about distributions and properties of error components and about variance-co-variance matrices of preference parameters. For example, the nested logit model relaxes IIA by allowing violations of IIA between nests, while requiring IIA to hold within nests (Lancsar & Louviere, 2008). A nested model is such when the choice set is partitioned into several subsets (nests) where each alternative belongs to exactly one nest. For example, transport attributes 'train' and 'bus' belong to a nest: public, where 'car' and 'bicycle' belong to nest: private. Other models that relax IIA include multinomial probit and mixed logit (MXL) (Lancsar & Louviere, 2008).

2.6.3 Random parameter model (mixed logit model)

A mixed logit model, which is less restrictive than the conditional logit, extends the conditional model by allowing one or more of the parameters in the model to be randomly distributed. Therefore, the coefficients in the model may vary across the individuals (McFadden & Train, 2000). The strength of the mixed logit model is its ability to account for unobserved preference heterogeneity, with the model being favoured in the analysis of DCE datasets (Soekhai, De Bekker-Grob, et al., 2019). Briefly, in an MXL model the random parameters are assumed to follow a normal distribution (default) and the resulting model is estimated through simulated maximum likelihood (Hole, 2007; Pacifico & Yoo, 2013). However, other distributions can be specified for the model in different statistical packages, such as, log-normal, triangular or uniform (Train & Weeks, 2005).

Based on Equation 3 and including the vectors of the attribute related variables only, the utility can be divided into two parts, as before, the observable and unobservable. Assuming that β can vary among respondents, the β_n is decomposed into fixed and random parts ($\beta_n = \beta + \eta_n$), allowing for β to be a vector of coefficients, η_n to be a random term that captures non-observable individual effects (distributed with mean zero and covariance W). As the IIA is relaxed, a utility of respondent *n* choosing alternative *j* in choice task *t* as a function of alternative's attributes, *X*, is:

$$U_{\mathrm{njt}} = V_{\mathrm{njt}} + \varepsilon_{\mathrm{njt}} = \beta_n X_{\mathrm{njt}} + \varepsilon_{\mathrm{njt}} = (\beta + \eta_{\mathrm{n}}) X_{\mathrm{njt}} + \varepsilon_{\mathrm{nj}} = \beta X_{\mathrm{njt}} + \eta_{\mathrm{n}} X_{\mathrm{njt}} + \varepsilon_{\mathrm{nj}} \quad \text{Equation 6}$$

where X_{njt} is a vector of observed attributes, β is the vector of coefficients associated with these attributes, η_{n} is a vector of *k* standard deviation parameters, and $\varepsilon_{\mathrm{njt}}$ is an unobserved random term that is independent of the other terms in the equation and IID extreme distributed.

As the distribution of $f(\beta)$ is unknown from $f(\beta_{\mathrm{n}})$, the parameters are estimated as mean β (the fixed part of $f(\beta)$ from Equation 6) and the variance-covariance *W*, which describes the distribution of the random part η_n.

The probability of choosing alternative *j* over alternative *i* in a choice task *t* is:

$$Pr_{njt} = \int \prod_{t}^{T} \left(\frac{e^{\beta' n X_{njt}}}{\sum_i e^{\beta' n X_{nit}}}\right) f(\beta) d\beta \,, \qquad \text{Equation 7}$$

where X_{njt} and X_{nit} are observed variables that relate to the alternatives *j* and *i* and the respondent β_n is a vector of coefficients of these variables for individual *n* representing that person's tastes. The coefficients vary over the respondents in the population sample with density $f(\beta)$, with mean β and covariance *W*, which determines the weight of each calculated probability in the overall likelihood function.

Additionally, as individual taste variations are captured in the variance *W* of the coefficients, and the IIA property does not hold with the denominator of the choice probability being inside the integral which does not cancel out. This allows the mixed logit model to produce unbiased estimates, although some unobserved heterogeneity may be present in the data (Haan, 2004).

The mixed logit model is estimated by inserting the estimated choice probabilities into a log-likelihood function and maximising the function. The maximum simulated likelihood (MSL) method allows for the use of the simulated probabilities of the observed choice of an observation. Additionally, a consistent MSL is achieved if the number of draws used increases with the sample size, and MSL is efficient if the number of draws increases faster than the square root of the sample size (Train & Weeks, 2005).

In the analysis of each DCE, the mixed logit model was estimated by varying the number of Halton draws from 100 to 10,000, in an attempt to obtain stable estimates (Ellis et al., 2019; Hole, 2007). The number of draws used in the final analysis depend on the estimated log-likelihood from each number of draws, and comparing it to the recommended number of draws required for better estimates of log-likelihood (Czajkowski & Budziński, 2019). For example, for a sample of 1,200 respondents that saw eight choice tasks with five attributes per choice task, the authors recommend a minimum of 874 draws.

The mixed logit model is estimated in Stata 17 (StataCorp, 2021) Statistical package, using 'mixlogit' command.

2.6.4 The linear model

In DCE, the representative utility V_{nj} is estimated with a linear function, thus for individual *n* to choose alternative *j* in choice task *t* is generally given by:

$$V_{njt} = \beta_{TC} * X_{TCnjt} + \beta_P * X_{Pnjt} + \beta_{COL} * X_{COLnjt} + \beta_{REC} * X_{RECnjt} \qquad \text{Equation 8}$$

where β_{TC} is the coefficient for the *total cost* attribute, β_P is the coefficient for the *product* attribute, X_{COL} is the coefficient for the *collection* attribute, and β_{REC} is the coefficient for the *pharmacist recommended* attribute.

2.6.5 Calculating marginal rates of substitution (willingness to pay)

In the context of this analysis, the marginal WTP is defined as the minimum monetary value that an individual is willing to pay (if WTP > \$0) or require to have a reduction in the cost (if WTP < \$0) for a change in the level of a certain attribute, in addition to/deducted from the price they are paying for the product

The inclusion of cost attribute in the DCE can be used to estimate the WTP, with a monetary term estimated for each attribute. Therefore, the results can be compared across different models, and different studies.

Since the respondents are not asked directly for their WTP, but have to trade cost for desired changes in the attribute, this is considered to be an indirect method. The estimated marginal WTP is a marginal rate of substitution in which the denominator is the *total cost* attribute. This indirect approach to estimating the WTP from DCE is considered an advantage since it reduces the focus on the cost aspect (Blamey et al., 2000).

Based on Equation 2 and Equation 4, when comparing two attributes, marginal rates of substitution are estimated, indicating the trade-off between two attributes that characterise the product. Hence, when one attribute is a cost, the marginal rate of substitution shows the WTP for a change in the qualitative attribute: marginal willingness to pay (mWTP).

In DCE, the representative utility V_{njt} is estimated with a linear function, thus for individual n to chose alternative j in choice set t is generally given by:

$$V_{njt} = \beta_{TC} * X_{TCnjt} + \beta_1 * X1_{njt} + \ldots + \beta_K * X_{Knjt}, \qquad \text{Equation 9}$$

where β_{TC} is the coefficient for the *total cost* attribute, and β_1,..., β_K are the coefficients for the attributes X_1,…, X_K. As per Hole (2007), the *total cost* is calculated by taking a derivative of U_{njt} with respect to changes in attribute X_K and *total cost* is estimated by taking the derivative of the function. Solving this expression for $dTC / d X_K$ yields the change in *total cost* that keeps utility unchanged, given a change in X_K:

$$\frac{dTC}{dX_K} = WTP_K = -\frac{\beta_K}{\beta_{TC}} \qquad \text{Equation 10}$$

This equals the willingness to pay for an improvement in X_K, WTP_K. It can be seen, from Equation 9, that WTP_K is given by the negative ratio of the coefficients for X_K and TC (*total cost*) (Hole, 2007). In addition to the estimated marginal WTP, the confidence intervals for the WTP were also estimated using the delta method in Hole (2007).

The model is estimated in Stata 17 (StataCorp, 2021) statistical package, using 'wtp' a user-written command written by Arne Hole (Hole, 2007)[33].

2.6.6 Latent class analysis (LCA)

One of the objectives of this research is to explore individual heterogeneity in the choice data. It is possible to analyse the data by stratifying respondents into homogeneous classes based on the reported characteristics (i.e., gender, age, education); however, this approach can be limited by the small sample size that can be created with a larger number of variables (Zhou et al., 2018). Alternatively, analysing respondents based on classes or segments with similar interests and needs can help identify services and products that could be offered to each of several segments that are relatively homogeneous internally but heterogeneous among segments (Deal, 2014).

Segmentation classifies respondents into classes or clusters based on the patterns of outcome variables (i.e., individual choices in SP surveys) and is commonly performed via latent class analysis (LCA) (Deal, 2014). In LCA, segmentation is estimated simultaneously with the choice model to identify subsets of participants with homogeneous preferences within classes and heterogeneous preferences between classes. While segmentation is probabilistic (i.e., respondents are allocated to the group they are most likely to be a member of), multivariate statistics can be used to describe differences in characteristics across groups (Deal, 2014).

The use of LCA models in health economics has been on the rise from 2010 (Soekhai, De Bekker-Grob, et al., 2019; Soekhai, Whichello, et al., 2019). In the LCA each alternative is described by alternative specific characteristics and each individual (respondent) by individual-specific characteristics (Pacifico & Yoo, 2013). The LCA assumes that there are Q distinct sets (classes) of preference parameters, and each respondent is assumed to belong to one of the Q classes, and preferences vary across the classes, but not within (Hole, 2013).

The addition of respondent characteristics to the estimation allows the analyst to understand whether there are differences between the classes, and which significant characteristics define them.

The model is estimated in Stata 17 (StataCorp, 2021) statistical package using 'lclogit' command (Pacifico & Yoo, 2013), and in the LatentGold (Statistical Innovations, (Vermunt & Magidson, 2005)) 'Choice' statistical package, and RStudio (RStudio Team) using 'gmnl' (Sarrias & Daziano, 2017) and 'mlogit' (Croissant, 2020). In Stata and LatentGold the analysis used the expectation-maximisation algorithm for fitting a latent class logit model. This guarantees numerical stability and convergence to a local maximum even when the number of latent classes is large. This is in contrast to the (quasi)Newton methods (RStudio 'gmnl' package), as inversion of the (approximate) Hessian becomes

[33] The code for 'wtp' is downloaded via Stata by typing "ssc install wtp".

numerically difficult (Bhat, 1997; Pacifico & Yoo, 2013; Train, 2009). The three software platforms were used to compare the results, specifically of the estimated optimal number o of classes in the dataset.

2.6.7 Other statistical tests

Descriptive statistics

The socio-demographic responses collected from respondents are compared to the corresponding Australian population data by testing the equality of proportions test. The respondents' characteristics were also compared across the three DCEs using *t*-statistics, for significant differences between the three samples.

Test of significance

The assessment of results of the data analysis is based on a 5% significance level for all parameters, although a 1% and a 0.1% significance level also reported for all results.

Model valuation

The assessment of goodness of fit of the estimated statistical models was based on the likelihood ratio test, and Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) estimates.

The likelihood ratio (LL) statistics and AIC and BIC estimates were reported for each model. Larger (less negative) values of LL are associated with a greater ability of a model to explain the pattern of choices in the data (Hauber et al., 2016).

Log-likelihood and pseudo *R*-squared values can inform goodness of fit of estimated models. Model selection is informed by economic and behavioural theory, and statistical considerations such as likelihood ratio (LR) tests for nested models and the AIC and BIC for non-nested models (Lancsar & Louviere, 2008).

As there were randomisation components in the survey (Arm1 and Arm2, doctors' script attribute) the LR test was used to compare models used to test whether the respondents' preferences were stable across the two arms. The LR test was also used to compare the randomised groups between the two doctors' scripts presented to the respondents. The LR test estimated chi-square shows whether estimating the two groups together improves model fit. The LR test equation used is:

$$\text{LR test} = -2*(\text{LLR} - \text{LLU}), \qquad \text{Equation 11}$$

where LLR is the log-likelihood of the model estimated on the full sample which allows for scale differences but assumes that estimated parameters do not vary across arms. The restricted model was estimated using Stata 17 (StataCorp, 2021) module 'clogithet' (Hole, 2009). The LLU is the sum of the log likelihoods of the two models estimated on them specific subsamples. Under that null hypothesis this test is chi-square distributed with *k* degrees of freedom and the test carried out at α=0.05 significance level (Hole, 2006). The chi-square distributed statistics are used with the degrees of freedom given by the number of parameters in the unrestricted model minus the number of parameters

in the restricted model. If the value of the LR test exceeds the critical chi-squared value then the null hypothesis is rejected (Wilcox, 2017).

The AIC and BIC estimates are means of statistical model selection; both penalise models to reduce the risk of overfitting and each provides a standardised way to balance sensitivity and specificity (Dziak et al., 2020). Both criteria are specified as ($-2LL + K\gamma$), where LL is the maximum log-likelihood value of the full model, K is the number of parameter estimates corresponding to the number of explanatory variables in the model, and γ is a penalty constant that changes between AIC ($\gamma = 2$) and BIC (γ = ln[sample size]) (Hauber et al., 2016). These criteria assist in estimating the plausibility of each model to other models in minimising the information loss. Models with lower AIC and BIC measures are preferred over models with higher measures (Hauber et al., 2016).

Each estimated model (conditional, mixed logit, latent class) in this thesis was assessed using the AIC and BIC.

Using a model to represent the process that generated the data leads to some information loss, as the model attempts to explain the process. AIC estimates the relative amount of information lost by a given model: the less information a model loses, the higher the quality of that model.

For AIC, the probability of a model to minimise the information loss is based on estimating the model with the lowest estimated criterion is selected as the base case (AIC_{min}), and the AIC estimates from other models (AIC_n):

$$exp\ \frac{AIC_{min} - AIC_n}{2} \qquad \text{Equation 12}$$

known as the relative likelihood of model n. It is closely related to the likelihood ratio used in the LL-test, but without being limited to nested models (Burnham & Anderson, 2002; Murtaugh, 2014).

The equations for AIC and BIC are presented in Equation 13 Equation 14, respectively. The BIC, unlike the AIC, includes the sample size (observations or respondents) in the equation.

$$AIC = -2*\ln(likelihood) + 2*k \qquad \text{Equation 13}$$

$$BIC = -2*\ln(likelihood) + \ln(N)*k \qquad \text{Equation 14}$$

where, k is model degrees of freedom and N is number of observations.

The BIC value increases if the number of explanatory variables increases or if unexplained variation in the dependent variable increases. Less than two points difference between two BIC estimates signifies that there is little difference between the model; 2–6 points that there is positive evidence against using the model with the higher BIC; 6–10 there is strong evidence; and >10 that the model with lower BIC is preferred.

2.7 Implementation of the DCEs

The presentation of the survey was constructed using SurveyEngine online software platform technology with an online panel of general population recruited from Toluna,[34] a panel provider. All questions used in the survey were entered into SurveyEngine,[35] with the constructed DCE design entered into an inbuilt design setting. The randomisation components for the survey were input by the SurveyEngine design team using constraints presented in the survey flow in Table 2-7.

In Part 1 of the survey each DCE was answered by 400 respondents, and the total number of respondents in Part 2 was 1,200. There is no absolute method to estimate the sample size needed to achieve statistical efficiency for the estimated coefficients (de Bekker-Grob et al., 2015; Johnson et al., 2013). The estimate used in this study was based on two methods, one by Lancsar and Louviere (Lancsar and Louviere, 2008), and the other by Johnson and Orme (Johnson and Orme, 2010). The former states that if all respondents receive the same DCE design, 20 respondents per choice task would be sufficient to estimate a reliable model; the latter provides a formula to estimate the minimum number of respondents needed to have statistical power in a choice-based conjoint analysis (Lancsar and Louviere, 2008; Johnson and Orme, 2010). The Johnson and Orme method has been used in various health care related studies (de Bekker-Grob et al., 2015; Johnson et al., 2013; Speckemeier et al., 2021). The estimated minimum sample size is based on the following calculation:$(N*t*a/c) \geq 500$, where **N** is the number of respondents, **t** is the number of tasks, **a** is number of alternatives per task and **c** is equal to the largest number of levels for any one attribute (for main effects estimations). In this study the calculation is as follows, $N \geq (500 * c) / (t*a)$, where **c** is 10 (cost has the highest attribute levels), **t** is equal to 12 (choice tasks presented to respondents), and **a** is equal to two (2 alternatives per choice task). The result is as least 208 respondents are needed to have statistical power of hypothesis test on the estimated coefficients. However, the funding to conduct the DCE was available to collect almost double the responses and further increase statistical power.

Similarly to check that the results of the DCE 4 have statistical power, the minimum sample size required is 250 respondents.

There were quotas set to ensure that the sample was representative of the general Australian population, based on age ranges and gender. Respondents were excluded if they were under the age of 18 years old. The full sample was collected between 9 November 2018 and 12 December 2018. A total of 3,129 responders entered the survey: 1,481 respondents were over quota on age and gender criteria, 89 were screened out based on age, leaving 1,559 respondents eligible to be analysed as part of the survey.

[34] Toluna is a survey platform with a panel size of more than 220,000 respondents in Australia (2017).
[35] SurveyEngine is an online platform for application of choice modeling methods and techniques.

A pilot study was administered prior to rolling out the full survey; this resulted in 104 completed responses. The collected data were analysed using a conditional logit model estimated using the Stata 17 (StataCorp, 2021) 'clogit' command. The coefficients on attribute levels were observed for sign and magnitude, showing consistent results across all DCEs and statistical significance for the *total cost* variable, although if there is a large heterogeneity among the respondents the smaller sample (DCE 1 (n=28), DCE 2 (n=35) and DCE 3 (n=33)) results may not be statistically significant.

During the pilot survey, it was decided not to include internal validity tests in the DCEs, such as practice tasks, or repeated or dominate choice tasks. There was only a small number of attributes with low cognitive burden on the respondent, and the setting of purchasing prescription medicines was mostly familiar to the respondents. The feedback during focus groups and from the pilot survey demonstrated that the choice tasks were easy to complete, and additional test were not necessary. Additionally, there were post survey assessment of time it took the respondents to complete the survey, as well as assessment for any one-sided option selection (i.e. selecting only Option A or Option B). The results from the post survey analysis were considered low risk and are discussed further in Section 2.8.1.

2.7.1 Ethics

Data were collected online from the general population and those self-reporting a health condition. The data collection is part of the research program approved by the Human Research Ethics Committee (UTS HREC REF NO. ETH18 - 2507) under the Centre for Health Economics Research and Evaluation Program Ethics Process.

Asking the general population about their own health (medical conditions and health status) and to imagine a hypothetical medical issues has some potential to cause distress, and this was made clear in the information text, indicating that respondents can stop the survey at any time without penalty.

Data integrity is important given the survey asks respondents for personal details, including questions about an individual's health, Medicare card status and concession status. All data are kept anonymously, with participants only identified using a unique ID number that cannot be linked to any personal information stored by the panel provider. Only aggregate level data is reported in any report or publication arising from the project. Responders were made aware of the aim of the study and the potential for the publication of the study results. The anonymised data is stored in an encrypted database and kept on password-protected computers only accessible by the project team.

2.8 Overview of the data

The dataset was downloaded from the SurveyEngine platform for cleaning and analysis. Using Stata 17 the dataset was assessed for duplicate entries and cleaned to include complete responses. As described above, the survey contained two parts: a first part which includes DCE 1, 2 or 3 with 12 choice tasks each, and DCE 4, which included eight choice tasks, so there were a total of 20 choice tasks to complete.

Only respondents who completed all 20 choice tasks were included in the final analysis presented in Chapter 3 (DCE 1), Chapter 4 (DCE 2 and DCE 3) and Chapter 5 (DCE 4).

Descriptive statistics for the demographic data and health care utilisation data were calculated and compared across the groups that answered the three different DCEs that made-up Part 1 of the survey. These results are presented below.

2.8.1 Survey completion analysis

A total of 1,233 (78.5% response rate) respondents completed all 20 choice tasks included in the survey. The respondents were notified that by completing the survey they indicated their consent for the data to be used in the research. It is assumed that if the respondent has continued to take the survey that they automatically consent for the data to be used for analysis and publication. However, it was also assumed that if the respondents have not completed the survey (the DCE component) then they may have decided to withdraw consent. Since it was impossible to identify who of the respondents withdrew their consent, for ethical reasons, all those that have not completed all DCE components of the survey were not included in the final analysis for publication. Only data from respondents who have answered all the choice sets are used in the analysis, with incomplete responses considered to be 'withdrawal of consent'. Of the 1,559 respondents, 1,305 answered at least one choice task, and 1,256 answered all (12) choice tasks of DCE 1, DCE 2 or DCE 3. Of those 1,256, 1,248 commenced DCE 4 in Part 2 of the survey. The majority of withdrawal from the DCEs occurred in the first five choice tasks. The data in Table 2-10 shows the breakdown of the number of respondents who answered the choice task in each DCE.

Table 2-10. The number of respondents in each DCE

Completed ONLY number of choice tasks	DCE 1	DCE 2	DCE3	Policy (max eight tasks per respondent)
1	0	4	1	0
2	1	3	2	4
3	0	5	3	3
4	3	0	1	5
5	4	3	2	1
6	2	1	0	2
7	2	0	0	0
8	0	1	1	1,233
9	0	0	1	-
10	1	0	3	-
11	1	2	2	-
12	418	420	418	-
Total	432	439	434	1,248
Total used in analysis	**412**	**413**	**408**	**1,233**

After the removal of respondents who did not complete all 20 choice tasks presented in the survey, the final analysis included a total of 412 respondents who completed DCE 1; 413 respondents who completed DCE 2; and 408 respondents who completed DCE 3 as well as in DCE 4. The number of respondents in each DCE is similar.

In DCE 4, there were 26 respondents who always picked one option in all the task choices (either option

1 or option 2). The order of two alternatives (options) presented to the respondents was randomised, with the *pharmacy brand* product (which always appeared in the choice set) being presented randomly in option 1 or 2. Of the 26 respondents, there was a similar distribution across the three DCEs, with DCE 1 (n=9), DCE 2 (n= 7) and DCE 3 (n=10). It is impossible to conclude whether their choice was at random since these respondents chose different options in Part 1 of the survey answering the 12 choice tasks. These respondents were included in the final analysis.

The median time to complete the survey was 9 minutes and 40 seconds (25th quartile: 6 minutes and 55 seconds; 75th quartile: 14 minutes), ranging from 1 minute 55 seconds to 94 minutes. This does not include the respondents who completed the DCE component of the survey but did not hit the 'submit' button and for whom the session eventually timed out. The time-out could have been initiated by a respondent (n=1) by simply closing the survey page, or by the survey host system (n=29) because the survey page was idle for too long. During the setup and testing of the survey, I estimated that it would take the respondents 12–15 minutes to complete.

There were six respondents who completed the survey in under three minutes. These respondents were included in the final analysis. There were several respondents who did not respond to all the socio-demographic questions, with a number of observations missing.

2.8.2 Characteristics of respondents

In this section, I present the self-reported characteristics (demographic, socio-economic and health-related) of respondents who were randomised to DCE 1, DCE 2 and DCE 3, as well as the overall characteristics of the participants of the entire survey. I also present the post-DCE responses to the attitudinal questions related to the attributes presented in the DCEs. These characteristics are used in the empirical analysis of data in Chapters 3 to 5.

The respondents who answered demographic question at the start of the survey and were within the quota (age and gender) were randomised to one of DCEs 1, 2 and 3 in Part 1 of the survey. After completing the first DCE, all respondents were shown DCE 4. Therefore, the analysis of the data is performed on each DCE separately with the respondents to DCE 1, DCE 2 and DCE 3 being the subsamples of the entire survey population. DCE 4 includes the analysis of all respondents included in the survey. The respondents' characteristics collected during the survey are presented for each DCE separately and for the entire sample as well and is compared to the data available on the Australian population statistics.

The respondents analysed in the survey are generally representative of the Australian population (Table 2-11). There were also consistent similarities in characteristics across the three randomised groups (DCE 1, DCE 2 and DCE 3). It is safe to suggest that the randomisation to the different arms of the survey was successful.

In a more detailed analysis of the characteristics, there were slight differences between the sample population and the Australian population statistics for some levels of the demographic and socio-economic characteristics. These differences were tested with a proportion test using a 5% significance level. In particular:

- There were more males than females in the sample population compared to the Australian population; however, the differences were not significant with a p-value of 0.064.
- There were more respondents born in Australia (an average of 74.9%) than the proportions reported in the Australian population (66.7%) and these are significantly different (p-value 0.000).
- Overall, there were more respondents with higher education level compared to the general population. There were more respondents reporting having obtained a university degree than the general population (38.3% compared to 22.0%).
- There were more respondents reporting being in a relationship compared to the Australian population data, with a significant difference (p-value < 0.0001).
- There were fewer employed (full-time and part-time) respondents (50.8%) compared to the Australian population (88.1%). More respondents reported being unemployed (10.6%) compared to the Australian population (6.9%).
- The income distribution of the survey respondents appears to be slightly skewed towards the middle and high income earners ($50K–150K), which is a common occurrence in online panel surveys.

Table 2-11. Participant characteristics for DCE 1 survey results

Characteristics	DCE 1 Respondents	DCE 2 Respondents	DCE 3 Respondents	Total N=1,233	Australian Population
Sample size, N	412 (%)	413 (%)	408 (%)	1,233 (%)	%
Gender (male)	193 (46.8)	195 (47.2)	191 (46.8)	579 (47.0)	49.6
Age					
18–29	75 (18.2)	75 (18.2)	74 (18.1)	224 (18.2)	19.2
30–39	78 (19.0)	75 (18.2)	74 (18.1)	227 (18.4)	19.1
40–49	64 (15.4)	78 (18.9)	75 (18.4)	217 (17.6)	17.4
50–59	69 (16.8)	71 (17.2)	63 (15.4)	203 (16.5)	16.3
60–69	65 (15.8)	57 (13.8)	61 (15.0)	183 (14.8)	13.7
70 and above	61 (14.8)	57 (13.8)	61 (15.0)	179 (14.5)	14.4
Birth country, Australia	311 (75.5)	296 (71.7)	316 (77.5)	923 (74.9)	66.7
Education					
Year 10 and below	47 (11.4)	52 (12.6)	51 (12.5)	150 (12.2)	19.7[a]
Year 12	79 (19.2)	55 (13.3)	69 (16.9)	203 (16.5)	20.6
Diploma/ Trade	114 (27.7)	134 (32.5)	127 (31.1)	375 (30.4)	24.6
University degree	161 (39.1)	161 (39.0)	150 (36.8)	472 (38.3)	22.0
Prefer not to answer	3 (0.7)	2 (0.5)	4 (1.0)	9 (0.7)	10.4
Missing observations	8 (1.9)	9 (2.2)	7 (1.7)	24 (2.0)	NA
Living situation					
Married/ De facto relationship	217 (52.7)	224 (54.2)	223 (54.7)	664 (53.9)	48.1
Single	102 (24.7)	94 (22.8)	92 (22.6)	288 (23.4)	NR[b]
Widowed	16 (3.9)	13 (3.2)	11 (2.7)	40 (3.2)	5.2
Separated	8 (1.9)	10 (2.4)	12 (2.9)	30 (2.4)	3.2
Divorced	29 (7.0)	27 (6.5)	29 (7.1)	85 (6.9)	8.5
Missing observations	40 (9.7)	45 (10.9)	41 (10.1)	126 (10.2)	NA
Number of people living in the household					
Two or more people	285 (69.2)	293 (70.9)	286 (70.1)	864 (70.1)	75.6
Missing observations	40 (9.7)	45 (10.9)	41 (10.0)	126 (10.2)	NA
Of those, households with at least one child	*95 (33.3)*	*109 (37.2)*	*101 (35.4)*	*305 (35.3)*	NR
Of those, Carer responsibility (other than children)	*33 (11.6)*	*35 (11.9)*	*46 (16.1)*	*114 (13.2)*	11.3
Work status					
Full-time paid work	141 (34.2)	142 (34.4)	129 (31.6)	412 (33.4)	57.7
Part-time paid work	72 (17.5)	74 (17.9)	68 (16.7)	214 (17.4)	30.4
Self employed	19 (4.6)	23 (5.6)	25 (6.1)	67 (5.4)	NR
Unemployed	42 (10.2)	43 (10.4)	46 (11.3)	131 (10.6)	6.9
Studying	102 (24.8)	100 (24.2)	105 (25.7)	307 (24.9)	NR
Retired	13 (3.2)	15 (3.6)	21 (5.1)	49 (4.0)	NR
Prefer not to answer	15 (3.6)	7 (1.7)	7 (1.7)	29 (2.3)	NA
Missing observations	8 (1.9)	9 (2.2)	7 (1.7)	24 (1.9)	NA
Income (household)					
Negative or zero income	6 (1.5)	10 (2.4)	8 (2.0)	24 (1.9)	1.4
$1–$19,999 per year ($1–$379 per week)	16 (3.9)	19 (4.6)	17 (4.2)	52 (4.2)	10.5
$20,000–$49,999 per year ($380–$959 per week)	95 (23.1)	96 (23.2)	122 (30.0)	313 (25.4)	25.5
$50,000–$79,999 per year ($960–$1,539 per week)	83 (20.2)	75 (18.2)	81 (19.8)	239 (19.4)	15.0
$80,000–$109,999 per year ($1,540–$2,109 per week)	65 (15.8)	70 (16.9)	60 (14.7)	195 (15.8)	11.2
$110,000–$149,999 per year ($2,110–$2,879 per week)	58 (14.1)	54 (13.1)	46 (11.3)	158 (12.8)	15.7
$150,000–$199,999 per year ($2,880–$3,849 per week)	24 (5.8)	26 (6.3)	23 (5.4)	73 (5.9)	6.6
$200,000 or more per year ($3,850 or more per week)	13 (3.2)	11 (2.7)	11 (2.7)	35 (2.8)	3.4
Don't know	10 (2.4)	8 (1.9)	6 (1.5)	24 (1.9)	NR
Prefer not to answer	34 (8.4)	35 (8.5)	27 (6.6)	96 (7.8)	10.7
Missing observations	8 (1.9)	9 (2.2)	7 (1.7)	24 (1.9)	NA

Abbreviations: NR: not reported; NA: not applicable; na: not available.
Source: Age and gender only - Australian demographic statistics (ABS) December quarter 2018; Other population statistics - ABS Census 2016, from ABS.Stat website.
Note: slight difference between the survey and the Australian population statistics may be due to: population statistics of people in Australia if for aged 15 years and over; the survey included only respondents 18 years and over.
a: the total sum of 97.3% for the level of education was calculated from the ABS Stat website.
b: the ABS Stat reports on the 'Never married' (35%) marital status.

The results of the t-test for respondents' characteristics presented in Table 2-10 between the three vignettes showed that the difference of the means was not significantly different from zero, with no significant differences across the vignette groups. The randomisation into the three groups was successful. Although there are some differences between the survey respondents and the Australian population statistics, the population is well-represented in the survey.

During the survey, I collected data on self-reported health status and other health care usage data. Table 2-12 summarises the health-related characteristics of the respondents in the survey.

Generally, respondents reported worse health states compared to the data from the Australian population. Examining the data in combination with the self-reported health status, it is apparent that the respondents to the survey were experiencing poorer health, and almost a quarter (22.7%) indicated 'Fair' or 'Poor' health status compared to the Australian population statistics (14.2%). There are significant differences for 'Excellent', 'Very good', 'Good' and 'Fair' health states with p-values < 0.000), with only the 'Poor' response showing no statistically significant difference.

Only a third of the respondents reported no chronic (ongoing) medical condition, which is significantly different (p-value <0.000) from the Australian population, in which more than half self-report a chronic condition. Although this shows a significant difference from the general population, it does not have to indicate any bias in the responses. The survey focused on ana acute condition rather than chronic, and at most majority of the respondents have a bit more experience with the health care system.

Although there were statistically significantly more respondents (p-value < 0.0009) who reported attending a GP in the past 12 months, compared to the Australian population, the difference was not numerically large.

Although here is not exact data for the proportion of Australian population with Medicare cards, it is safe to assume that most people residing in Australia have one. All Australian citizens and permanent residents (including some other forms of residence), and New Zealand citizen are able to enrol into Medicare.

Although there appears to be a high proportion of respondents with concession card across all DCE sub-groups, this can be explained by the fact that at least 34% of the sample population is over the age of 60, and is thus qualified to have a concession. Additionally, at least a third of the respondents indicated that there is a child under 16 in the household and approximately 13% stated that they have other carers responsivities. As well as just over 60% of the indicated that they have at least on ongoing medical

condition, which could imply that they are eligible for a concession card.

Table 2-12. Respondents' health and health-related self-reported characteristics

Characteristics	DCE 1 Respondents	DCE 2 Respondents	DCE 3 Respondents	Total N=1,233	Australian Population
Sample size, N	412 (%)	413 (%)	408 (%)	1,233 (%)	%
Health status					
Excellent	42 (10.2)	46 (11.1)	26 (6.4)	114 (9.2)	21.3
Very good	127 (30.8)	109 (26.4)	132 (32.3)	368 (29.8)	35.8
Good	145 (35.2)	182 (44.1)	143 (35.0)	470 (38.1)	28.7
Fair	82 (19.9)	63 (15.2)	85 (20.8)	230 (18.6)	10.7
Poor	16 (3.9)	13 (3.1)	22 (5.4)	51 (4.1)	3.5
No ongoing medical condition	138 (33.5)	145 (35.1)	136 (33.3)	419 (34.0)	54.4
Concession card holders[a]	188 (49.6)	191 (50.4)	218 (53.4)	595 (48.3)	na
Missing observations	33 (8.0)	36 (8.7)	36 (8.8)	105 (8.5)	NA
Attend a GP in last 12 months	347 (84.2)	356 (86.2)	355 (87.0)	1,058 (85.8)	82.2
Of those who attended a GP Received a prescription	*318 (91.6)*	*316 (88.8)*	*326 (91.8)*	*960 (90.7)*	na
Medicare cardholders	390 (94.7)	391 (94.7)	394 (96.6)	1,175 (95.3)	na

Abbreviations: NA: not applicable; na: not available.
Source: ABS. National Health Survey: First results, 2017-18 -Australia (based on the data collected in 2017-18 from Australians aged 15 and over).
Note: a = concession cards included: Pensioner Concession Card, Commonwealth Seniors Health Card, Health Care Card (not a Medicare card), Department of Veteran Affairs White, Gold, or Orange Card, and Other health concession card(s).

A comparison of the populations of the three DCEs to the total sample, shows that there are statistically significant differences in the responses from DCE 2 for the health status of 'Good' and 'Fair'; as well as in DCE 3 in 'Excellent' response options.

Compared to the general population, DCE 1 and DCE 3 have similar proportions 'very good' Health status, all other indicators are different.

There were statistically significantly more concession card holders in DCE 3 compared to DCE 1 and DCE 2 respondents. These were analysed for each DCE separately and combined, and were found to not have a significant impact on the results.

DCEs are commonly used in health economics and patient-centred outcomes research to elicit preferences for healthcare interventions, treatments, or services. While DCEs are often conducted in the general population, the results may be limited in generalizability to the specific population in question (Bridges et al., 2011; de Bekker-Grob et al., 2012). DCEs present the respondents with a hypothetical situation, with choices designed to simulate real-life situations, but may not have the same impact. In particular, the presence of information bias where respondents may be unfamiliar with some concepts, or as the online surveys are voluntary, selection bias may be present. Also, patient choice could be impacted by unobserved factors, such as prior experiences or socio-demographic factors (Dobra et al., 2021). However, there are some approaches to address this issue. To improve generalizability of DCE results it is important to include stakeholders in the study design, and use appropriate sampling techniques, as well as a large enough sample of participants.

The results of this survey are most likely applicable to the general population. The area of research is well known to the participants of the survey, and it could also be expected that most of Australians have

received a prescription for a medication and have purchased it at the pharmacy. Additionally, the samples were strictly controlled for gender and age, thus it is expected that the respondents are representative of the Australian population.

2.8.3 Implementation of the analysis

The next three chapters present the analysis of the data. In Chapters 3 and 4, the details of the analysis of DCE 1–3 are presented. Chapter 3 focuses on the evaluation of the responses to DCE 1 with analysis identifying the key attributes in the respondents' decision making. Chapter 4 focuses on the attribute of brand premium and its potential impact on the individual's choice. Chapter 5 presents the results of DCE 4, with the introduction of the hypothetical government price policy, with an additional analysis of the post-DCE questionnaire related the respondents' experience with prescription medicines, as well as their attitude towards generic and branded medicines, the pharmaceutical companies, and the cost of the medicine.

CHAPTER 3. Consumer preferences for branded and generic medicines: a Discrete Choice Experiment

3.1 Overview

Australian medicine policy allows for several brands of medicine to be listed on the Pharmaceutical Benefits Scheme (PBS). When the patent for the original (branded) medicine expires, generic brands of the medicine are allowed to enter the market and be listed on the PBS. Medicines listed on the PBS are subsidised by the government, either partly or in full (depending on whether the consumer holds a concession card) for Medicare-eligible Australian consumers. As described in Chapter 1, the price of the medicine decreases when generic brand register on Australian market and the government agrees to subsidise all brands of that medicine at the same level.

A medicine that has several brand alternatives (an original brand and generic brands) may be available at more than one price on the PBS. For example, a 60-tablet package of 300 mg quetiapine, an antipsychotic prescription medicine used to treat schizophrenia, bipolar and acute mania, is currently listed on the PBS under 14 different brands. As of June 2021 the original brand, Seroquel (Alphapharm Pty Ltd) (approved by the TGA in 2001) costs the patient AUD50.11 whereas, for example, a generic brand, Quetiapine Apotex, is priced at AUD45.11 (at June 2021, pbs.com.au). The brands have the same active ingredient, dosage and mode of intake. However, the PBS schedule for the Seroquel (branded) includes an AUD5.00 additional charge (or brand premium) that is not subsidised through the PBS. For the consumer who chooses to purchase the original brand Seroquel, the AUD5.00 brand premium is paid by them no matter their concession status.

These medicines are priced above the general patient co-payment amount of AUD41.30 (general patient) and AUD6.60 (concessional patient). Therefore, for each time the medicine is dispensed, Medicare subsidises AUD3.81 per script for the general patient and AUD38.51 for a concessional patient. For concessional and Repatriation Pharmaceutical Benefits Scheme (RPBS) patients who have reached the Safety Net threshold in the calendar year, the government subsidises the entire cost of the medicine (except for any applicable brand premium). In calendar year 2020, there were a total of 97,875 services delivered to PBS/RPBS patients of quetiapine (300mg, 60 tablets) (Services Australia, PBS/RPBS Item Report for Items 8580N). Of these, only 15,107 were delivered under the general ordinary PBS patient (where the patients paid the full price for quetiapine without government subsidy). There were 82,768 concession services delivered (including patients who have reached their Safety Net threshold that year and became concessional patients, or concessional patients who reached their safety net threshold and did not pay anything for the medicine, and RPBS patients).

The publicly available information does not show which brand was dispensed to the patient. This lack of information restricts our ability to understand consumer demand for generic medicines and brands with brand premium. However, the annually published PBS expenditure reports indicate that there is demand for medicines with brand premium, even though cheaper alternative brands are available to consumers.

The presence of the brands with a brand premium that is priced higher than other brands may limit companies' willingness to compete on price. The generic brands of the medicine are priced at the regulated price, which is updated every six to twelve months based on the actual price at which brands were sold. However, the existence of the price difference (brand premium) across the brands with identical ingredients, dosage and use may decrease the willingness to lower or discount generic brand beyond what is stipulated by the pricing policy.

Medicines with brand premium are still in demand. In the 2019–20 financial year, there were 365 brands with brand premium listed on PBS and AUD35.7 million worth of prescriptions dispensed for medicine with a brand premium compared to AUD132.4 million dispensed for generic brands (includes items where at least one brand is listed with a brand premium). Therefore, it seems that 21.2% of the time, the consumer chose a branded medicine and paid an additional premium.[36]

As consumers demand new medicines and health technologies, they are open to engaging in learning about the impact they can exert on the market to lower prices in existing generic medicine in order to increase affordability in the new technologies.

The research undertaken for this PhD investigates how consumers respond to pricing policies, including the existence of brand premiums. As the consumer is, to an extent, a passive participant in the current policy context, this research aims to identify any triggers that would impact active consumer participation.

This research aimed to explore the decision the Australian consumers make when they are presented with a choice of prescription medicines by eliciting their preferences for the factors (including cost, product name and other attributes of prescription medicine) that may affect their decision. This chapter presents a discrete choice experiment to explore consumer preferences for branded and generic medicines in the context of the Australian pharmacy setting.

There is limited evidence of consumer preferences for the product of prescription medicines. Even if consumers can freely choose their doctors (as Australia does not have specific GP Registration) and freely choose the pharmacy(ies), they do not have a say in the brands that are available and at what prices. When

[36] PBS Expenditure and Prescriptions Report 1 July 2019 to 30 June 2020. https://www.pbs.gov.au/info/statistics/expenditure-prescriptions/pb-expenditure-and-prescriptions-report-1-july-2019 last accessed: September 2021

a consumer chooses a medicine, they consider a number of factors to make a decision, and the preference for a particular set of attributes determines their choice. As a non-market resource value evaluation technique, the DCE is an effective method to investigate such preferences (Ming-Zhu et al., 2020). Matching medicine policy with consumer preferences may lead to changes that can improve demand for generic brands (as was intended by the government with the introduction of the Brand premium policy in 1990). Exploring heterogeneity in consumers' preferences for prescription medicines in the context of cost and product (generic vs branded) can help inform recommendations to improve services and indicate the most important factors for consumers.

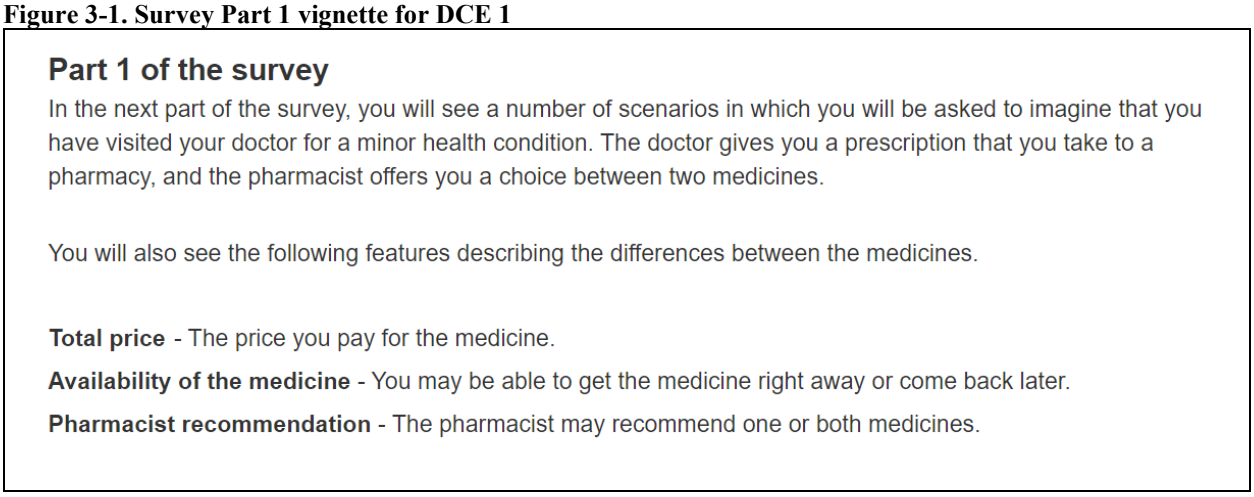
This chapter explores the preferences for prescription medicines based on the GP and pharmacist recommendation and availability of product (waiting time). Only two pieces of information are provided about the medicine: the product name and the cost. In Chapter 4, additional information about the medicine is provided, including whether a brand premium has been added (DCE 2) and the level of the brand premium (the amount) (DCE 3). Together, these three DCEs have the potential to reveal how consumer preferences change given additional information about the cost of the medicine.

This chapter is structured as follows. In Section 3.2 the DCE format and size of the data set are presented and discussed. In Section 3.3 the data analysis using selected econometric models is presented, and Section 3.5 is the discussion of the chapter.

3.1.1 The choice experiment

The respondents were given two medicines to choose between and asked which medicine they would most likely choose based on a number of attributes. The attributes were the medicine brand and price, the length of time that the customer has to wait for the medicine at the pharmacy and whether the pharmacist recommends the medicine. To mimic the real-life situation respondent are given two situations where a doctor's script is written for a branded medicine or for a generic medicine. As described in Chapter 2, after each respondent was randomised to one of the three DCEs in part 1 of the survey, they received several instructions about the task and components of the survey. Those randomised to DCE 1 saw information that described the three attributes: total price, the availability of the medicine and pharmacist's recommendation (Figure 3-1).

Figure 3-1. Survey Part 1 vignette for DCE 1



After the information page, the respondents were further randomised into two arms that differed in terms of how the doctor's script was presented. The use of the two different scripts was part of a context setting attribute, where it was important to identify the effect the name of the product written on the prescription (by the prescriber/doctor) has on the respondent's final choice between the two alternatives presented. As a doctor is assumed to play a major role in the patient's decision making about treatment, it was important to elicit any effect on the preferences of the respondent experiencing a minor (acute) health condition.

In both arms, the respondent saw scripts that described the medicine as a Medora branded medicine and a generic compound name, but the order differed. In Arm 1, the respondents would first see the script for the generic compound name of the medicine, followed by the doctor's script for Medora. In Arm 2, the order of the presentation of the two scripts was reversed. The additional randomisation of the participants in the DCE by different order of the two scripts was used to identify and control for any script order effect on the preferences.

The information page with the script contained a graphic picture of the script, as well as describing three products that can be purchased with that script: *Medora branded*, *Megorium generic*, *pharmacy brand generic*. The examples of the script's information page are presented in Figure 3-2 and Figure 3-3.

Figure 3-2. Information script with doctor's script (Medora branded)

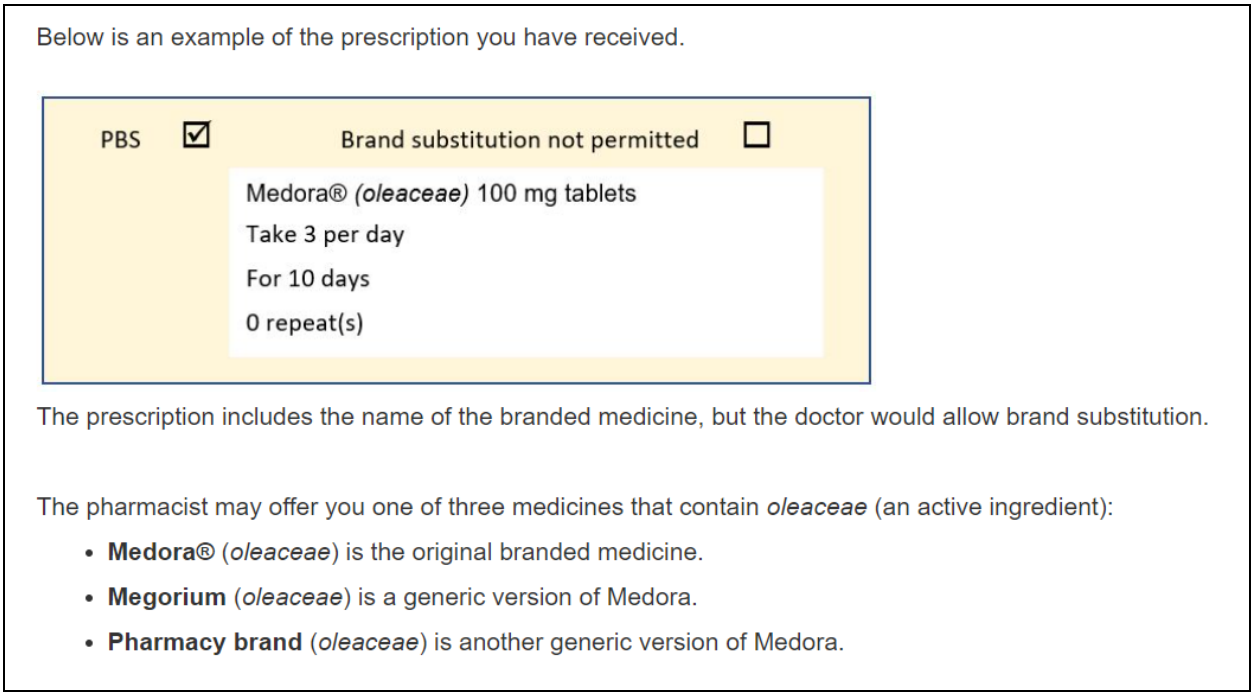
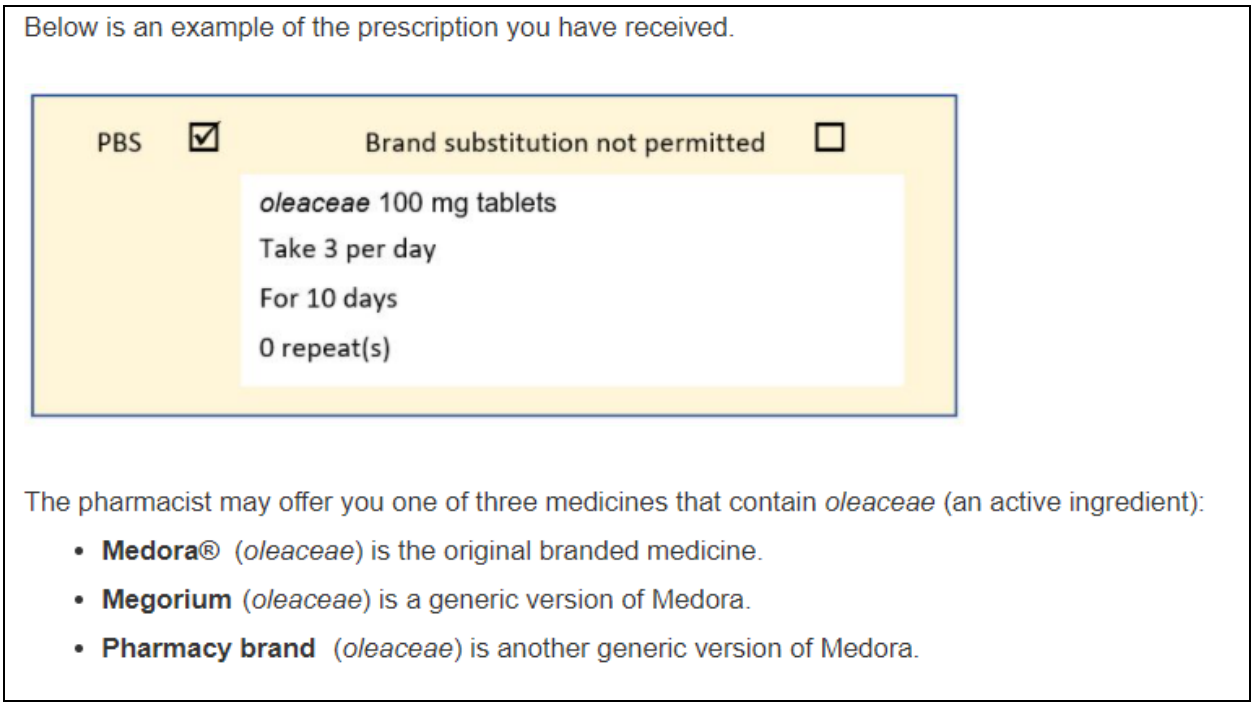


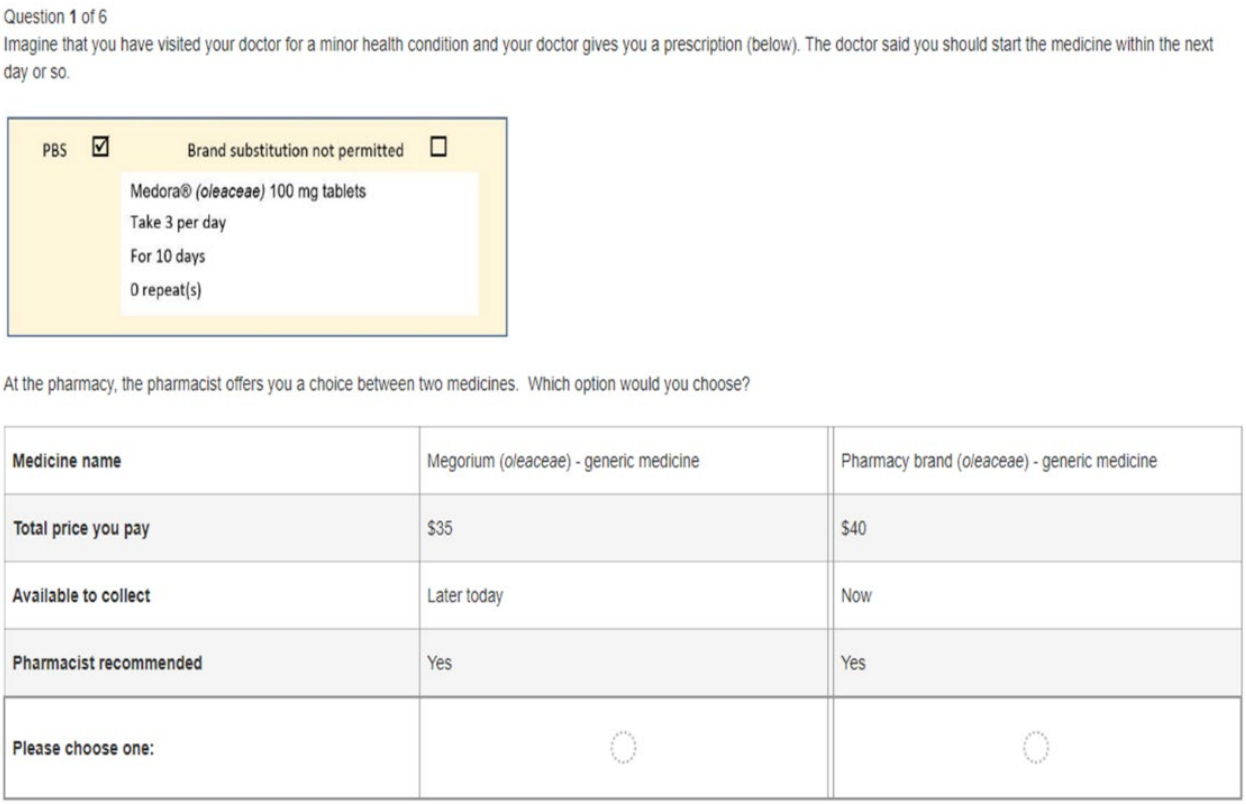
Figure 3-3. Information page with doctor's script (active ingredient (generic))



Each respondent was presented with a hypothetical situation in which they were asked to "Imagine that you have visited your doctor for a minor health condition. The doctor gives you a prescription that you take to a pharmacy, and the pharmacist offers you a choice between two medicines." An example of a choice task shown to the participants is presented in Figure 3-4. Both medicines were described by four attributes:

- the name of the brand (pharmacy brand generic, Megorium generic, Medora branded);
- the *total cost* of the medicine to the respondent (ranging $0–60);
- the *availability* of the medicine *for collection* (available for pick up immediately, or needs to be picked up later in the day); and
- whether or not the *pharmacist recommended* the medicine.

Figure 3-4. Example of a choice task shown in DCE 1 (*total cost* only)



3.1.2 The attributes in the choice task

There are four alternative specific attributes in DCE 1 and one context specific attribute. The doctor's script is a context specific attribute. The alternative specific attributes were: total cost, product, collection time of the dispensed medicine and the pharmacist's recommendation.

The attributes and levels used in the choice tasks presented to the respondents are shown in Table 3-1.

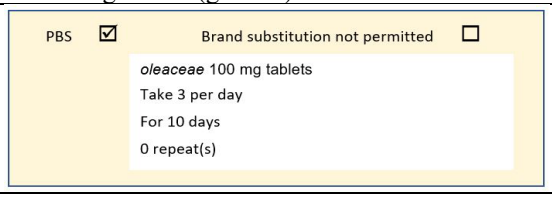
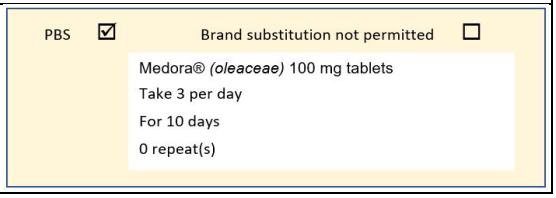
Table 3-1. Attributes and levels in DCE 1

Context attribute	**Levels (indicated in italics)**	**Notes**
Prescription from GP	*oleaceae* – generic active ingredient or *Medora (oleaceae)*	Arm 1 consists of the first six choice tasks of generic active ingredient scripts followed by six choice tasks of Medora branded scrips. Arm 2 consists of six Medora branded scripts followed by six generic active ingredient scripts,
Alternative specific attributes	**Levels (indicated in italics)**	**Notes**
Total cost	*$30; $32; $35; $37; $40; $42; $45; $50; $55; $60*	
Product	*Pharmacy brand (oleaceae)** *Megorium brand (oleaceae)* *Medora® (oleaceae) – branded*	It is a generic medicine that can only cost $30, $35 or $40. It is another generic medicine that has a brand name similar sounding to the original. Original brand medicine.
Available to collect (Collection)	*Now** *Later today*	Indicates whether the medicine is available immediately for dispensing or if the respondent has to pick it up later from the pharmacy.
Pharmacist recommended	*(-)* * no recommendation *Yes*	Indicates whether the pharmacist recommends the medicine product (by mentioning or suggesting it to the consumer) or if the pharmacist says nothing about the product to the consumer.

Note: the * denotes the base case level in the analysis

The respondent saw a hypothetical doctor's prescription that indicated either an *oleaceae* - generic active ingredient or *Medora (oleaceae)*-branded medicine. An example of the two prescriptions is in Figure 3-5.

Figure 3-5. Two types of doctor's prescriptions presented to the respondents in Part 1 of the survey.

Active ingredient (generic)	Branded medicine
	

Then the respondents were presented with a choice between two options described by four attributes. The respondents had to choose one of the options. Each respondent is presented with 12 choice tasks.

The *pharmacist recommended* and the *collection* attributes had two levels each, the *product* attribute had three levels and the *total cost* attribute had ten levels. The two-level attributes appear at the same level in half of the choice tasks. *Pharmacist recommended* appeared at level 'yes' in both options only when both collection levels appear in the choice task. This was done to force respondents to think about these attributes independently of each other.

3.2 The data

3.2.1 Dataset overview

The data were collected with the use of an online survey on the Survey Engine platform, via a registered database, Toluna (Toluna, Inc), a panel maintained to be representative of the Australian population, and the sample was collected to meet an age and gender distribution consistent with that of the Australian population.

The data were downloaded from the SurveyEngine platform (SurveyEngine GmbH). Using Stata 17 (StataCorp, 2021) all duplicate entries were identified and removed. Descriptive statistics for the demographic data and health care utilisation data of the respondents were presented and compared to the Australian demographic data; see Chapter 2. The results of the analysis of DCE 1 are discussed in Section 3.3. The analysis was conducted as per the statistical framework presented in Chapter 2, section 2.6.

3.2.2 The variables: attributes and levels

Arm1 and Arm 2

As the respondents were allocated to two different arms, the first step was to test whether the data from Arm 1 and Arm 2 can be combined for analysis by, effectively, testing if there is a script order effect on the change in preferences. The arm (doctor's prescription) context attribute level becomes the variable on which the scale parameter is assumed to depend. The aim is to identify if the order of the script presented to the respondents: active ingredient (generic) first and *Medora branded* second, or *Medora branded* first and active ingredient (generic) second, had an effect on the responses in which case the data cannot be analysed without accounting for these. Arm 1 and Arm 2 data were assessed for poolability[37] across the two doctor's scripts presented to the respondents.

A heteroskedastic conditional logit (HCL) model is estimated to see if it is reasonable to pool the data from the two arms. It models the relationship between the error variance and a list of user-specified variables, by accounting for heterogeneity in the scale factor (Hensher et al., 1998). In a conditional logit model the scale parameter (that is inversely related to error term variance) is usually normalised to unity (Bech et al., 2011). and the conditional logit model assumes the error term variance to be constant across individuals (Hole, 2006). The HCL model allows for unequal variance across individuals (Hole, 2006) by specifying an

[37] Pooling that data is a process where data from several sources (from different response setting) is combined. In this case the respondents in DCE 1 were randomised to two arms where they were presented two doctors' scripts in different order. Respondents randomised to Arm 1 first saw doctor's script for a generic compound name of the medicine and then saw doctor's script for the branded (Medora) product name. The respondents in Arm 2, saw the doctor's scripts in the reverse order.

individual-specific scale parameter as the function exp ($Z_n * \gamma$) where Z_n is a vector of individual characteristics (for example, age, gender), and γ is a vector of parameters reflecting the influence of these characteristics on the error variance (Bech et al., 2011). Since the HCL model allows scale to differ, it is used as a tool to investigate the source of variance (i.e., unobserved response variability) (Bech et al., 2011).

The LR test, based on Swait and Louviere (1993), was used to test for equal parameters across the groups. In this LR test, two times the difference between the Log Likelihood (LL) values from a common HCL model including all observations and the sum of the LL values from the separate conditional logit models is chi-squared distributed with the degrees of freedom being equal to $k+s$, where k is the number of parameters in the models and s is the number of scale parameters estimated. The common HCL model accounts for differences in scale across the two arms *generic compound* and *Medora branded*, respectively (Bech et al., 2011).

The HCL can be estimated using maximum likelihood methods in Stata (Stata Corp. 2021) using 'clogithet' command (Hole, 2009). The analysis utilised the conditional logit 'clogit' command in Stata to compare the restricted (two single arms: Arm1 and Arm, 2) and the HCL 'clogithet' unrestricted (pooled) models. The estimated scale parameter in the HCL model indicates the error variance, where a statistically significantly smaller value would suggest increased error variance.

DCE 1 attributes

There are four attributes in DCE 1. The *total cost* attribute is included in the model as a continuous variable. The attribute levels for each *product* were modelled as dummy variables with the *pharmacy brand generic* product selected as base level (omitted level) and the estimated levels *Megorium generic* and *Medora branded* (estimated levels). The *available to collect* (*collection*) of dispensed medicine is a dummy variable with two levels: *collect now* (omitted level) and *collect later today* (estimated level). The *pharmacist recommended* attribute is a dummy variable with two levels: *(-)* no recommendation (omitted level); *Yes* (estimated level).

The conditional logit model is used to analyse the data, including the exploration of different specifications of the *total cost*. The random parameters (mixed) logit, followed by latent class analysis, is used to further explore the heterogeneity within the sample. The estimation of marginal willingness to pay is used to analyse any trade-offs the respondents make with respect to attribute levels presented to them.

The dataset from DCE 1 consists of the responses from 412 respondents, comprising 12 choice tasks per respondent (a total of 9,888 observations).

3.3 Results DCE 1

This section presents the results of the quantitative analyses of the choice data. The first analysis tests for poolability between Arm 1 and Arm *2* to see if the respondents' preferences are stable and the information on the scripts does not influence preference.

3.3.1 Randomisation into two Arms (order of scripts)

Table 3-2 presents the results of the test of whether it was reasonable to pool the data across Arm1 and Arm2, which saw the scripts in different orders. The estimations of the conditional logit models had three steps: estimation of separate models for the two arms; estimation of the restricted model, combining both arms and imposing a common preference parameter (Arm); testing if the restricted model is accepted compared to the unrestricted models.

The unrestricted model has ten parameters since each arm is modelled using five variables (*total cost*, *Medora branded* product, *Megorium generic* product, *collection* and *pharmacist recommended*), while the restricted model had these five variables and a scale parameter.

The test statistic is compared to the critical value of the chi-square distribution with four degrees of freedom at a 5% significance level. (The number of degrees of freedom is given by the number of parameters in the unrestricted model minus the number of parameters in the restricted model (df: 10-6 = 4) (Hole, 2006).

The LR test of equal parameters across the two arms has a LR test statistic equal to 4.77 to be compared to the critical value 9.48 at a 5% significance level in the chi-squared distribution with four degrees of freedom. Given this test statistic, the hypothesis of overall equal parameters across the two arms is not rejected. This means that there is no evidence that the preferences differed across the two arms for all of the attributes. Hence, the two arms in the DCE data can be pooled and analysed independently of the arm to which the respondents were randomised.

Table 3-2. Testing the poolability of the two arms of the DCE 1

Attributes (base case)	Arm 1[a]	Arm 2[b]	Heteroskedastic clogit (restricted)
	Mean (SE)	Mean (SE)	Mean (SE)
Total cost ($)	−0.162*** (0.012)	−0.153*** (0.011)	−0.154*** (0.011)
Products ('pharmacy brand generic')			
Megorium generic	0.201** (0.068)	0.171* (0.073)	0.182*** (0.049)
Medora branded	0.377*** (0.065)	0.283*** (0.064)	0.323*** (0.048)
Collect later today ('Now')	−0.513*** (0.072)	−0.508*** (0.073)	−0.500*** (0.059)
Pharmacist recommended 'Yes' ('-' no recommendation)	0.178* (0.088)	0.132 (0.082)	0.152* (0.067)
Scale term (Arm 1)			0.042 (0.061)
Observations	4,944	4,944	9,888
AIC	2439	2503	4936
BIC	2472	2536	4979
Log-likelihood	−1215	−1247	−2462
LR test of equal parameters df=4, critical $X^2_{0.95}$: 4.77 (9.49)			

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; df: degrees of freedom; LR: likelihood ratio; S: standard error; $X^2_{0.95}$: chi-square area in upper tail at 5% critical value.
Note: *** p<0.001, ** p<0.01, * p<0.05.
a=Arm 1 consisted of six choice tasks with active ingredient (generic) medicine prescription followed by six choice tasks with Medora branded doctor's prescription.
b: Arm 2 consisted of six Medora branded doctor's prescriptions, followed by six active ingredient (generic) medicine prescription.

The estimated means in the two separate conditional logit models are very similar for both arms. The significance and sign of the estimates are the same across all variables, except for the term *Pharmacist recommended* in Arm 2 where the result is not statistically significant at the 5% level; however, the sign and magnitude of the result is similar to that in Arm 1.

As the poolability of the two arms was confirmed, the dataset can be tested for any differences in parameters across the doctor's scripts: active ingredient (generic) medicine and Medora branded medicine. A LR test was conducted by separating the dataset into two groups (Table 3-3). The LR test of equal parameters across the two groups reveals a LR test value equal to 0.89 with the critical value 9.48 at a 5% significance level in the chi-squared distribution with four degrees of freedom. Given this test statistic, the hypothesis of

overall equal parameters across the two groups was not rejected. This means that the preferences did not differ significantly across the two doctor's scripts for all of the attributes.

There are no major differences in the estimates of the two models. The sign of the estimates is the same across the two models. There is a difference in significance for two attribute levels: the *Megorium generic* medicine (product attribute) and the *pharmacist recommended (Yes*) attribute level. When respondents saw the active ingredient (generic) doctor's script there is no difference in preferences between the *Megorium generic* and the *pharmacy brand generic* (base case). Similarly, the results for *pharmacist recommended* show that with Medora branded doctor's script, the respondents may not rely on the pharmacist's recommendation. However, the overall results show no difference for the attribute levels.

Table 3-3. Testing the differences in parameters across the two doctor's scripts (active ingredient (generic) and Medora branded) of the DCE 1

Attributes (base case)	**Active ingredient (generic) scripts** Mean (SE)	**Medora branded scripts** Mean (SE)	**Heteroskedastic clogit (restricted)** Mean (SE)
Total cost ($)	−0.163***	−0.153***	−0.167***
	(0.014)	(0.014)	(0.033)
Products ('pharmacy brand generic')			
Megorium generic	0.135	0.235***	0.195**
	(0.074)	(0.069)	(0.067)
Medora branded	0.329***	0.330***	0.349***
	(0.069)	(0.067)	(0.084)
Collect later today ('Now')	−0.444***	−0.580***	−0.542***
	(0.085)	(0.081)	(0.118)
Pharmacist recommended 'Yes' ('-' no recommendation)	0.218*	0.097	0.166*
	(0.103)	(0.092)	(0.083)
Scale term (generic scripts)			−0.040
			(0.126)
Sample (observations)	4,968	4,920	9,888
AIC	2449	2489	4936
BIC	2482	2522	4979
Log-likelihood	−1220	−1240	−2462
LR test of equal parameters df=4, critical $X^2_{0.95}$: 0.89 (9.49)			

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; df: degrees of freedom; LR: likelihood ratio; SE: standard error; $X^2_{0.95}$: chi-square area in upper tail at 5% critical value.
Note: *** p<0.001, ** p<0.01, * p<0.05.

3.3.2 Choosing the functional form for *total cost* attribute

There are four alternative specific attributes in DCE 1. In the previous section it was established that the data from Arm 1 and Arm 2 could be pooled; therefore, the data from the context attribute of *doctor's script* is not analysed in the main models.

Additionally, since the levels of the cost attribute are on a numerical scale, *total cost* can be treated as a continuous variable. The impact of increasing the cost of the medicine is to make it less likely to be chosen. In these models the *total cost* variable is continuous with the values presented in dollar amounts. However, it is important to test the functional form of this continuous variable for the best model selection that is most parsimonious with the data (Zucchini, 2000). Presenting the monetary attribute in different functional forms can help understand whether adding a polynomial term (quadratic or cubic) of the *total cost* variable would provide an improved fit compared to using only a linear term.

In Table 3-4, there are four models presented – one with *total cost* as linear variable (Model A), one with *total cost* as a quadratic polynomial (Model B), one with *total cost* as a cubic polynomial (Model C) and finally a model with *total cost* treated as categorical (Model D), with dummy variables for each level of the *total cost* (and using $30 as the base).

The statistical measures using the AIC and BIC criteria as well as the log-likelihood and the R^2 parameters all indicate that the model with the *total cost* represented by a cubic polynomial is the best fit model. In addition, the quadratic and cubic terms were statistically significant. However, from the plot of the results of these models presented in Figure 3-6, it can be seen that the quadratic and dummy (categorical) terms have a minimal impact on the quantitative values while complicating the model, while the cubic term would considerably complicate the interpretation without materially altering the conclusions.

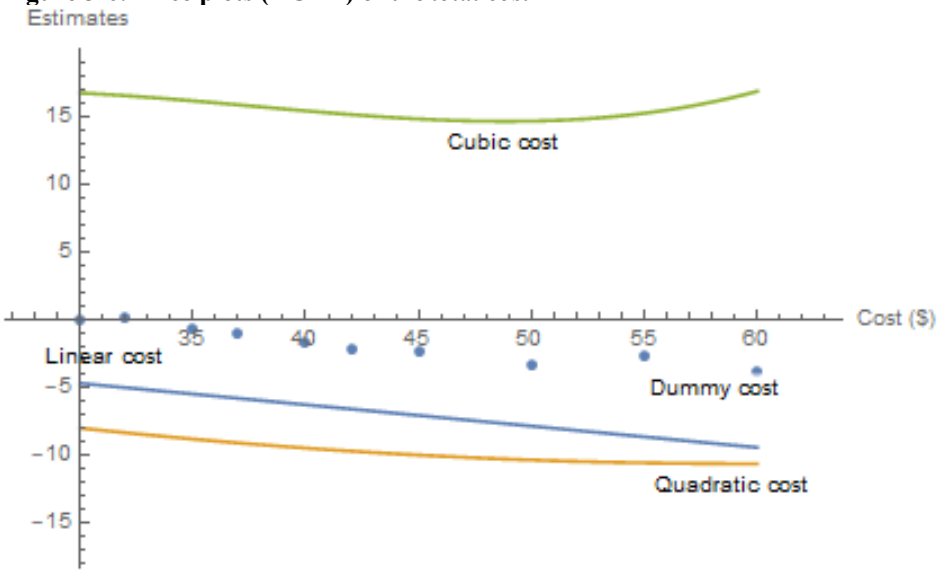
The model with the linear representation of the *total cost* attribute is used as base case model to analyse the DCE 1 data in what follows.

Table 3-4. Presentation of different forms of the *total cost* attribute in DCE 1 (linear, quadratic, cubic and categorical (dummy))

Attributes (base case)	**Model A linear Mean (SE)**	**Model B quadratic Mean (SE)**	**Model C cubic Mean (SE)**	**Model D dummy Mean (SE)**
	linear	quadratic	cubic	dummy
Total cost linear ($)	−0.158***	−0.358***	1.5523***	
	(0.010)	(0.042)	(0.2483)	
Total cost quadratic ($)		0.003***	−0.0452***	
		(0.001)	(0.0063)	
Total cost cubic ($)			0.0004***	
			(0.0001)	
Total cost categorical (dummy, $30)				
$32				0.164
				(0.191)
$35				−0.660***
				(0.068)
$37				−1.078***
				(0.242)
$40				−1.749***
				(0.112)
$42				−2.302***
				(0.168)
$45				−2.465***
				(0.180)
$50				−3.333***
				(0.206)
$55				−2.729***
				(0.220)
$60				−3.859***
				(0.719)
Products				
(‘pharmacy brand generic’)				
Megorium, generic	0.185***	0.152**	0.1737**	0.095
	(0.051)	(0.053)	(0.0541)	(0.057)
Medora branded	0.329***	0.294***	0.3144***	0.327***
	(0.048)	(0.051)	(0.0514)	(0.057)
Collect ‘Later today’ (‘Now’)	−0.512***	−0.509***	−0.5261***	−0.600***
	(0.059)	(0.060)	(0.0613)	(0.063)
Pharmacist recommended ‘Yes’ ('-' no recommendation)	0.155*	0.215**	0.2514***	0.241***
	(0.069)	(0.067)	(0.0686)	(0.072)
Observations	9,888	9,888	9,888	9,888
Pseudo R^2	0.2816	0.2852	0.2910	0.2950
R^2	0.3610	0.3619	0.3691	0.3709
AIC	4934	4911	4873	4858
BIC	4970	4954	4924	4952
Log-likelihood	−2462	−2449	−2430	−2416

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; SE : standard error.
Note: *** p<0.001, ** p<0.01, * p<0.05. The attribute levels in parenthesis are ‘base-line’ levels.

Figure 3-6. Price plots (DCE 1) of the *total cost*



3.3.3 Conditional logit

The pooled model is estimated using the 'clogit' command in Stata and shows the preferences for pharmaceutical products based on the attributes included in the model. The results of the conditional logit model and linear *total cost* variable is included in the model are presented in Table 3-5.

Table 3-5. Conditional logit results for DCE 1

Attributes (base case)	**Mean (SE)**
Total cost ($)	−0.158***
	(0.010)
Products ('pharmacy brand generic')	
Megorium generic	0.185***
	(0.051)
Medora branded	0.329***
	(0.048)
Collect later today ('Now')	-0.512***
	(0.059)
Pharmacist recommended 'Yes' ('-' no recommendation)	0.155*
	(0.069)
Sample (observations)	9,888
AIC	4934
BIC	4970
Log-likelihood	−2462

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; N: total participants in group; SE: robust standard errors; *** p<0.001, ** p<0.01, * p<0.05.

Note: *total cost* is continuous variable represented in dollar value; Reference categories for the attributes: for *Brand premium* it is '*No* brand premium'; for Medicine *product* attribute is '*Pharmacy brand (generic)*'; for *collect* it is '*Now';* for *recommend* it is *'(-) no recommendation'*

To summarise the impact of the other attributes, respondents prefer lower cost of the medicine, which is expected, especially since the Australian prescription medicines are subsidised and usually would not cost more than AUD40 per script.

Respondents also show a preference for the *Megorium generic* and *Medora branded* compared to *pharmacy brand generic*, with the larger magnitude of the estimate for the *Medora branded*. This can be seen as a signal that respondents attaching some value to the brand name and are willing to choose it over the other two generic products. This is despite the fact that an invented brand name was used in this DCE, which means that there can be no actual brand name recognition or prior knowledge of the hypothetical medicine. This result suggests there is a value attached to branded medicines per se. As the *Megorium generic* brand is also preferred to the base case *pharmacy brand generic*, this may indicate that respondents may not like the pharmacy brand and may consider it inferior to a 'fancier' named generic medicine. Additionally, the pharmacy brand may have a negative connotation for the respondents, if they had a negative experience with other 'pharmacy brand' products, or respondents may be suspicious that the pharmacist is trying to sell 'their own' brands.

The sign and magnitude on the *collect later today* coefficient indicate that respondents value their own time and prefer the product that is available at the time of purchase. Finally, the coefficient for the *pharmacist recommended* is statistically significant, showing that respondents listen to and/or trust the pharmacist when making decisions regarding purchasing a medicine.

To further understand the presence of any heterogeneity in the data, a latent class model, a mixed logit model and a generalised multinomial logit model were estimated. These models are discussed in turn below.

3.3.4 Mixed logit model (MXL)

The conditional logit model imposes the assumption that mean preferences do not vary across the population. Implementing a random parameter (mixed logit) model relaxes this assumption where unobserved heterogeneity is modelled by allowing the parameters to vary randomly over individuals according to a continuous, discrete or discrete-continuous mixture distribution (Sarrias & Daziano, 2017). MXL generalises the MNL and conditional logit models by allowing the preference or taste parameters to be different for each individual (McFadden & Train, 2000; Train, 2009).

The parameters estimated in the mixed logit model are the same as those used in the conditional logit model, but now all the coefficients are assumed to be drawn from a cumulative distribution function (McFadden & Train, 2000), with both mean effects and standard deviation precisely estimated. In this analysis the MXL model is considering uncorrelated random parameters from a normal distribution function, with the estimated mean and standard deviation.

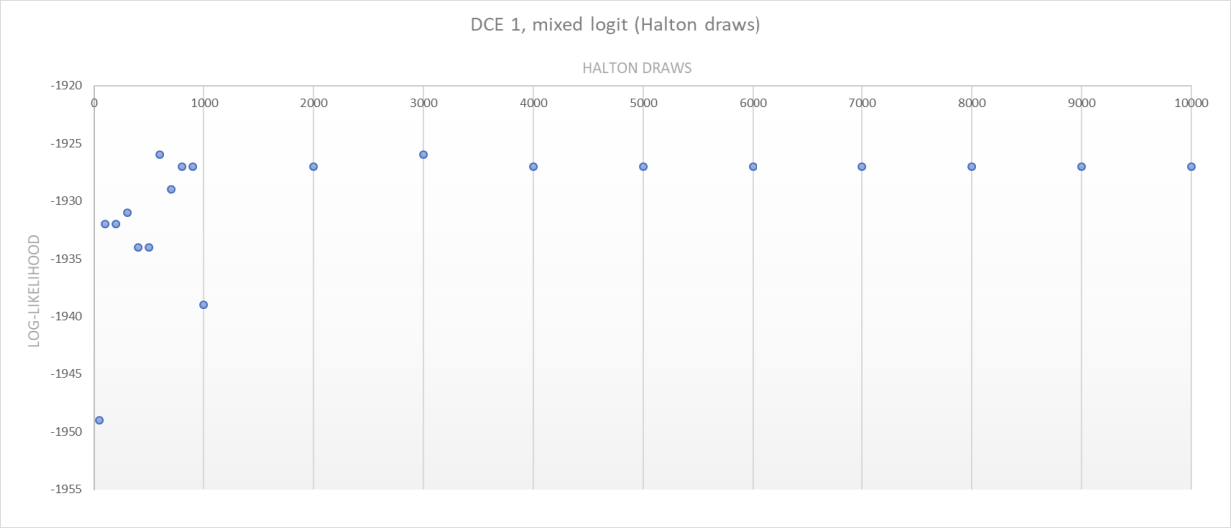
The mixed logit model estimates choice probabilities from distribution of random draws through the simulated maximum likelihood (Hole, 2007; Pacifico & Yoo, 2013). The use of Halton sequences[38] for mixed logit estimations were found to be superior to random draws, with the variance of the estimated parameter considerately smaller even with a lower number of draws (Train, 2000).

The mixed logit command in Stata17 software, allows for the number of Halton draws to be specified. The optimal number of the Halton draws was investigated to help test the assumption that the estimated random parameters are uncorrelated. The model was estimated with different numbers of Halton draws, ranging from 50 (Stata default) to 10,000 which indicates that number of elements that are generated, and the number of initial sequence elements to drop (Stata command default is n=15) when creating the Halton sequence (Hole, 2007). The results of log-likelihood statistics of the twenty estimations of the mixed logit model were matched to the Halton draws 50 to 10,000 and are reported in Figure 3-7. Based on the visual inspection of the log-likelihood, it was decided that 2000 Halton draws was an acceptable number, due to the observed stabilisation of the estimated log-likelihood. There is an additional burden in terms of computation time required with a larger number of Halton draws, but this has the benefit of achieving stable

[38] The computation and evaluation of likelihood functions is performed using simulation. This involves taking pseudorandom draws from standard uniform distributions, one for each random parameter. In applying simulation techniques the numerical integration is not as important as their uniform coverage over the domain integration. The more the uniform coverage over the domain of integration, the better the numerical approximation, which can be improved by using quasirandom sequence. The Halton sequence uses number-theoretic methods to ensure a high degree of uniformity in their point sets (Note: sequences are the functions use to generate point sets) (Drukker & Gates, 2006).

estimates. For example, the computation time for a model with 50 Halton draws was around five minutes, compared with 25 minutes for the model with 2000 Halton draws.

Figure 3-7. DCE1 - Mixed logit model for various number Halton draws



The MXL model is estimated using 'mixlogit' command in Stata by specifying at least one parameter as random. The estimated model has no alternative specific constant, as the data comes from an unlabelled choice experiment, with the alternatives randomly assigned as Option A or Option B. This imposes the assumption that the alternatives have no utility over and above the characteristics assigned to them in the experiment (Hole, 2007).

Results in Table 3-6 show the estimated mean coefficients and standard deviations using the mixed logit, with all five parameters specified as random. This is reasonable, since the estimated standard deviations are all significant, indicating heterogeneity within the sample. The mean coefficients are similar to the ones reported in the conditional logit.

It appears that respondents prefer lower cost, non-pharmacy brand generic medicine, shorter waiting time at the pharmacy, and the medicine that is recommended by the pharmacist.

Table 3-6. Results of the mixed logit model for DCE 1

Attributes (base case)	Mean (SE)	SD (SE)
Total cost ($)	−0.491*** (0.032)	0.379*** (0.029)
Products ('pharmacy brand generic')		
Megorium generic	0.304** (0.097)	0.728*** (0.173)
Medora branded	0.488*** (0.103)	1.033*** (0.147)
Collect later today ('Now')	−1.283*** (0.134)	1.561*** (0.163)
Pharmacist recommended 'Yes' ('-' no recommendation)	0.957*** (0.149)	1.818*** (0.174)
Sample (observations)	9,888	
AIC	3800	
BIC	3872	
Log-likelihood	−1890	

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; df: degrees of freedom; p: p-value; SD: standard deviation; SE: standard error.
Note: *** p<0.001, ** p<0.01, * p<0.05

Based on the magnitude of the standard deviation relative to the mean coefficients, the majority of respondents (90%) prefer a lower priced medicine, approximately two-thirds of the respondents considered *Megorium generic* (67%) and the *Medora branded* (68%) products better than *pharmacy brand generic*, 79% would prefer to *collect now* rather than *collect later today*, and 70% would prefer the medicine that was recommended by the pharmacist[39]. These results are supported by the kernel density plots for the parameters.

Kernel density plots for the variables (attribute levels)

The kernel density plots for each of the estimated parameters are presented in this section. The kernel density is a modification of the familiar histogram used to describe the distribution of a sample of observations graphically, and is better suited to present results when the underlying distributions is assumed to be continuous (Hensher & Greene, 2002). The derived individual-specific parameter estimates can be plotted non-parametrically using kernel densities (Greene & Hensher, 2003) to reveal their distribution across the sampled population (Hensher & Greene, 2002).

[39] Calculations performed in Wolfram Mathematica. The formula is as follows, normal (mean/standard deviation)-, given by $100\times\Phi(-b_k/s_k)$, where Φ is the cumulative standard normal distribution and b_k and s_k are the mean and standard deviation, respectively, of the *k*th coefficient (Hole, 2007).

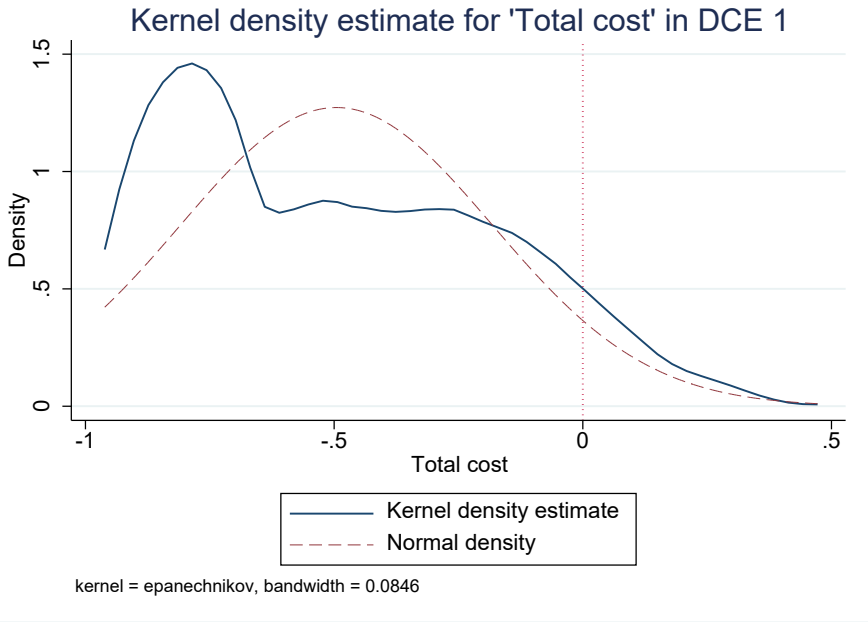
Each plot is fitted with a normal density distribution (where the mean is zero and variance is one) for comparison and a vertical reference line at zero (negative and positive preferences). The optimal bandwidth (the scale factor of the kernel density curve) is based on the Epanechnikov method.[40]

Each figure was visually inspected with respect to its shape, size and location with respect to the zero.

The total cost attribute

The kernel density plot for the *total cost* attribute is shown in Figure 3-8. The shape of the distribution appears to have a kink (break) after a peak at the far left (negative preference) area. The peak indicates that a lot of respondents have those β_i estimates (−0.5 and −1.0) and a tendency to skew towards the right (zero), with the tail of the plot pulled towards the positive preferences of the high total cost. The majority of the function is located to the left of the zero.

Figure 3-8. Kernel density estimate for the *total cost* in DCE 1



[40] Analysis conducted using Stata 17 command [kdensity] estimating univariate kernel density (Silverman, 1986).

The product attribute

The kernel density plots for the two product attributes, Megorium generic and Medora branded, are shown in Figure 3-9 and Figure 3-10. The shape of the distributions appears to be similar for both parameters. The curves have symmetric shape, with a long right tail (although with a lower density). The majority of the curves are located to the right of zero. The high narrow peaks indicate that most respondents had very strict preferences by preferring each of the products to the pharmacy brand generic.

Figure 3-9. Kernel density estimate for *Megorium generic* in DCE 1

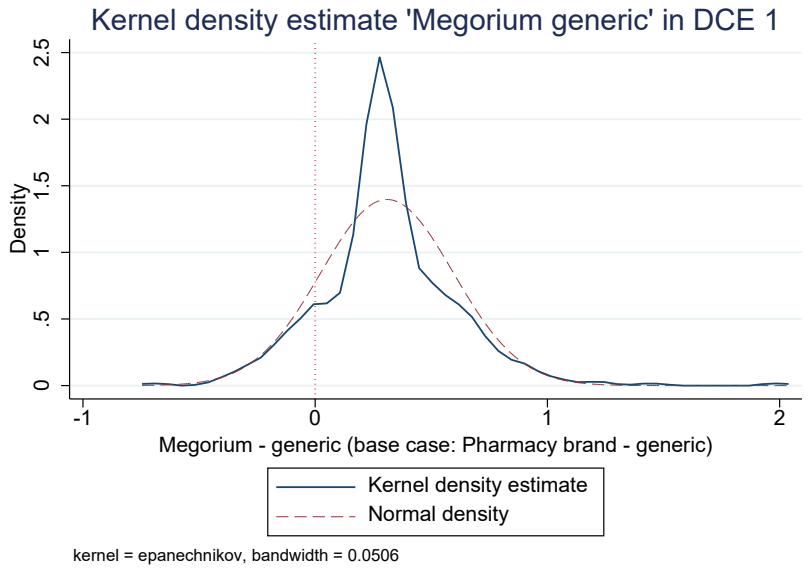
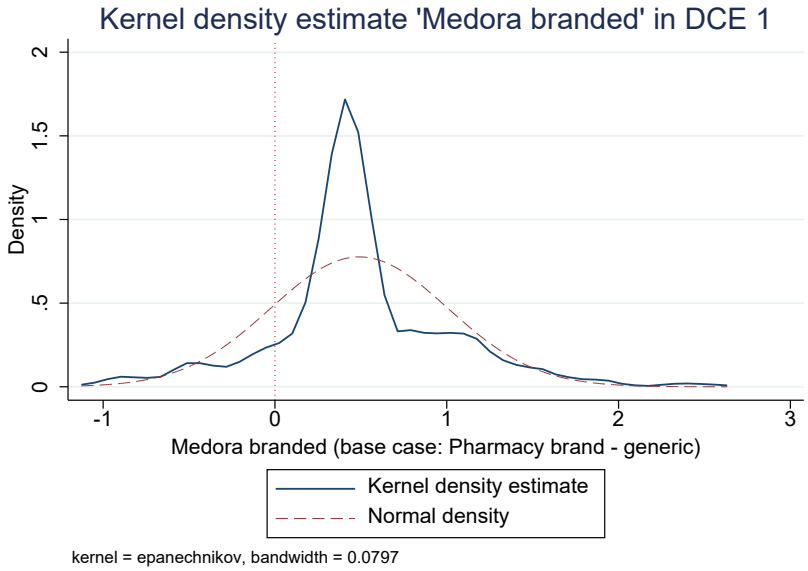


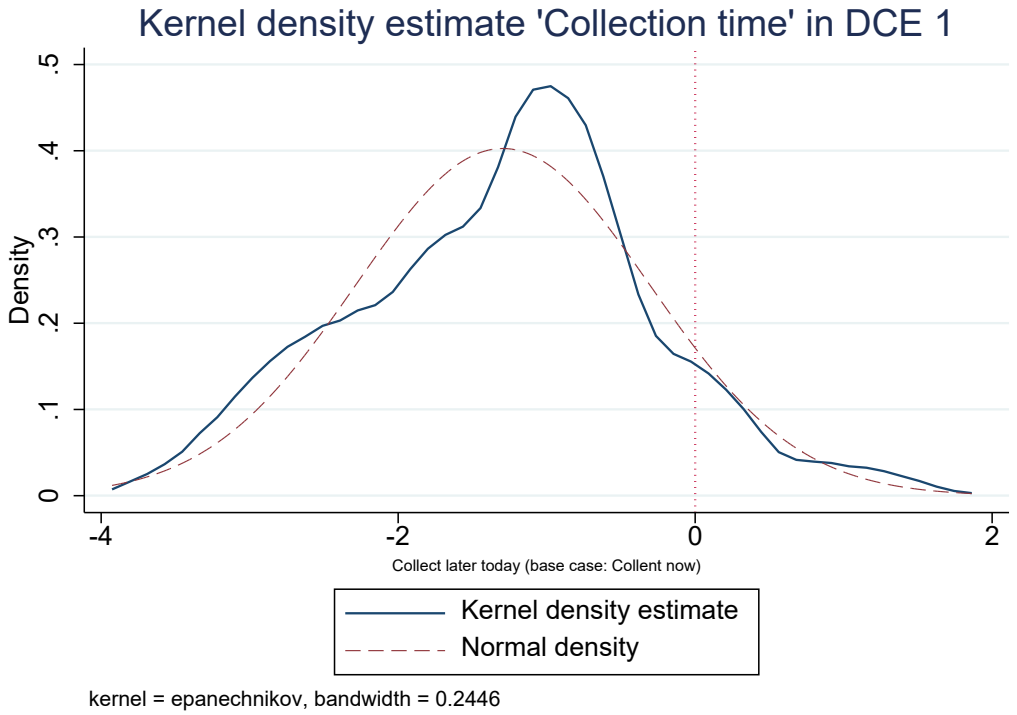
Figure 3-10. Kernel density estimate for *Medora branded* in DCE 1



Collection attribute

The kernel density plot for the *collection* attribute is shown in Figure 3-11. The shape of the distribution appears to be symmetric. The majority of the curve is located to the left of the zero, indicating respondents' aversion to having to return to the pharmacy to collect the medicine, compared to collecting it immediately. The distribution width is also significant (from −4 to +2), indicating very strong preference against *collect later today* compared to *collect now*. The majority of the distribution is located to the left of the zero.

Figure 3-11. Kernel density estimate for *collection* in DCE 1



Pharmacist recommended attribute

The kernel density plot for the pharmacist recommendation attribute is shown in Figure 3-12. The shape of the distribution appears to skew to the right, with the highest peak of the curve closer to zero. The peak indicates that many respondents have positive β_i estimates although not strongly so. The majority of the curve is located to the right of the zero.

Figure 3-12. Kernel density estimate for *pharmacist recommended* in DCE 1

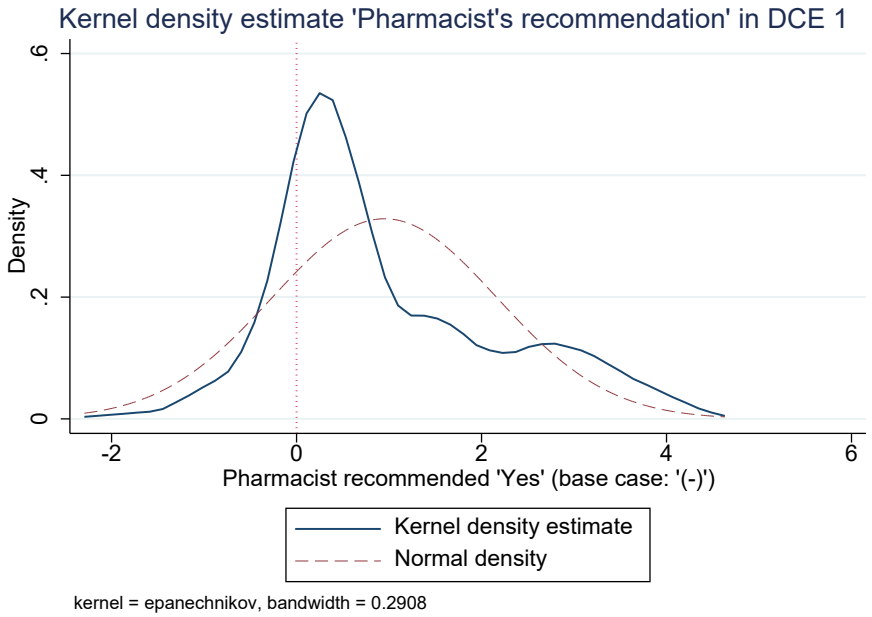


Table 3-7 provides a comparison of fit across the conditional and MXL models. To select the preferred model from conditional logit and mixed logit, the AIC, BIC and log-likelihood values are compared across each model. The improved fit of mixed logit model compared to conditional logit model is confirmed by the considerable improvement in measures of AIC, BIC and log-likelihood.

Table 3-7. Comparison of statistical fit

Model estimation	Log-likelihood	AIC	BIC
Conditional logit	−2462	4934	4970
Mixed logit (2000 Halton draws)	−1890	3872	3800

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion.

Interactions MXL

An MXL model with two demographic variables (gender and age) was run to identify whether these two covariates are significant with respect to any of the attribute levels presented in the model. As the sample population was stratified based on these two characteristics, with the data available for all the respondents. The results are presented in Table 3-8. The inclusion of covariates impacted on the significance of the two product attribute levels making them non-significant. However, the estimated standard deviations for all

variables are significant and large compared to the estimated means, indicating a high level of heterogeneity in the sample.

The results of interaction with the gender characteristic show that the significant coefficients were positive for the *total cost* and *collection* attributes. This indicates that a male was more likely to choose a product with a slightly higher *total cost* compared to a female, and was slightly more likely to choose collecting the medicine *later today* compared to a female.

Regarding the age characteristic, people older than 30 years old were significantly more likely to choose a lower *total cost* compared to younger group (18–29 years old). Respondents who were over 70 years old were significantly more likely to choose *Medora branded* medicine compared to younger groups. Those 60 and older were significantly less likely to prefer to collect later today. Compared to younger groups, those aged 30–59 and 70-plus years were significantly less likely to prefer pharmacist recommendation for the medicine.

Table 3-8. Results of mixed logit model with gender and age covariates (DCE 1)

Attributes (base case)	Mean (SE)	SD (SE)
Total cost ($)	−0.360***	0.333***
	(0.042)	(0.023)
Products ('pharmacy brand generic')		
Megorium generic	0.238	0.769***
	(0.220)	(0.179)
Medora branded	0.333	0.966***
	(0.222)	(0.144)
Collect later today ('Now')	−1.137***	1.448***
	(0.258)	(0.164)
Pharmacist recommended 'Yes' ('-' no recommendation)	2.076***	1.774***
	(0.316)	(0.171)
Interaction with Gender (female)		
Total cost – Male	0.161***	
	(0.037)	
Megorium generic– Male	−0.086	
	(0.195)	
Medora branded – Male	−0.045	
	(0.203)	
Collect later today ('collect now') - Male	0.591*	
	(0.230)	
Pharmacist recommended 'Yes' ('-' no recommendation) – Male	−0.215	
	(0.265)	
Interaction with Age		
Total cost ($) X Age (18–29yo)		
Age 30–39	−0.109*	
	(0.053)	
Age 40–49	−0.363***	
	(0.064)	
Age 50–59	−0.291***	
	(0.059)	
Age 60–69	−0.331***	
	(0.064)	
Age 70+	−0.253***	
	(0.061)	
Megorium generic		
Age 30–39	0.011	
	(0.286)	
Age 40–49	0.273	
	(0.334)	
Age 50–59	−0.109	
	(0.325)	
Age 60–69	0.040	
	(0.331)	
Age 70+	0.533	
	(0.332)	
Medora branded		
Age 30–39	−0.084	
	(0.290)	
Age 40–49	0.155	
	(0.358)	
Age 50–59	0.236	

Attributes (base case)	Mean (SE)	SD (SE)
	(0.330)	
Age 60–69	0.386	
	(0.349)	
Age 70+	0.884*	
	(0.361)	
Collect later today ('Now')		
Age 30–39	−0.232	
	(0.337)	
Age 40–49	−0.773	
	(0.397)	
Age 50–59	−0.252	
	(0.375)	
Age 60–69	−0.840*	
	(0.399)	
Age 70+	−1.100**	
	(0.395)	
Pharmacist recommended 'Yes' ('-' no recommendation)		
Age 30–39	−1.149**	
	(0.398)	
Age 40–49	−2.397***	
	(0.488)	
Age 50–59	−1.236**	
	(0.441)	
Age 60–69	−0.862	
	(0.458)	
Age 70+	−1.489**	
	(0.459)	
Observations	9,888	
AIC	3759	
BIC	4047	
Log-likelihood	−1840	

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; N: total participants in group; SD: standard deviation; SE: standard error.
Note: *** p<0.001, ** p<0.01, * p<0.05.
total cost is continuous variable represented in dollar values; Reference levels for the attributes: for Medicine product attribute is 'pharmacy brand generic'; for collect it is 'Now'; for recommend it is '(-) no recommendation'.

Testing additional model

An additional analysis of taste heterogeneity in respondents of the DCE 1 was conducted using a generalised multinomial logit model (G-MNL). The G-MNL model nests the scale heterogeneity model (S-MNL), MXL and MNL models (Sarrias & Daziano, 2017), as it presents the preference heterogeneity as 'scale' heterogeneity, meaning that by fixing the attribute coefficient the individual-specific scale of the idiosyncratic error term is greater for some consumers than it is for the others (Gu et al., 2013). The error term can be described as the respondent heterogeneity in tastes for unobserved product attributes (Fiebig et al., 2010). The G-MNL is a scale heterogeneity[41] multinomial logit model that accommodates both preference and scale heterogeneity.

An uncorrelated G-MNL model was run with the results presented in Table 0-3 of Appendix B. However, the model only converged using very low (50–100) Halton draws that varied depending on the assumptions of scale for each attribute level. For the unscaled G-MNL model (50 Halton draws) the goodness of fit criteria showed a worse fit than in MXL model (Table 0-4 at Appendix B). The results are not presented in the main body, and not used in further analysis.

3.3.5 Estimation of marginal willingness to pay (mWTP)

The result of the analysis showed the respondent's preferences based on the alternatives that they have chosen. As the cost parameter was included as an attribute, marginal utility estimated from the DCE model can be converted into the willingness to pay for changes in the levels of other attributes (Jiang et al., 2020).

The estimated results from the mixed logit model are used to calculate the marginal WTP, as shown in Figure 3-13. The WTP was estimated using conventional approach (estimation in preference space) by assuming a distribution for the coefficients and deriving WTP for an attribute as the ratio of the attribute coefficients to a monetary coefficient, with the WTP given by the ratio of two randomly distributed terms (Hole & Kolstad, 2012). The coefficients in the mixed logit model were assumed to be normally distributed. As was seen in the kernel density plot for the *total cost* attribute, the distribution of the β_i estimates was skewed to the right, and so the assumption of normality was violated. However, using another approach (i.e., specifying the *total cost* as fixed) would potentially erroneously assume that all individuals have the same marginal utility of price (Hole & Kolstad, 2012; Meijer & Rouwendal, 2006). Meijer and Rouwendal (2006) also argue that although typically the coefficient of the price (denominator) needs to be restricted to

[41] Scale heterogeneity is described as can describe preference heterogeneity when the attribute coefficient is fixed and the scale of the unobserved error term is greater for some consumers than it is for the others (Gu et al., 2013).

be negative, this does not have to be the case if the mean of the random coefficient is far from zero relative to its standard deviation.

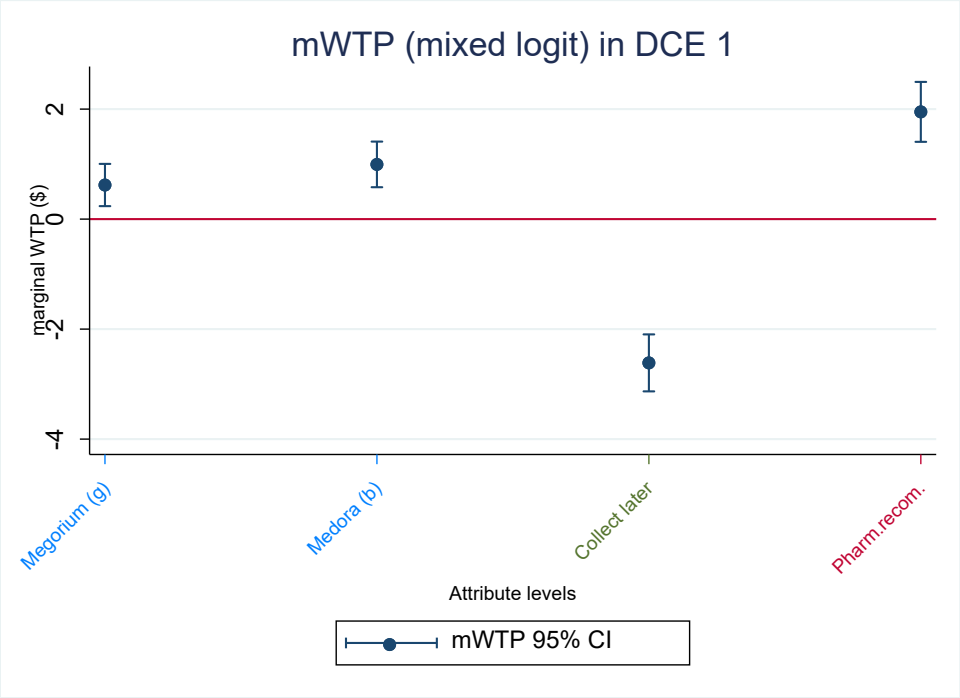
Additionally, in the topic of this research there is evidence that some consumers prefer high prices, presumably since they believe that these may indicate higher quality. Thus, restricting the *total cost* coefficient to be negative or assuming a different distribution (i.e. log-normal) may result in a highly skewed WTP distribution (Hole & Kolstad, 2012).

The results from the WTP estimates show that respondents are willing to pay on average an additional $0.62 ($0.24–1.00) for a *Megorium generic* and additional $0.99 ($0.58–1.41) for *Medora branded* medicine compared to the *pharmacy brand generic* medicine. In this case it is likely that the respondents are attributing additional benefits to the non-pharmacy generic brand.

The results also indicate that if the pharmacist recommends the medicine brand the respondents are willing to pay an additional $1.95 ($1.41–2.50) for the brand. This shows that the respondent's trust the pharmacist's professional advice.

Additionally, the estimated results also indicate that an average compensation of $2.60 ($2.10 –3.13) per script is required if the respondent needs to return to the pharmacy to collect the medicine (*collect later today*) compared to collecting the medicine immediately (*Now*). The respondents value their time from *collect now* to *collect later today* as much as they value a price drop by an average of $2.60. This particular preference could be attributed to the DCE relating to the acute condition, where the medicine is only being used for a short period of time.

Figure 3-13. Estimated mWTP based on mixed logit model results



Abbreviations: CI: confidence interval; mWTP : marginal willingness to pay.

3.3.6 Latent class analysis (LCA)

Another approach to allow for heterogeneity in the data is to use a LCA model, which is similar to MXL and is useful if the sample population in the dataset consists of several segments (classes), each with its own preferences (Train, 2000). For each class β takes on one of a finite set of distinct values (Train, 2000). The latent class approach assumes that respondents can be characterised as having preferences drawn from two or more finite distributions, defined as classes, each determined by a value for β. Membership of a particular class may be characterised by shared observed demographic characteristics that determine choice, or by other unobserved factors that drive preferences. This model has gained popularity in recent years in the health economics domain in relation to SP studies (Zhou et al., 2018). Respondents in the same class may share demographic characteristics that determine choice. For each respondent the posterior probability that the respondent is a member of each class can be calculated, with the highest probability used to allocate respondents to classes.

After identifying the number of classes, the characteristics of the respondents within these classes were explored using socio-demographic responses of the survey participants in order to identify any specific groups and the possible reasons for the choices they made.

Three software packages were used to determine the optimal number of latent classes to identify homogeneous groups of respondents in DCE 1: Stata 17 (StataCorp, 2021), LatentGold[42] (Statistical Innovations) and RStudio (RStudio Team). The use of the three software programs was useful in terms of comparing the number of optimal classes identified by each statistical software program, as well as confirming the output of the model. The final estimation of the model was performed in Stata (for consistency with previously estimated models).

In the Stata software, the user-written 'lclogit' and 'lclogitml' packages (Pacifico & Yoo, 2013) were used to estimate the models. In LatentGold the embedded 'Choice' package was used. In RStudio a user-written package 'gmnl' (Sarrias & Daziano, 2017) was used to estimate the latent class models.

In Stata and LatentGold the analysis used the expectation-maximisation algorithm for fitting a latent class logit model. This guarantees numerical stability and convergence to a local maximum even when the number of latent classes is large. This is in contrast to the (quasi) Newton methods (RStudio 'gmnl' package), as the inversion of the (approximate) Hessian becomes numerically difficult (Bhat, 1997; Pacifico & Yoo, 2013; Train, 2009). Nevertheless, the expected number of optimal classes in these dataset samples is not high (in DCE 1: 412 respondents, 12 choice task each).

[42] LatentGold is a latent class program that allows estimation of discrete choice models.

The latent class model was tested for up to nine classes, where possible, to determine the optimal number of classes.

The selection of number of optimal classes was based on information criteria (used to select the statistical measure of fit) such as AIC and BIC statistics as well as an examination of reasonableness of the results with different number of classes (Train, 2009). There is an indication that BIC is the preferred statistical criterion for this setting (Dziak et al., 2020).

The output from the three software packages is presented in Table 3-8. There are some differences between the results as estimated across the three software packages. The output form Stata shows that the model is minimised at five classes (BIC); in LatentGold at six classes. In RStudio, the model was minimised at four classes. The six-class model reported in R Studio became stuck in a flat region of the log-likelihood due to numeric overruns in the Hessian (Sarrias & Daziano, 2017).

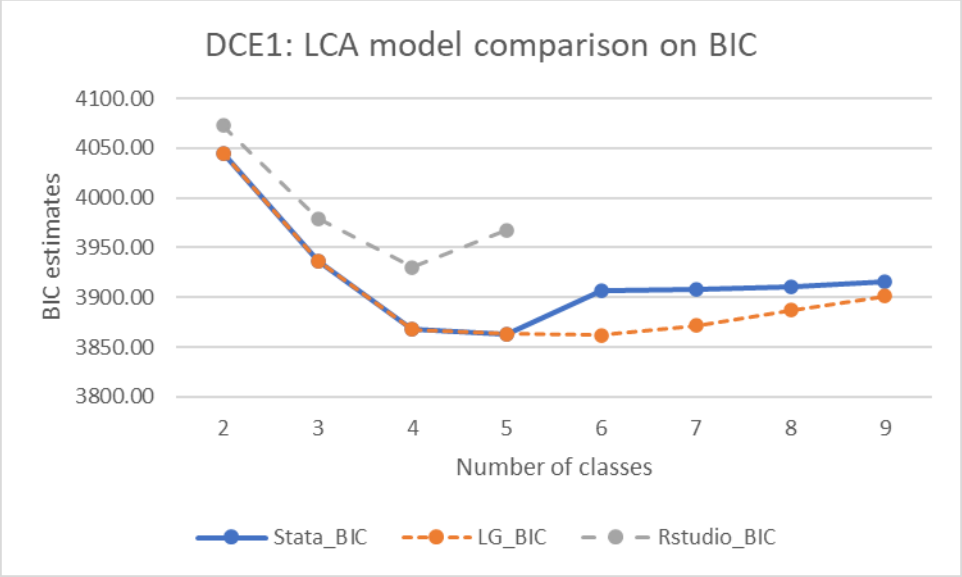
There is consistency across the software packages in terms of observed changes in BIC output measure, with the results plotted in Figure 3-14. The results of the BIC are similar across the three software packages. Based on a small observable change in the BIC statistics between a four-class model and a five-class model (in Stata, LatentGold and RStudio) as well as considering the number of respondents (N=412) in the DCE, it was decided to estimate the latent class model with four classes.

Table 3-9. Latent class model statistical measurements comparison - DCE1

Stata Output				
Classes	Parameters, N	Log-likelihood	AIC	BIC
1	5	−2462.02	4934.047	4954.152
2	11	−1989.05	4000.955	4045.187
3	17	−1917.34	3868.669	3937.027
4	23	−1864.66	3775.319	3867.802
5	29	−1844.38	3746.768	3863.377
6	35	−1847.86	3765.726	3906.462
7	41	−1830.73	3743.452	3908.314
8	47	−1813.83	3721.666	3910.654
9	53	−1798.34	3702.671	3915.785
LatentGold Output				
Classes	Parameters, N	Log-likelihood	AIC	BIC
1	5	−2462.02	4934.047	4954.152
2	11	−1989.48	4000.958	4045.189
3	17	−1917.33	3868.666	3937.023
4	23	−1864.67	3775.344	3867.828
5	29	−1844.39	3746.775	3863.385
6	35	−1825.55	3721.103	3861.839
7	41	−1812.48	3706.97	3871.832
8	47	−1801.92	3697.841	3886.829
9	53	−1791.18	3688.351	3901.465
RStudio Output				
2	5	−1989.5	4000.956	4072.521
3	11	−1917.3	3868.692	3979.293
4	17	−1867.2	3780.249	3929.985
5	23	−1860.6	3779.251	3967.923

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion.
The row for a Class 1 (conditional logit model) is presented for comparison and confirmation that both statistical packages can provide the same estimates.

Figure 3-14. DCE 1, latent class model comparison of statistical measures (Log-likelihood, AIC and BIC)



Abbreviation: BIC: Bayesian information criterion; LCA: latent class analysis; LG: LatentGold software.

The results of the latent class model estimated with four classes are presented in Table 3-9. The class membership was estimated with different shares across the classes: Class 1 (12%), Class 2 (28%), Class 3 (40%) and Class 4 (20%).

The smallest group, Class 1, indicates that there is a group of respondents for whom the Megorium generic and Medora branded medicines were preferred to the pharmacy brand generic. The group also showed a statistically significant preference for the medicine that was recommended by the pharmacist compared to when the pharmacist does not say anything about the medicine.

The estimated preferences across the four classes, show that the two largest classes (Class 2 and Class 3) have similar preference patterns: with respondents showing a statistically significant preference for lower cost and a strong negative coefficient for the collect later today parameter. Although it was decided to go with the four-class model, the magnitude of the preferences in these two classes are different. An analysis of each class using demographic information is presented in the next section.

The estimates in Class 4 contains the respondents who had statistically significant preference for all attribute levels compared to the base case levels, thus showing that all the presented attributes are important to this group.

Table 3-10. Latent class model estimates estimated in Stata with 4 classes in DCE 1

Attributes (base case)	**Class 1**	**Class 2**	**Class 3**	**Class 4**
Class share	0.12	0.28	0.40	0.20
Total cost ($)	−0.001	−0.196***	−0.961***	−0.154***
SE	(0.011)	(0.020)	(0.156)	(0.018)
Products				
('Pharmacy brand generic')				
Megorium generic	0.622***	-0.053	0.361	0.344*
SE	(0.151)	(0.128)	(0.257)	(0.145)
Medora branded	0.940***	-0.155	0.846	0.749***
SE	(0.162)	(0.140)	(0.507)	(0.172)
Collect later today ('Now')	0.188	−1.009***	−2.368***	−1.069***
SE	(0.146)	(0.145)	(0.574)	(0.155)
Pharmacist recommended 'Yes'	0.410**	−0.123	0.760	2.438***
('-' no recommendation)				
SE	(0.148)	(0.157)	(0.657)	(0.253)
Constant	−0.543	0.298	0.693	Base class
SE	(0.229)	(0.232)	(0.183)	

Abbreviations: SE: standard error.

The model's ability to make in-sample predictions of the actual choice outcomes was assessed by estimating the class membership posterior probability and then predicting the unconditional probability of actual

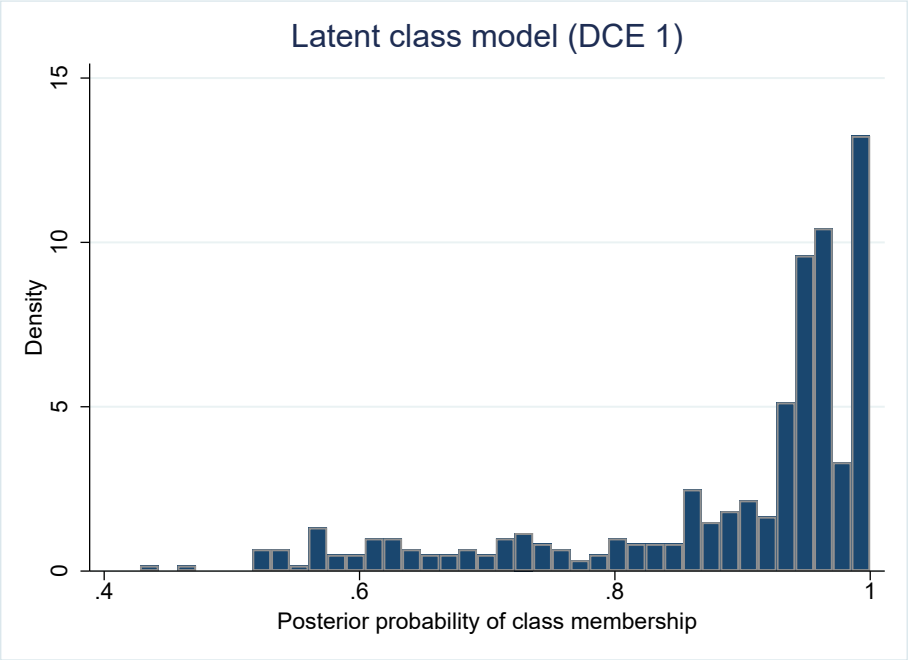
choice and the probability of actual choice conditional on being in specific class. This assessment was performed for all 12 choice tasks for each responded with the median value reported in Table 3-10.

Table 3-11. Class membership probability (DCE 1)

Observations in each class	Number of respondents in each class	Class number	Unconditional probability	Conditional probability
588	49	1	0.45	0.58
1176	98	2	0.69	0.74
2160	180	3	0.78	0.96
1020	85	4	0.63	0.76

The performance of the model was evaluated by estimating the average of the highest posterior probability of class membership, 0.89 with the majority of values falling between 0.80 and 1 (distribution presented in Figure 3-15). The four-class LCA does well in capturing different underlying taste patterns for the observed choice behaviour (Pacifico & Yoo, 2013). Given that there are two alternatives per choice, random prediction would give rise to values close to 0.5. The results for unconditional choice probability show three classes with higher than 0.5 probability and one class (Class 1) with 0.45, indicating that model is describes the observed behaviour well. The unconditional choice probabilities for all classes are all above 0.5.

Figure 3-15. Highest posterior probability of class membership (DCE 1)



Class heterogeneity

The LCA was extended to look for the differences in respondents across the classes. This was undertaken by using multinomial logistic regression to model the relationship between assigned class (the dependent variable) and the demographic characteristics of the respondents as independent variables.

The following variables were tested in the analysis: age, sex, country of birth, education status, household income, employment status, concession card holders, carer responsibility, number of children in the household and self-reported health status. The results are presented for outcomes that showed some statistical significance in at least one of the classes at 5% critical value. These characteristics in DCE 1 were sex (male or female), age and income by categories, presented in Figure 3-16. These characteristics showed significance when analysed simultaneously, rather than one by one.

The base category for the sex variable is *female*, and the *male* level is shown in the results. For the categorical variable age the base level was the *18 year old to 29 years old*. As for the income variable, the first category of negative to zero income was combined with the second category $1 to $19,000 since there are fewer responses with this category, and there are none in the base case Class 4, which leads to a very large (non-significant) estimated coefficient for this category in classes 1 to 3.

Class 4 is used as the base class in the analysis, since all the attribute levels in this class are statistically significant, and hence the interpretation against this class is more definite.

Relative to Class 4, Class 1 members were more likely to be male and less likely to have low to medium income ($20,000–79,000).

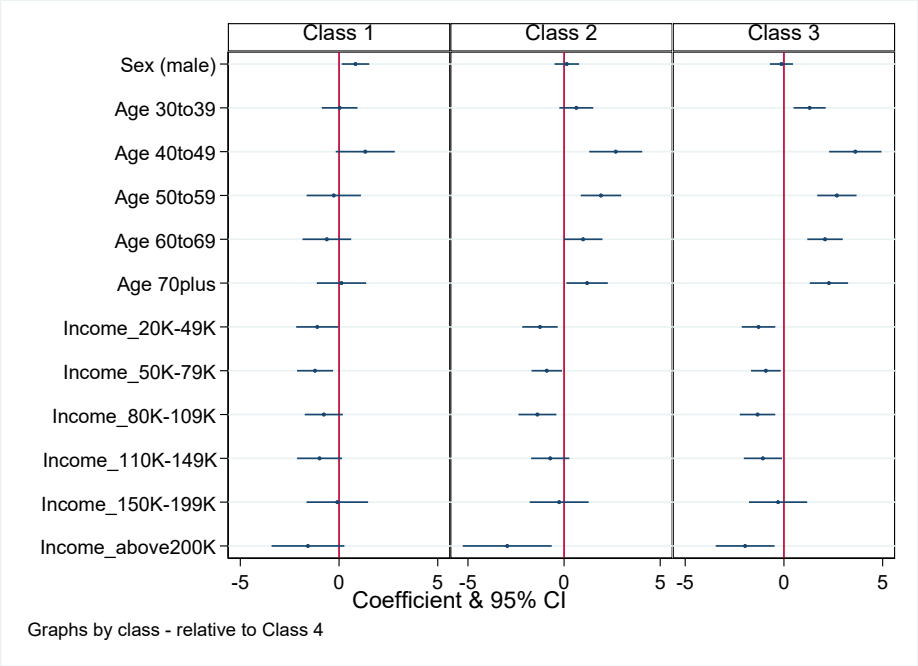
The results of this analysis help look further into the interesting case of the two similar classes Class 2 and Class 3, where *total cost* and *collection* of the medicine were statistically significant. The magnitude of the coefficients in Class 3 were much bigger than in Class 2.

Overall, relative to Class 4, Class 2 members were more likely to be middle-aged (40–60 years), while Class 4 members were more likely to be older (40–70 years) and less likely to have a low to mid- or very high income ($200K).

Class 3 members were more likely to be older with a results pattern for the income variable similar to that observed in Class 2.

As both Class 2 and Class 3 members preferred lower cost and less time spent on purchasing the medicine, it could be inferred that a group that has a relatively older population has stronger preferences towards lower cost and collection time.

Figure 3-16. LCA by class with respondent characteristics (DCE 1)



Abbreviation: CI: confidence interval.

3.4 Discussion

The aim of this chapter was to explore preferences for branded and generic prescription pharmaceuticals in a SP experiment. Overall, the results of DCE 1 responses showed that when respondents are presented with factors impacting choice of the prescription medicine (doctor's prescription, cost, medicine name, time of collection of the medicine at the pharmacy and pharmacist recommendation), they opt for a cheaper cost, a medicine with a branded name, a shorter wait time for collection and are open to engaging with the pharmacist and buying the medicine that the pharmacist recommended, while the doctor's prescription does not have a significant impact on the final choice.

The survey presented the two types of doctor's prescription to all respondents, with the order of the prescriptions randomised to either seeing doctor's scripts with Medora branded or an active ingredient (generic) name. The use of the two different scripts was part of a context attribute setting, where it was important to identify the effect (if any) of the name of the product written on the prescription (by the prescriber/doctor) has on the respondent's final choice between the two alternatives presented. The two scripts were presented in sets of six, with respondents randomised into two arms, with the order of the scripts reversed in the two arms. The results showed that in this DCE, the order of the scripts did not have a significant effect on the respondents' preferences, nor did the type of the doctor's script. However, there was an indication that a doctor's script has some impact on preferences, especially when the script was for the active ingredient (generic), the respondents did not distinguish between the two generic products (*pharmacy brand generic* and *Megorium generic*) compared to the responses in the context of the Medora branded doctor's script. Similarly, in the context of the active ingredient (generic) script, respondents were significantly more likely to prefer pharmacists' recommendation. These results indicate that consumers respond to/take note of the product name written on the doctor's script, but possibly other factors play a more important role in making a choice. Since this survey focuses on an acute, short-term condition with a short treatment period, this may also show that in these settings the doctor's script is not a major factor. Previous research does indicate that patients with chronic conditions may have stronger preferences for the brand of the product they choose (Babar et al., 2010; Denoth et al., 2011).

A more detailed analysis revealed that all attributes were significant determinants of prescription medicine choice. There is significant preference heterogeneity in the population. Information about preference heterogeneity may help stakeholders understand individual's preferences for prescription medicine choice, as well as inform policy.

There were differences in preferences across the population. While on average most respondents preferred a lower cost, a review of different groups (LCA model) showed that there are groups who have significant

positive preferences for the brand of the medicine, preferring a branded name (original brand) to a pharmacy brand.

The analysis presented in this chapter provides some evidence that Australian respondents prefer a branded medicine. Although the survey instructions specified that generic and branded medicines have the same efficacy and side effects, the preference for the *Medora branded* was still very strong. This effect cannot be explained by the name of the drug used in this survey, since this brand does not exist (an invented name). Thus, the effect may come from the word 'branded' and the unobserved characteristics that respondents attribute to it. Similarly, the strong preference for the *Medora branded* medicine compared to pharmacy brand generic could be explained by an aversion of consumers towards generic medicines. Although awareness of generic medicines has increased in the past 20 years (M. A. Hassali et al., 2010; M. A. A. Hassali et al., 2010), this does not automatically increase acceptance and use (Lofgren, 2009), as beliefs that generic medicines are less effective and have more side effects persist (Alrasheedy, Hassali, Stewart, Kong, Aljadhey, Mohamed Ibrahim, et al., 2014; Babar et al., 2014).

The strength of this study is that it uses a choice model to elicit preference from a representative sample of the Australian population in contrast to other studies conducted in Australia and New Zealand that used interviews of small groups of consumers in Melbourne (Victoria) and Perth (Western Australia) (Bulsara et al., 2010; Hassali et al., 2005), or survey questionnaires (Babar et al., 2010). Considering international research, studies that have focused on consumer preference between generic and branded medicines used Likert scale-style questionnaires focusing on a set of illnesses (presented in different order to the respondents) (e.g., (Denoth et al., 2011; Figueiras et al., 2010; Guttier et al., 2017)). A more recent study of Indian consumer perceptions of generic drugs in comparison to branded drugs by Joshi and Gandhi (2020) was conducted using a qualitative in-depth interview methodology. A study of observational (non-representative) panel data (insurance claims in Japan for Pitavastatin[43] prescriptions) modelled utility preferences for branded medicines compared to generic using a maximum likelihood approach (for mixed logit model) (Ito et al., 2020). The study focused on incorporating purchasing inertia (i.e. tendency to repurchase a product) and found that it had a substantial effect on choice of branded medicine. Similar to the results in DCE 1, the study showed that on average consumers preferred lower prices; however, the significant preference for branded medicine (and its standard deviation) was larger. This for one, demonstrates that the use of data collection methods with representative samples and statistical power can lead to reliable estimate of coefficients, and estimate the relative preferences for the products.

[43] A lipid lowering medicine

Another strength of this study was the use of an unnamed 'minor/acute' health condition, which helps to capture a general view about the attitudes towards product generic or branded, rather than a complication of the preferences for products for a specific condition. These may be different depending on the illness presented to the respondent including how familiar the respondent is with the illness, as illness label does influence respondents' views (Figueiras et al., 2010).

Additionally, the strength of this study is aided by the work done in relation to 'inventing' name for the branded medicine *Medora branded* and the second generic *Megorium generic* to create a realistic complement to *pharmacy brand generic*. This helped avoid bias in preference for a medicine brand in those respondents who may have had past experience with a real brand of the medicine.

This chapter has explored how preferences for prescription medicine vary in the population. The results indicate that when respondents are shown basic information about the medicine, their choices are to a degree predictable. However, the next step is to look at the respondents' preferences when additional information (attribute) is presented that may contain facts that impact the perceived understanding of the medicine and its cost.

The testing of a number of Halton draw sequences in the mixed logit model was part of the validation of model. Since MXL uses maximum simulated likelihood, the final estimates are sensitive a number of factors, the number of draws used, where the number of draws used should be increased until the estimates stabilise (Sarrias and Daziano, 2017).

Three software programs were used for estimation of latent class models, each with a different algorithm to fit the data. This was useful in terms of comparing the number of optimal classes identified by each statistical software program, as well as confirming the output of the model.

In Stata and LatentGold, the analysis used the expectation-maximisation algorithm for fitting a latent class logit model. This guarantees numerical stability and convergence to a local maximum even when the number of latent classes is large. This is in contrast to the RStudio results using a (quasi) Newton (Newton-Raphson maximisation) methods ('gmnl' package), as an inversion of the (approximate) Hessian becomes numerically difficult (Bhat, 1997; Pacifico & Yoo, 2013; Train, 2009). There are other maximisation methods available in the R 'gmnl' package (i.e., Broyden-Fletcher-Goldfarb-Shanno[44] (BFGS) (default)).

[44] The BFGS is a second order optimisation algorithm, and is an extension of the (quasi)Newton methods that make use of Hessian matrix (Cottle & Thapa, 2017).
The BFGS curvature matrix does not require matrix inversion, its computational complexity requires use of Jacobian matrix to solve linear systems of $O(N^2)$ (where N is the dimension of the matrix), compared to $O(N^3)$ in Newton's method. Newton's method requires computation of the Jacobian matrix and its inversion.

The final estimation of the model using in analysis was performed in Stata (for consistency with other estimated models).

A number of limitations of this study arise from the use of the DCE method, which presents a hypothetical situation to the respondent filling out the survey online. DCE as a SP method is different to the revealed preference dataset. However, by conducting DCE 1, DCE 2 and DCE 3 and analysing them using same econometric models with same model specifications it is possible to explore the change, if any, in preferences when respondents see additional information about the components of the *total cost* of the medicine. Thus, an existing data would not be able to help identify the factors that influence preferences of the consumers, while a DCE is a well-used method to test this.

The design of the DCE 1 is a point of control for DCE 2 and DCE 3 in the space of information framing of the *total cost* attribute. In DCE 1, the *total cost* attribute was presented as a single attribute, an out-of-pocket cost to the individual for the medicine. The potential limitation of DCE 1 is the deliberately provided limited information on the brand premium. Respondents randomised to DCE were told about brand premium at the start of the survey (initial information), but it was not made explicit (in the choice tasks) whether a brand premium or the total cost of the product was included. Hence, this does not quite match the real-life situation, since consumers can be told of the brand premium and its value.

The next two chapters explore the effect of additional attribute of brand premium that is a part of the *total cost* and its effect on the respondents' preferences.

CHAPTER 4. Consumer preferences for brand premium in prescription medicine: Discrete Choice Experiments

4.1 Overview

In Chapter 3, respondents' preferences for medicines with a brand premium were explored in an experiment with the fact that there was a brand premium not made explicit to the respondents. In this chapter, we extend this analysis in a choice experiment that makes the existence of the brand premium explicit

As discussed in Chapter 1, the brand premium policy was a mechanism whereby manufacturers of the original brand of the medicine who did not agree to the regulated price across all brands of the medicine could continue to supply their brand, but at a higher price to the consumer. This raises the question of how consumers respond to a brand premium, particularly when they are aware of the fact that a product has a brand premium as part of its price.

As the example in Chapter 3 showed, the original brand for quetiapine, Seroquel, attracts a AUD5.00 brand premium to every purchase, irrespective of the consumer's concession state.

There is a potential positive impact of the word 'brand premium' on consumer preferences that may offset the negative impact of the higher price. In general terms, a 'brand' is a version of a product made by one particular manufacturer, while the word 'premium' indicates a good of higher than usual quality (Collins Australian Dictionary: HarperCollins Australia). Hence, even outside the context of brand products, the word 'premium' is suggestive of higher quality.

The impact of the 'brand premium' attribute on consumer preferences for prescription medicines has not been explored in the literature. Research in other areas (e.g., food, clothes, automobiles) has shown that quality or perceived brand quality was a significant determinant of accepted price premium (Anselmsson et al., 2014; Dwivedi et al., 2018; Munir et al., 2017). Finkelman (1993) finds that satisfied customers (those reporting that they receive a high quality of service or feel better about the product) have a greater willingness to pay for the product or service. Homburg et al. (2005) conclude that companies could charge a price premium if they create high levels of customer satisfaction, suggesting that consumers are willing to pay more for brands where they perceive higher quality.

An experienced consumer (in a certain market) might be willing to pay a brand premium for a brand because of its known high quality (Rao & Bergen, 1992). Therefore, it is also possible that such a consumer would behave similarly in a market in which they have no experience. In the absence of information other than price difference, consumers may be willing to pay a price premium for a product based on an assumption that it indicates higher quality – even though the objective quality is the same for branded and generic

medicines (as assessed by the TGA).

The perceived quality of branded medicines has been researched; for example, a survey on generic and branded uptake of venlafaxine in New Zealand (Mackrill & Petrie, 2018) showed that more than half of surveyed participants (58.1%) preferred branded medicines to generics. In particular, respondents who had previously purchased the branded version were statistically significantly more likely to report believing that the branded version was better and safer, and that generics had more side effects.

Perceived brand quality may play a major role in explaining demand for branded medicines or for medicines that have the word 'brand premium' associated with them. This chapter explores consumers' preferences for prescription medicines in the context of cost and product (generic vs branded) when respondents are presented with additional information about the brand premium. The results of these DCEs can be used to understand whether consumers attach value the to the brand premium label when purchasing prescription medicines. There are two DCEs reported in this chapter. In the first (DCE 2), the effect of brand premium is tested by creating a specific brand premium attribute in the choice task that indicates whether the product has a brand premium (the attribute takes the indicator Yes/No value). In the second (DCE 3), the attribute provides information about the dollar value of the brand premium. In both DCEs consumers also see the *total cost* to them of the medicine, with the difference being that in DCE 2 they do not know how much the brand premium is contributing to that cost, whereas in DCE 3 this is made explicit. Together, these DCEs have the potential to reveal how consumer preferences change given the additional information provided about the cost of the medicine.

4.2 Introduction

Consumers in Australia who have been prescribed a medicine often have a choice about whether to buy a branded or a generic version of the medicine. This choice can be guided by the attributes of the product (e.g. price, brand name, availability) or by positive or negative recommendations by health professionals, such as prescribing doctors or dispensing pharmacists.

At the time of purchase a consumer may be aware that there are different medicine brands available to them at differing out-of-pocket cost. However, there may be limited information or understanding of which medicine to buy. The market for pharmaceuticals is characterised by imperfect information. The consumer has information about the price, the brand name, and possibly about the manufacturer, but may otherwise have limited knowledge about quality (i.e., efficacy and side effects), and may rely on other indicators including health professionals' recommendations , manufacturer or brand.

While there has been some research using the brand of the medicine to explore consumer preferences, there appears to be no current literature exploring the 'brand premium' indicator, especially in multiple formats

to investigate the impact on consumer preferences.

In general, consumers have experience in markets where higher prices are charged for 'branded' products – for example. telecommunication devices, car models (hybrid, electric), wine and medicines. The higher price of the branded product may be used as a signal of higher quality, particularly for products where it is hard for the consumer to judge quality directly. There is evidence that higher quality is inferred from higher prices (Monroe, 1973). In some cases, this is because the higher price product is marketed as having additional features, or may be advertised as high quality (Hayakawa et al., 2018). A study of wine regions in Europe showed that when people are less knowledgeable about the product, price is the main item of information used to infer quality (Gergaud & Livat, 2007). In another study, it was found that a global brand was preferred to local brands based on perceived quality, awareness and psychological benefit (Em Steenkamp et al., 2003). Evidence the wine industry suggests that there is a strong positive perceived relationship between price and quality, with the effect being stronger for smaller price differentials (EUR5–8) than for larger ones (EUR8–12) (Mastrobuoni et al., 2014).

In other research, Verma and Gupta (2004) find that for non-durable products (e.g., toothpaste) in India, brand loyalty and brand reputation was taking precedence over the price; therefore, pricing the product very low could impart an inferior image to the brand. As medicines are a non-durable product, large difference in price between different brands may have a similar impact on consumer choice.

In the USA, Bronnenberg et al. (2015) explored the relationship between the purchase of branded and generic drugs and consumer characteristics. As branded and generic medicines have the same ingredients, with similar production processes, the quality difference between the two products should be negligible. However, in the USA, often the prices of branded drugs are many times higher than those of generic drugs. The authors find that the more educated and the more knowledgeable the consumers, the larger the proportion who buy generic drugs. They conclude that most of the price difference between branded-generic drugs is due to misinformation from advertising.

In Australia, direct-to-consumer advertising is not permitted for prescription medicines, so there is limited opportunity for manufacturers to communicate quality directly to consumers. However, the prohibition of advertising does not apply to over-the-counter (OTC) medicines. Therefore, consumers may be influenced by branded OTC medicine advertisements and apply these perceptions about the quality to prescription medicines.

Linnemer (2002), in a study of markets of non-prescription (i.e., OTC) medicine, shows that although companies can use higher prices to signal high quality, this is unsustainable as future demand (repeat purchases) would fall as a result. Thus, companies can use a combination of price and advertising to signal

its quality as well as to enlarge future demand.

In the case of pharmaceutical products, TGA-approved and PBS-listed brands of the same medicine are assessed as being bioequivalent[45], and there is no difference in therapeutic effect of products that have the same active ingredient.

However, it is important to acknowledge that there may be other reasons why consumers choose the branded version – they may be used to the brand, or they like the packaging, the shape of the medicine, or the colour or size of the tablet (all of which can differ between brands).

As these factors can influence the preference for a particular brand, the design of the DCEs focused on isolating the brand effect by presenting the respondents with a hypothetical medicine and an acute (non-chronic) condition. Given that both products contain the same active ingredient, the base case assumption would be that the consumer would choose the cheaper drug, if the consumer bears the full cost of the medicine and if price is the only differentiating attribute. However, as noted earlier, there is evidence that that is not the case, and some consumers continue to choose a more expensive 'branded medicine'.

The design of DCE 1 was a control for DCE 2 and DCE 3 in terms of information framing of the cost of product attribute. DCE 2 and DCE 3 explore the effect of the additional attribute of *brand premium* – where the brand premium is included in the *total cost* of the medicine either implicitly (DCE 2) or explicitly (DCE 3) – on respondents' preferences for prescription medicines.

These DCEs are the first to attempt to elicit consumer preferences for prescription pharmaceuticals that include *brand premium* as an attribute. The aim of conducting these two DCEs was to assess changes in the preferences when consumers receive extra information about the product they are about to purchase, specifically, the additional information on the components of the *total cost* of medicine.

The chapter is split into analyses of DCE 2 and DCE 3 following the same format as presented for DCE 1 (Chapter 3). There is an additional section comparing the results of DCE 2 and DCE 3 with respect to the *brand premium* attribute and the estimation of willingness to pay for each estimated parameter.

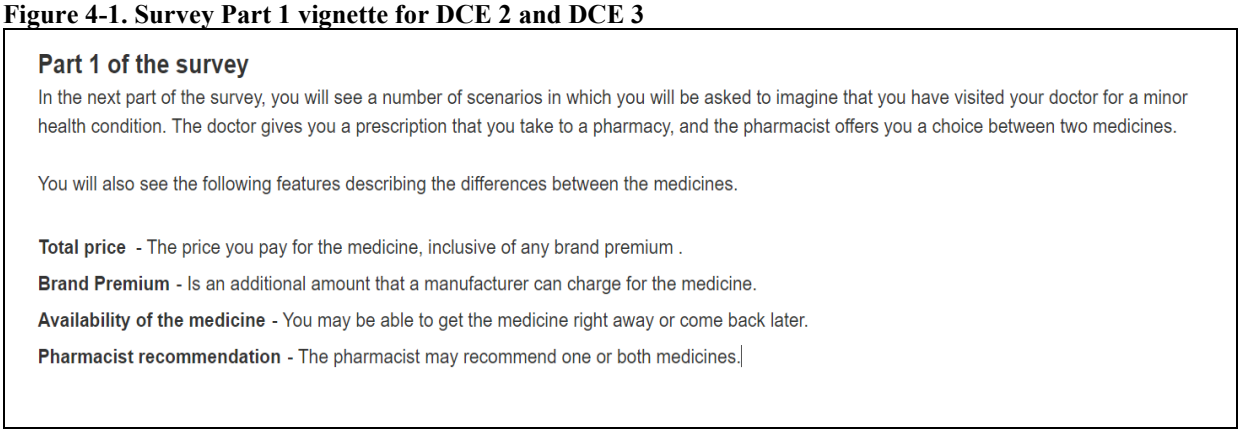
4.3 Overview of the choice experiment

As described in Chapter 2, respondents were randomised to one of the three DCEs in part 1 of the survey. Those randomised to DCE 2 and DCE 3 were presented with an information page that described the general

[45] Bioequivalence indicates that is, if you take the same dose of a generic medicine as an existing medicine, the same amount of active ingredient is absorbed by your body over the same period of time (TGA, Consumer Information and education).

scenario for the choices and the four attributes: total price, brand premium, the availability of the medicine and pharmacist's recommendation (Figure 4-1).

Figure 4-1. Survey Part 1 vignette for DCE 2 and DCE 3



The variables: attributes and levels

4.3.1 The variables: attributes and levels

Context specific attribute: Arms 1 and 2

After the information page, the respondents were further randomised into two arms that differed in terms of how the doctor's script was presented.

As in DCE1 (and described in detail in Chapter 3, Section; The choice experiment), respondents in DCEs 2 and 3 saw two different versions of the doctor's script, with either the brand name or the active ingredient name. This is a context attribute that is common across all DCEs 1–3. All respondents saw both types of script but were randomised in terms of the order in which they saw the scripts. In Arm 1 the script was for the active ingredient (generic) first and then for the branded medicine; in Arm 2 this was reversed. In each case, respondents were presented with 12 choice sets for each script type.

DCE 2 and DCE3 attributes

Similarly to DCE 1, respondents were presented with a choice between two options. In each choice set, the two options were described by four attributes: the name of the product brand (branded – Medora, generic – Megorium or generic – pharmacy brand), the *total cost* of the medicine to the respondent (ranging from $0 to $60), the *collection* of the medicine (available for collection now, or to be collected later in the day) and whether or not the pharmacist recommends the medicine. Each option was described by five attributes with some levels the same and some different across the two options. The respondents had to choose one of the options.

In the estimation of the model the attribute levels for each *product* attribute were modelled as dummy variables with the *Pharmacy brand generic* product selected as base level (omitted level) and the estimated levels *Megorium brand generic* and *Medora branded*; *total cost* was a continuous variable, while *collection*

of the dispensed medicine (*collect now* (omitted level)), *collect later today* (estimated level) and *pharmacist recommended* (*(-) no recommendation* (omitted level); *Yes* (estimated level)) were dummy variables.

As described in Chapter 2, the design of the three DCEs was the same; therefore, the underlying choices between DCE 1 and DC2–DCE 3 are the same.

The *total cost* attribute was based on all possible combinations three base level cost ($30, $35, and $40) and six levels of *brand premium* attribute ($0, $2, $5, $10, $15, $20).

The information of *brand premium* was reduced in DCE 2 (an indicator attribute (Yes/No)) and removed in DCE 1. The effect of the *brand premium* attribute in DCE 2 could act as an indicator, and respondents' preferences can either shift away from the Medora branded medicine as they understand that the *brand* can signify a higher cost, or the opposite, some consumers would be attracted to the *brand premium* attribute by using it as a signal of higher quality and thus have strong preference for the Medora branded medicine.

Each option is characterised by five attributes. The attributes and levels used in the choice tasks presented to the respondents are shown in Table 4-1.

Table 4-1. List of attributes and levels used in DCE 2 and DCE 3

	DCE 2	DCE 3 (all levels same as in DCE 2, except for Brand Premium)
Context Attribute	Levels	
Prescription from GP (picture attribute)	Medora (branded);	
	Active ingredient (generic)	
Alternative specific attributes		
Product	Pharmacy brand generic (oleaceae)*	
	Megorium brand generic (oleaceae)	
	Medora® (oleaceae) branded (original brand)	
Total price	$30*; $32; $35; $37; $40; $42; $45; $50; $55; $60 (continuous variable)	
Brand premium	No*	$0*, $2, $5, $10, $15, $20
	Yes	(continuous variable)
Available to collect (*collection*)	Now*	
	Later today	
Pharmacist recommended	(-) * (no recommendation)	
	Yes	

Note: the * denotes the 'base' level within the attributes.

Examples of the choice sets presented to the respondents randomised to DCE 2 and DCE 3, are presented below in Figure 4-2 and Figure 4-3.

Each respondent was presented with a hypothetical situation, being asked to "imagine that you have visited your doctor for a minor health condition. The doctor gives you a prescription that you take to a pharmacy, and the pharmacist offers you a choice between two medicines. Which medicine will you choose?"

Figure 4-2. Example of choice set with active ingredient (generic) script (DCE 2)

Question **1** of 6
Imagine that you have visited your doctor for a minor health condition and your doctor gives you a prescription (below). The doctor said you should start the medicine within the next day or so.

PBS ☑ Brand substitution not permitted ☐

oleaceae 100 mg tablets
Take 3 per day
For 10 days
0 repeat(s)

At the pharmacy, the pharmacist offers you a choice of two medicines.

Medicine name	Pharmacy brand (*oleaceae*) - generic medicine	Megorium (*oleaceae*) - generic medicine
Total price you pay	$30	$45
Brand Premium	No	Yes
Available to collect	Now	Later today
Pharmacist recommended	-	-
Please choose one:	○	○

Figure 4-3. Example of choice set with active ingredient (generic) script (DCE 3)

Question **1** of 6
Imagine that you have visited your doctor for a minor health condition and your doctor gives you a prescription (below). The doctor said you should start the medicine within the next day or so.

PBS ☑ Brand substitution not permitted ☐

oleaceae 100 mg tablets
Take 3 per day
For 10 days
0 repeat(s)

At the pharmacy, the pharmacist offers you a choice of two medicines.

Medicine name	Megorium (*oleaceae*) - generic medicine	Pharmacy brand (*oleaceae*) - generic medicine
Total price you pay (including a Brand Premium, if any)	$40 (Price includes a Brand Premium of $5)	$40 (No Brand Premium, $0)
Available to collect	Now	Later today
Pharmacist recommended	Yes	Yes
Please choose one:	○	○

4.3.2 The data

Analysis plan

All analyses were performed using Stata 17 (StataCorp, 2021, with additional LCA model also performed using LatentGold (Statistical Innovations) and RStudio (RStudio Team) 'gmnl' package (Sarrias & Daziano, 2017). The two DCE datasets were analysed using the conditional logit model, and the random parameters (mixed) logit model to determine the model with the best fit. Additionally, a WTP analysis was performed to determine the attribute resulting in the greatest WTP. To further explore heterogeneity in preferences in the data sets, latent class modelling was also undertaken.

Similarly to the statistical analysis used for DCE 1, there were several objectives in relation to the presentation of the survey and framing of the choice tasks in DCE 2 and DCE 3. The results are first presented for DCE 2, and then for DCE 3.

One of the objectives of the survey design was to explore whether respondents' preference changed depending on the order of the script that they saw in the 12 choice tasks. The first objective was to test whether there is a change in preferences depending on the type of script (*active ingredient (generic*) vs Medora branded). The second objective was to explore the existence of order effects based on what the doctor had written in the prescription – that is, whether respondents answered the differently if they first saw the doctor's scripts for an active ingredient (generic) compared to first seeing scripts for Medora branded medicine.

It is necessary to take account of possible variance between the groups. In the conditional logit model the parameter estimates are scaled by variance, which is normalised to unity in the model. However, when data are drawn from two samples, or from experiments that differ for the same sample, it cannot be assumed that the variance is the same, and so the normalisation assumption cannot be applied across the samples without testing for difference in variance. datasets. A heteroskedastic conditional logit (HCL) model is estimated to see if it is reasonable to pool the data from the two arms. The estimations of models were undertaken in three steps: (1) estimation of separate models for the two arms (CL models); (2) estimating a HCL model (allowing for unequal error variances across individuals in a dataset); (3) testing if the restricted model is accepted compared to the unrestricted models (using LR test).

As in DCE 1, the model with the best fit was chosen based on the AIC and BIC criteria, and the pseudo R^2 squared measure.

The results of the analysis of DCE 2 and DCE 3 are presented separately, with the final section in this chapter comparing the results with a focus on the information for brand premium presented in the respective choice tasks. The estimated WTP allows comparison across the three DCEs.

The initial hypotheses were that people would be indifferent to the *brand premium* attribute in DCE 2 (brand premium (BP) as dummy variable), and that they would have negative preference for the *brand premium* attribute in DCE 3 (when *brand premium* explicitly indicated the dollar amount associated with the brand premium).

Dataset overview

The data were downloaded from the SurveyEngine platform (SurveyEngine GmbH). The data were collected with the use of an online survey via the registered database Toluna (Toluna, Inc) a panel maintained to be representative of the Australian population, and satisfied the criterion of age and gender distribution.

4.4 Results DCE 2

DCE 2 – Randomisation into two arms (order of scripts) Table 4-2 shows the results of pooled and separate models for the two randomised groups within DCE2 for the order of script (as was presented for DCE 1 in Chapter 3). The first two columns show the results of conditional logit model for Arm 1 and Arm 2 samples respectively.

The first four columns show the means and standard errors for the conditional logit models for arms 1 and 2 respectively, and the final columns shows the means and standard errors for the pooled model estimated using the 'clogithet' command (Hole, 2009) (which accounts for differences in scale across the two samples). The presence of additional information, the *brand premium* attribute, in DCE 2 and DCE 3 is unlikely to have a significant impact on this aspect of the DCE.

The scale term in the restricted model is not significant, indicating no order effect across the two arms. The LR test of equal parameters across the two arms reveals a LR test value equal to 15.39 with the critical value 11.07 at a 5% significance level in the chi-squared distribution with five degrees of freedom. Given this test statistic, the hypothesis of overall equal parameters across the two arms has to be rejected. This means that the preferences differ across the two arms for at least one of the attributes. However, the scale term result (Arm 1) is not significant, indicating that the two models (Arm 1 and Arm 2) can be pooled.

Table 4-2. Pooled and separate estimates of DCE 2 data for two randomised groups

Attributes (base case)	Active ingredient (generic) script	Medora (branded) script	Heteroskedastic conditional logit model
	Mean (SE)	**Mean (SE)**	**Mean (SE)**
Total cost ($)	−0.143***	−0.141***	−0.128***
	(0.013)	(0.013)	(0.027)
Brand premium (No)	0.599***	0.223*	0.366***
	(0.108)	(0.102)	(0.105)
Products (Pharmacy brand – generic)			
Megorium, generic medicine	−0.050	−0.041	−0.040
	(0.088)	(0.085)	(0.056)
Medora, branded medicine	0.151	0.150	0.134*
	(0.088)	(0.081)	(0.061)
Collect later today ('Now')	−0.583***	−0.539***	−0.509***
	(0.079)	(0.082)	(0.115)
Pharmacist recommended 'Yes' ('-' no recommendation)	0.155	0.079	0.108
	(0.096)	(0.092)	(0.064)
Scale term (Arm 1)			0.067
			(0.131)
Observations	4992	4920	9912
AIC	2673	2583	5261
BIC (N=413)	2713	2622	5312
Log-likelihood	−1331	−1285	−2624
LR test of equal parameters df=5, critical $\boldsymbol{X^2_{0.95}}$: 15.36 (11.07)			

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; df: degrees of freedom; LR: likelihood ratio; SE: standard error; $X^2_{0.95}$: chi-square area in upper tail at 5% critical value.
Note: *** p<0.001, ** p<0.01, * p<0.05.
Note: *total cost* is continuous variable represented in dollar value; Reference categories for the attributes: for *Brand premium* it is '*No brand premium*'; for Medicine *product* attribute is '*Pharmacy brand generic*'; for *collect* it is '*Now';* for *recommend* it is *'(-) no recommendation'*

The analysis for any differences across the doctor's script active ingredient (generic) medicine and Medora branded medicine is presented in Table 4-3.

The LR test shows no significant differences between the preferences in depending on the type of the script seen by the respondent. However, when respondents saw the Medora branded script they were more likely to have a strong positive preference for the *brand premium* attribute. This result may indicate that the doctor prescribing the branded medicine has a positive effect on respondents' preferences for the branded medicine, even when it has a brand premium. To explore the effect of the brand premium on respondents' preferences further analysis of DCE 2 is presented.

Table 4-3. Pooled and separate estimates of DCE 2 data for two types of doctor's script (active ingredient generic and Medora branded)

Attributes (base case)	Active ingredient (generic)script	Medora (branded) script	Heteroskedastic conditional logit model
	Mean (SE)	Mean (SE)	Mean (SE)
Total cost ($)	−0.135***	−0.150***	−0.147***
	(0.011)	(0.010)	(0.010)
Brand premium "Yes" (No)	(0.108)	0.533***	0.431***
		(0.109)	(0.079)
Products			
(Pharmacy brand generic)			
Megorium generic	−0.080	−0.000	−0.043
	(0.084)	(0.083)	(0.063)
Medora branded	0.139	0.155	0.154*
	(0.072)	(0.081)	(0.063)
Collect 'later today' ('now')	−0.493***	−0.638***	−0.586***
	(0.070)	(0.072)	(0.060)
Pharmacist recommended 'Yes'	0.146	0.094	0.124
('-' no recommendation)	(0.080)	(0.078)	(0.069)
Scale term (Arm 1)			−0.072
			(0.059)
Observations	4,956	4,956	9,912
AIC	2669	2595	5261
BIC (N=413)	2693	2619	5289
Log-likelihood	−1329	−1292	−2624
LR test of equal parameters df=5, critical $X^2_{0.95}$: 6.84 (11.07)			

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; df: degrees of freedom; LR: likelihood ratio; SE: standard error; $X^2_{0.95}$: chi-square area in upper tail at 5% critical value.
Note: *** p<0.001, ** p<0.01, * p<0.05.
Note: *total cost* is continuous variable represented in dollar value; Reference categories for the attributes: for *Brand premium* it is '*No brand premium'*; for Medicine *product* attribute is '*Pharmacy brand generic*'; for *collect* it is '*Now';* for *recommend* it is *'(-) no recommendation'.*

4.4.1 DCE 2 – Conditional logit

Having established that the two arms can be combined, the analysis was performed on the entire DCE 2 dataset starting with a conditional logit model. All variables included in the model were dummy coded except for the *total cost* attribute, which was included as continuous variable. As with the analysis in Chapter 3, the functional form of the *total cost* attribute was tested by adding a polynomial term in one parametrisation, and including dummy variables in a second parametrisation. The results, presented in Table 4-4, of the linear form (Model A) showed a strong preference for lower levels of the cost attribute, and where a medicine was indicated to have a *brand premium* there was a significant positive preference for the Medora branded medicine relative to the *Pharmacy brand generic* and a strong aversion to the *collecting later in the day* attribute level. Similar results were seen across the different specifications of the cost attribute in the model: in the *total cost* quadratic form (Model B) and cubic form (Model C), as well as when *total cost* was included using dummy variables (Model D). A graphic form of the *total cost* function for the three models is presented in Figure 4-4. The graph shows that the Model A, Model B and Model C

have similar shape and slope, while the interpretation of the cubic model would complicate the interpretation of the results. A similar approach is taken here as was taken for DCE 1, such that the linear model is treated as main model.

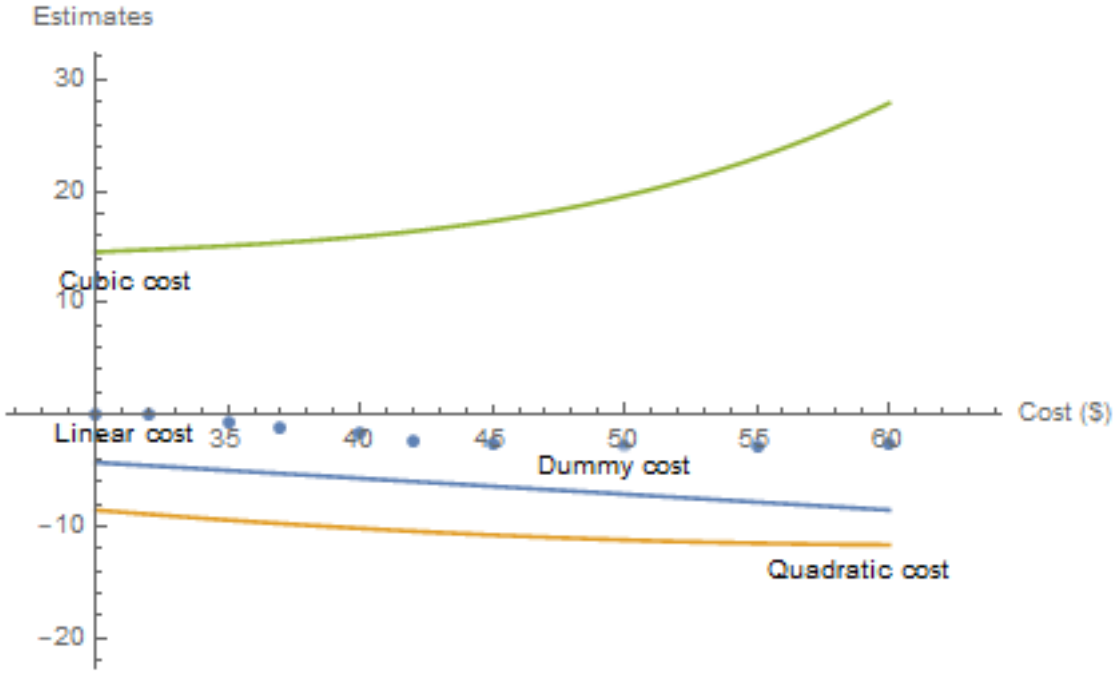
Table 4-4. Presentation of different forms of the Total cost attribute in DCE 2 (linear, quadratic, cubic and categorical (dummy))

	Model A	**Model B**	**Model C**	**Model D**
	linear	**quadratic**	**cubic**	**dummy**
Attributes (base case)	Mean (SE)	Mean (SE)	Mean (SE)	Mean (SE)
Total cost linear ($)	−0.142***	−0.374***	1.2269***	
	(0.009)	(0.039)	(0.2783)	
Total cost quadratic ($)		0.003***	−0.0367***	
		(0.000)	(0.0069)	
Total cost cubic ($)			0.0003***	
			(0.0001)	
Total cost categorical (dummy, $30)				
$32				−0.055
				(0.196)
$35				−0.684***
				(0.067)
$37				−1.106***
				(0.243)
$40				−1.568***
				(0.103)
$42				−2.286***
				(0.169)
$45				−2.607***
				(0.188)
$50				−2.922***
				(0.203)
$55				−2.876***
				(0.225)
$60				−2.629***
				(0.368)
Brand premium ‘Yes’ (No)	0.412***	0.258**	0.3700***	0.455***
	(0.075)	(0.081)	(0.0847)	(0.103)
Products				
(Pharmacy brand generic)				
Megorium generic	−0.045	−0.026	−0.0412	−0.074
	(0.061)	(0.064)	(0.0645)	(0.062)
Medora branded	0.148*	0.168**	0.1520*	0.171**
	(0.060)	(0.063)	(0.0619)	(0.064)
Collect ‘later today’ (‘now’)	−0.563***	−0.552***	−0.5759***	−0.610***
	(0.057)	(0.058)	(0.0597)	(0.061)
Pharmacist recommended ‘Yes’	0.120	0.205**	0.2318***	0.194**
('-' no recommendation)				
	(0.066)	(0.066)	(0.0680)	(0.072)
Observations	9,912	9,912	9,912	9,912
AIC	5261	5226	5198	5200
BIC	5304	5277	5256	5301
Log-likelihood	−2624	−2606	−2591	−2586

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; N: total participants in group; SE: robust standard errors; *** p<0.001, ** p<0.01, * p<0.05.

Note: *total cost* is continuous variable represented in dollar value; Reference categories for the attributes: for *Brand premium* it is ‘*No brand premium’*; for Medicine *product* attribute is ‘*Pharmacy brand generic*’; for *collect* it is ‘*Now’;* for *recommend* it is *‘(-) no recommendation’*

Figure 4-4. Plot of *total cost* functional forms DCE 2



To assist in interpretating the importance of each attribute (normalising the coefficient), marginal rates of substitution are calculated by dividing each coefficient by the coefficient of *total cost*. This is presented in Table 4-5. The results show that respondents ranked *collection* (now vs later in the day) as the most important aspect, indicating that waiting for the medicine is the least preferred attribute. The results indicate that the second strongest preference was for a medicine with a brand premium compared to one without brand premium. Third, respondents ranked the Medora branded medicine in the top three preferred attributes. These results indicate that respondents would be most likely to select a Medora branded medicine with a brand premium 'label' that was available to collect immediately.

Table 4-5. Conditional logit results for DCE 2 and ranked rates of substitution

Attributes (base case)	Mean (SE)	Rates of substitution
Total cost ($)	−0.142***	1.00 (base)
	(0.009)	
Brand premium 'Yes' (No)	0.412***	−2.90141
	(0.075)	
Products		
(Pharmacy brand generic)		
Megorium generic	−0.045	0.316901
	(0.061)	
Medora branded	0.148*	−1.04225
	(0.060)	
Collect later today ('Now')	−0.563***	3.964789
	(0.057)	
Pharmacist recommended 'Yes' ('-' no recommendation)	0.120	−0.84507
	(0.066)	
Observations	9,912	
AIC	5261	
BIC (N=413)	5285	
Log-likelihood	−2624	

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; N: total participants in group; SE: robust standard errors; *** p<0.001, ** p<0.01, * p<0.05.
Note: *total cost* is continuous variable represented in dollar value; Reference categories for the attributes: for *Brand premium* it is '*No* brand premium'; for Medicine *product* attribute is '*Pharmacy brand generic*'; for *collect* it is '*Now';* for *recommend* it is *'(-) no recommendation'.*

The results of DCE 2 is different from those of DCE 1, where the *generic* product was preferred to the *pharmacy brand generic*, suggesting that the extra information about brand premiums may have influenced preferences. It is important to note that in this DCE there was no explicit information about the cost attached to the brand premium label.

The analysis of DCE data using the conditional logit model (multinomial logit) is a useful starting point but assumes that respondents' preferences are homogeneous. To further understand the presence of any heterogeneity in the data, the mixed logit model was estimated and is discussed below.

4.4.2 DCE 2 – Mixed logit model (MXL)

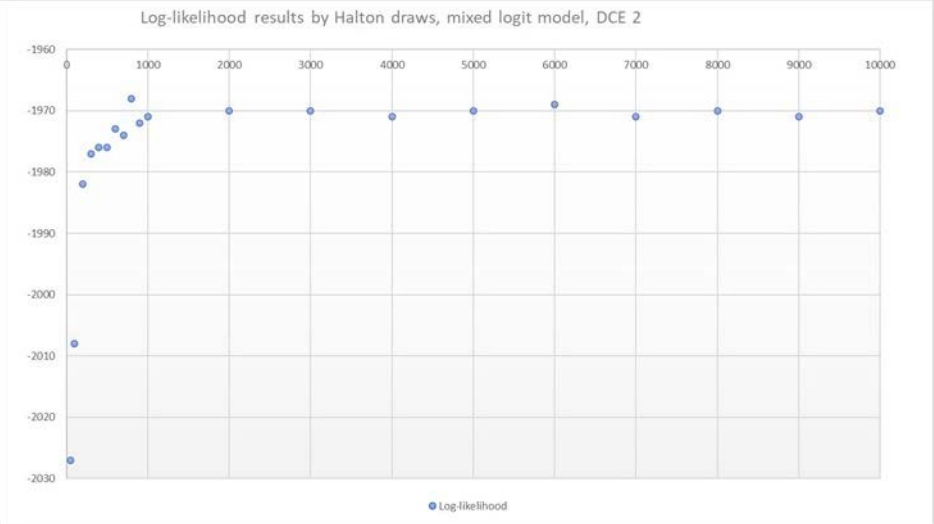
The analysis of DCE 2 using a mixed logit model follows the same pattern as presented in Chapter 3.

The estimated MXL has six explanatory variables that are treated as random and assumed to be, independently normally distributed. The *total cost* is specified as a continuous variable in the model.). The product attribute has two parameters that are estimated with respect to the base case (*pharmacy brand generic*). The *brand premium*, *collection* and *pharmacist recommended* attributes are each represented in the model by a single parameter.

The MXL model was estimated in Stata 17 using simulated maximum likelihood. The results of log-likelihood statistics of the 20 estimations of the MXL were matched to Halton draws 50 to 10,000 and are reported in Figure 4-5 Based on the visual inspection of the log-likelihood, it was decided that 2000 Halton

draws was an acceptable number due to the observed stabilisation of the model.

Figure 4-5. Simulations used in MXL for varying number of Halton draws (DCE 2)



The results of the MXL model showed that, on average, respondents prefer lower costs, medicines with a *brand premium*, the *branded (Medora)* product, collecting the medicine *now* (rather than *later*) and a medicine that was recommended by the pharmacist. The estimated standard deviation values are statistically significant for all parameters, indicating that the preferences for the associated attribute levels are not homogeneous across the sample (Regier et al., 2009).

The standard deviations are large relative to mean coefficients. Most respondents preferred medicines with a *brand premium*, but a significant minority (27%)[46] preferred no *brand premium* attached. For the brands, 48% and 41% preferred *Pharmacy brand generic* to *Megorium generic* and Medora branded respectively. Additionally, 33% of respondents preferred collecting the medicine *later today* to collecting *now* and 31% preferred no recommendation from the pharmacist. Results of the mixed logit model for DCE 2 are presented in Table 4-6.

Table 4-6. Results of the MXL for DCE 2

Attributes (base case)	**MXL (2000 Halton draws)**	
	Mean (SE)	**SD (SE)**
Total cost ($)	−0.530***	0.431***
	(0.038)	(0.034)
Brand premium "Yes" (No)	0.549***	0.892***
	(0.152)	(0.236)
Products (Pharmacy brand generic)		

[46] Calculations performed in Stata with -normal (mean/standard deviation)-, given by $100\times\Phi(-b_k/s_k)$, where Φ is the cumulative standard normal distribution and b_k and s_k are the mean and standard deviation, respectively, of the *k*th coefficient (Hole, 2007).

Attributes (base case)	MXL (2000 Halton draws)	
	Mean (SE)	SD (SE)
Megorium generic	0.049	0.997***
	(0.122)	(0.174)
Medora branded	0.309*	1.406***
	(0.130)	(0.161)
Collect 'later today' ('now')	−1.430***	1.916***
	(0.154)	(0.195)
Pharmacist recommended 'Yes'	1.000***	1.943***
('-' no recommendation)	(0.160)	(0.189)
Observations	9,912	
AIC	3965	
BIC (N=413)	4013	
Log-likelihood	−1970	

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; N: total participants in group; SD: standard deviation; SE: standard error.
Note: *** p<0.001, ** p<0.01, * p<0.05.
total cost is continuous variable represented in dollar values; Reference levels for the attributes: for *Brand premium* it is '*No* brand premium'; for Medicine *product* attribute is '*Pharmacy brand generic*'; for *collect* it is '*Now';* for *recommend* it is *'(-) no recommendation'.*

Preferred model

The measures of statistical fit show that the MXL is the preferred model when compared to the conditional logit model showing improvement in maximised log-likelihood (−1970 vs −2624), as well as minimised AIC (3965 vs 5261) and BIC estimates (4013 vs 5304) respectively.

The results of the MXL is used to estimate the marginal WTP for each attribute level in DCE 2, as well as compare the results with the mWTP of DCE 3, towards the end of this chapter.

Kernel density plots for attribute levels in DCE 2 (MXL)

The kernel density plots for each of the estimated parameters are presented in this section. Each distribution is inspected with respect to its shape, size and location with respect to zero.

Total cost and brand premium attributes

The kernel density plot for the *total cost* attribute is shown in Figure 4-6. The distribution dips slightly after a peak at the far left (negative preference) area. The peak indicates that many respondents had β_n estimates around the −1.0 mark and a tendency to skew towards the right (zero), with the tail of the plot pulled towards the positive preferences of the high *total cost*. The majority of the function is located to the left of the zero. This shows that although most respondents preferred lower cost, there were some respondents who saw a benefit in paying more for the prescription medicine.

Figure 4-6. Kernel density estimate for the *total cost* in DCE 2

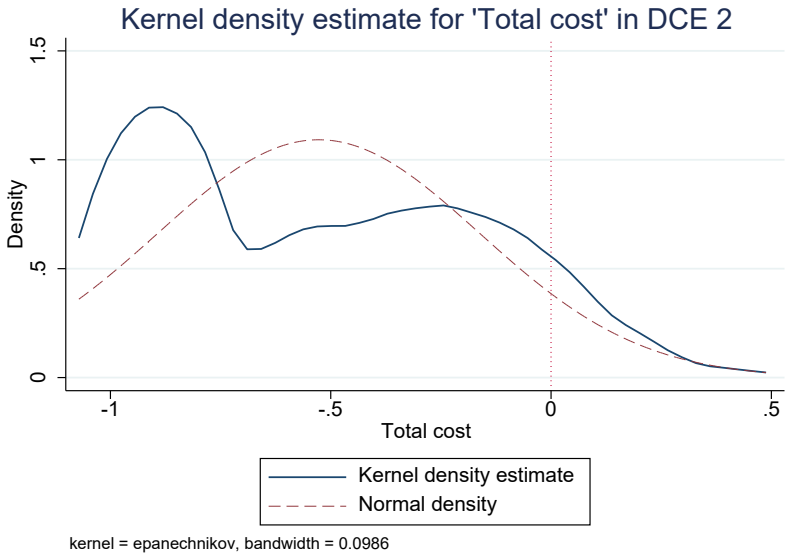
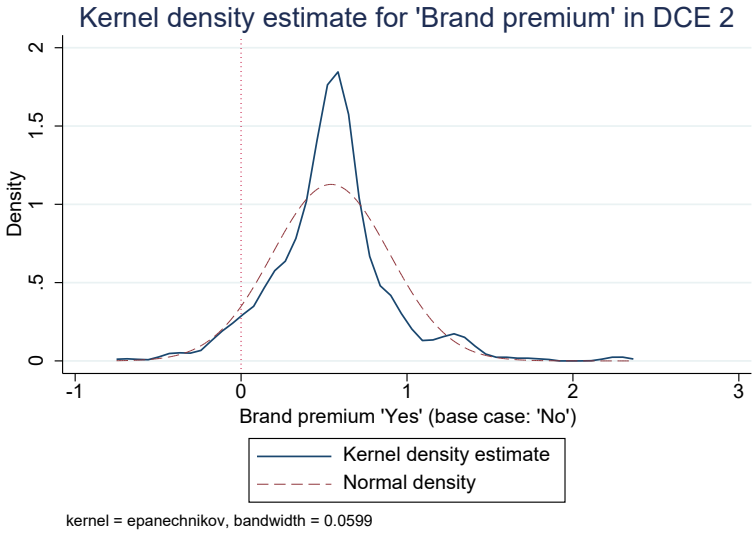


Figure 4-7 shows the kernel density of the *brand premium* attribute ('Yes' level) with the shape of the curve close to the normal distribution shape, with a slight skew to the left. There is a peak around the 0.7–0.8 mark, indicating that there were many respondents with particular preference. The estimated mean of the *brand premium* attribute level was significant and positive, showing that respondents had a strong preference for the medicine with a brand premium. However, this curve shows that some respondents who preferred no brand premium attached to the product.

Figure 4-7. Kernel density estimate for the *brand premium 'Yes'* in DCE 2



Medicine product attribute

Figure 4-8 and Figure 4-9 represent the kernel density plots for the product attribute. The shaper of the of the curves appear symmetric and the distribution is similar for both attribute levels (Megorium generic and Medora branded). The majority of the curves are located to the right of zero. The high narrow peaks indicate that most respondents had very strong preferences for both products over the pharmacy brand generic.

While the estimated mean of the *Megorium* generic medicine attribute level was not statistically significantly different from zero, the standard deviation was large and statistically significant, indicating that there is significant heterogeneity in preferences towards generic brands.

The mean of the Medora branded medicine attribute level was positive and statistically significant, indicating that, on average, respondents reported a preference for the original brand as opposed to the *Pharmacy brand generic*. The significant standard deviation (1.406) indicates that at least 41% of the coefficients were below zero, with those respondents preferring *pharmacy brand generic* medicine.

The shape of the distributions appears to be similar for both variables. The curves have symmetric shapes.

Figure 4-8. Kernel density estimate for the *Megorium generic* in DCE 2

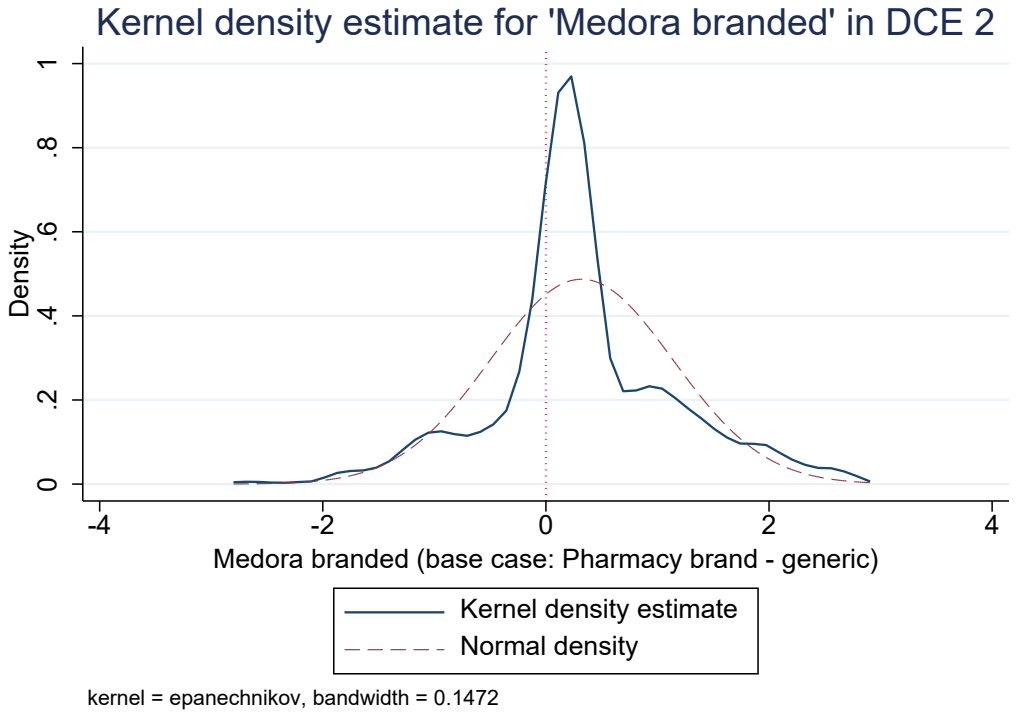
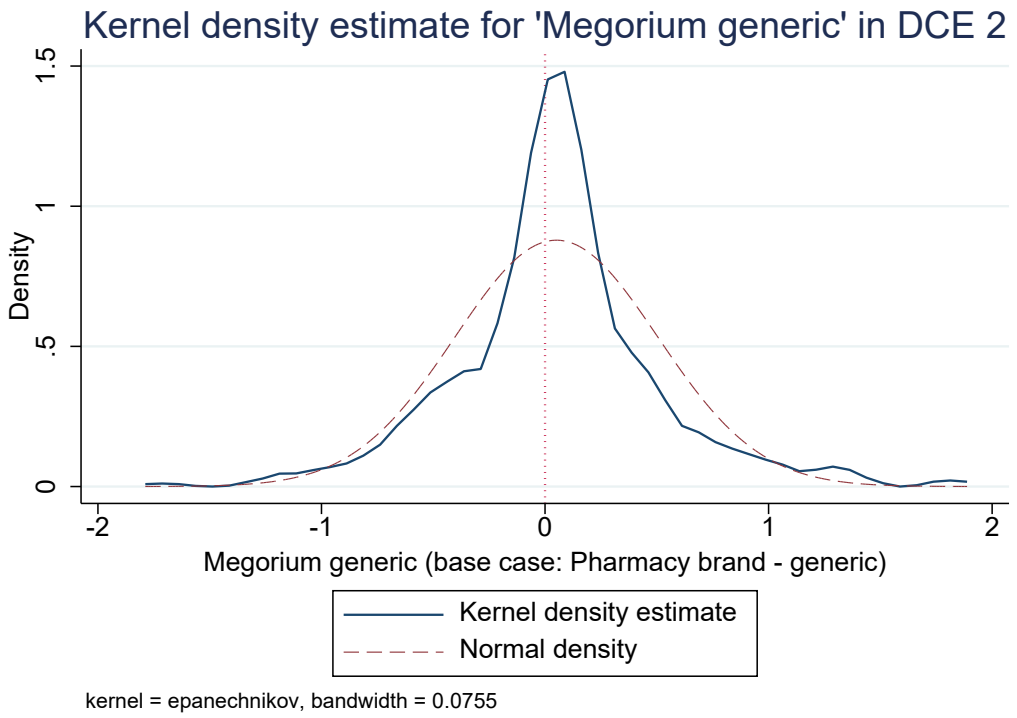


Figure 4-9. Kernel density estimate for the Medora branded in DCE 2



The estimated probabilities of choosing each level of the product are presented in Table 4-7. The probability was estimated based on the coefficients from the mixed logit model, where only the estimated coefficient for Medora branded has statistical significance. Therefore, the probability of choosing either of the generic brands is similar (no difference), however the probability for the Medora branded to be chosen is higher, given all other attributes are fixed.

Table 4-7. Probability of choosing a product attribute level, DCE 2.

Product attribute level	Probability of choosing
Pharmacy brand generic	0.29
Megorium generic	0.31
Medora branded	0.40

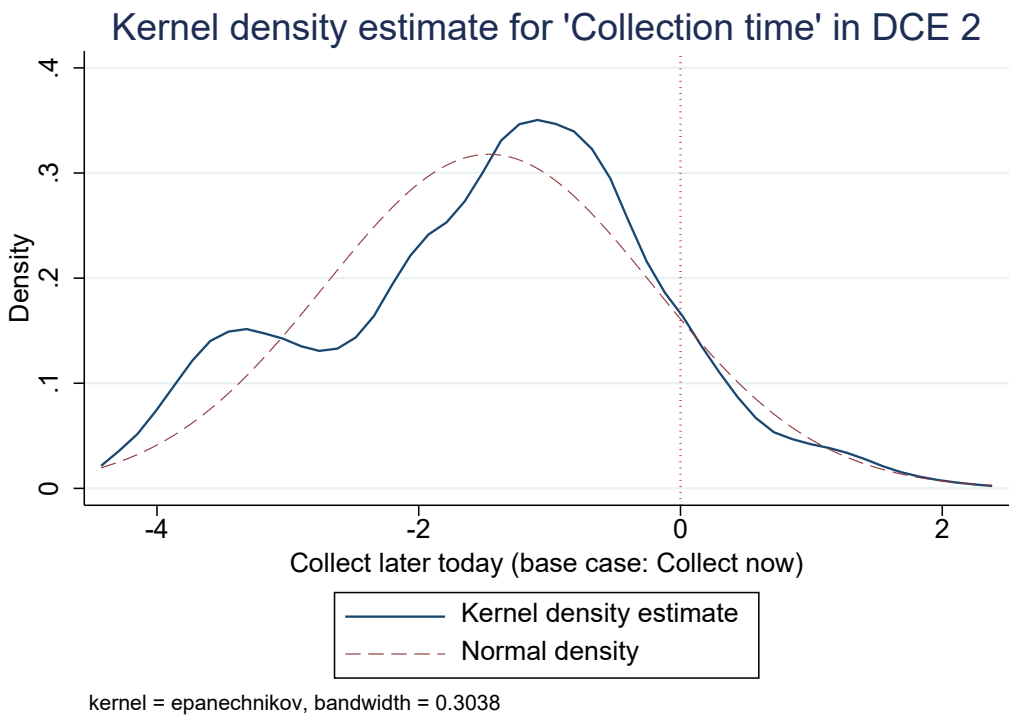
Collection attribute

Figure 4-10 shows the kernel density curve for the *collection* attribute. The curve is skewed to the left, with the majority of the distribution located to the left of zero. This shows that there are strong preferences against collecting the medicine later. This attribute may also indicate the preferences for the 'cost' of time spent collecting the medicine, with most respondents valuing their time.

The estimated mean for the collect 'Later today' attribute was negative and significant, showing that respondents had a strong preference for collecting the medicine 'Now' rather than having to come back, but with 23% of the preference still estimated to be above zero when respondents would be willing to come

back if their preferred medicine was guaranteed to be available. While on average respondents preferred not to have to come back to the pharmacy, there is a small but significant proportion for whom this was not the case.

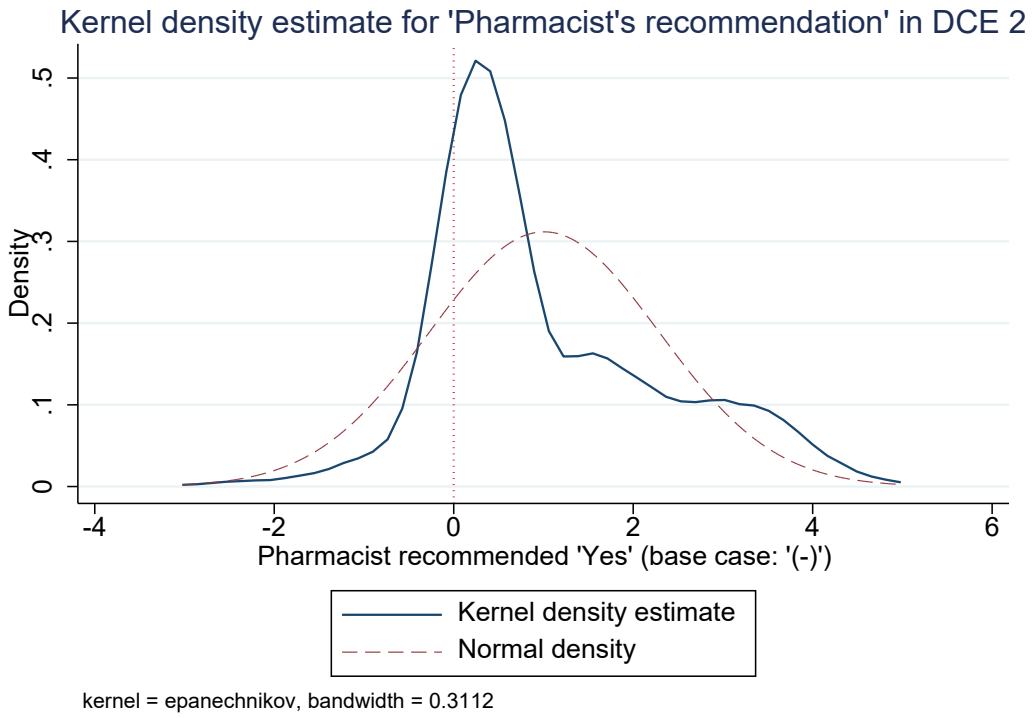
Figure 4-10. Kernel density estimate for the *collect later today* in DCE 2



Pharmacist recommended attribute

Figure 4-11 presents the kernel density curve for the pharmacist recommended attribute. The curve has a high density close to the zero mark; however, the curve is heavily skewed to the right, indicating a heterogeneity in preferences. The estimated coefficient showed that respondents preferred medicine that the pharmacist recommended; however, the large and significant standard deviation showed that at least 30% of the respondents had a negative coefficient, indicating that some respondents may be indifferent to pharmacist recommendation.

Figure 4-11. Kernel density estimate for the *pharmacist recommended (Yes)* in DCE 2



Interactions MXL

A further MXL model was run to explore demographic covariates. This model included interactions of all the attributes with variables for gender and age of the respondent run to identify whether these two covariates are significant with respect to any of the attribute levels presented in the model. The sample was stratified based on these two characteristics, so there is good representation across gender and age and there are no missing observations. The results are presented in Table 4-8. The inclusion of covariates did not affect the significance or sign (direction) of any of the estimated attribute levels compared to the original mixed logit model presented in the section above. The standard deviations for all variables are significant and large compared to the estimated coefficients, indicating a high level of heterogeneity of preferences in the sample.

The results of this model show that there is a significant difference between males and females for the *total cost* attribute; on average, male respondents were more likely to choose a product with a slightly higher *total cost* compared to female respondents.

The results with respect to age show that people older than 30 years were significantly more likely to prefer a lower *cost* medicine compared to younger group (18–29 years).

The estimates for the interaction with other attribute levels were not significant. The heterogeneity in preferences is explored further in the next section using a latent class model.

Table 4-8. Results of mixed logit model with gender and age covariates (DCE 2)

Attributes (base case)	Mean (SE)	SD (SE)
Total cost ($)	−0.412***	0.402***
	(0.050)	(0.029)
Brand premium 'Yes' ('No')	0.651*	0.667**
	(0.332)	(0.231)
Products ('Pharmacy brand generic')		
Megorium generic	0.148	−0.976***
	(0.278)	(0.176)
Medora branded	0.448	1.381***
	(0.302)	(0.155)
Collect later today ('Now')	−1.490***	1.791***
	(0.307)	(0.178)
Pharmacist recommended 'Yes' ('-' no recommendation)	0.995**	1.891***
	(0.328)	(0.179)
Interaction with Gender (female)		
Total cost – Male	0.116**	
	(0.042)	
Brand premium 'Yes' – Male	−0.064	
	(0.293)	
Megorium generic– Male	−0.220	
	(0.242)	
Medora branded – Male	−0.186	
	(0.258)	
Collect later today ('Now') – Male	0.319	
	(0.261)	
Pharmacist recommended 'Yes' ('-' no recommendation) – Male	0.018	
	(0.288)	
Interaction with Age		
Total cost ($) X Age (18y.o.-29y.o.)		
Age 30–39	−0.005	
	(0.056)	
Age 40–49	−0.213***	
	(0.056)	
Age 50–59	−0.253***	
	(0.056)	
Age 60–69	−0.310**	
	(0.096)	
Age 70+	−0.195**	
	(0.067)	
Brand premium 'Yes' ('No') X Age (18y.o.- 29y.o.)		
Age 30–39	−0.083	
	(0.434)	
Age 40–49	−0.310	
	(0.448)	
Age 50–59	−0.639	
	(0.482)	
Age 60–69	0.285	
	(0.525)	
Age 70+	0.482	
	(0.512)	
Megorium generic		
Age 30–39	−0.091	
	(0.358)	
Age 40–49	−0.000	

	(0.376)	
Age 50–59	0.513	
	(0.402)	
Age 60–69	−0.317	
	(0.433)	
Age 70+	−0.297	
	(0.435)	
Medora branded		
Age 30–39	−0.086	
	(0.382)	
Age 40–49	0.296	
	(0.404)	
Age 50–59	−0.385	
	(0.417)	
Age 60–69	0.568	
	(0.473)	
Age 70+	−0.473	
	(0.456)	
Collect later today (‘Now’)		
Age 30–39	0.322	
	(0.381)	
Age 40–49	−0.049	
	(0.416)	
Age 50–59	−0.614	
	(0.422)	
Age 60–69	−0.226	
	(0.482)	
Age 70+	−0.189	
	(0.490)	
Pharmacist recommended ‘Yes’		
('-' no recommendation)		
Age 30–39	0.286	
	(0.435)	
Age 40–49	−0.116	
	(0.444)	
Age 50–59	−0.498	
	(0.441)	
Age 60–69	0.185	
	(0.523)	
Age 70+	0.160	
	(0.542)	
Observations	9,912	
AIC	3967	
BIC	4313	
Log-likelihood	−1936	

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; N: total participants in group; SD : standard deviation; SE : standard error.
Note: *** p<0.001, ** p<0.01, * p<0.05.
total cost is continuous variable represented in dollar values; Reference levels for the attributes: for Brand premium it is ‘No brand premium’; for Medicine product attribute is ‘Pharmacy brand generic’; for collect it is ‘Now’; for recommend it is ‘(-) no recommendation’.

4.4.3 DCE 2 – Latent class analysis (LCA)

One method of exploring heterogeneity in the data is a LCA model, which is essentially a version of a MXL with a finite number of possible values for β (Train, 2009). The latent class approach assumes that

respondents can be characterised as having preferences drawn from two or more finite distributions, defined as classes, each determined by a value for β. Membership of a particular class may be characterised by shared observed demographic characteristics that determine choice, or by other unobserved factors that drive preferences. For each respondent the posterior probability that the respondent is a member of each class can be calculated. This model has gained popularity in the recent years in the health economics domain in relation to SP studies (Zhou et al., 2018).

Similarly to the analysis in DCE 1 dataset, three different software packages were used to determine the optimal number of latent classes to identify homogeneous groups of respondents in DCE 2: Stata 17 (StataCorp), LatentGold (Statistical Innovations) and RStudio (RStudio Team).

The latent class model was tested for up to nine classes where possible, to determine the optimal number of classes. To select the statistical measure of fit the AIC, BIC, and log-likelihood results were presented for comparison across different number of classes for each software package. The BIC measure was used as the determinant of the optimal number of classes.

The results in Stata, for five-class and eight-class models, indicated that some respondents had zero probability to be allocated to an additional class. Results of LatentGold estimated all eight models (class two to class nine). In RStudio, from the six-class model onwards the models were not estimated, reporting in each case that the 'matrix is singular' and cannot be inverted, most likely indicating collinearity in the variables.

In this dataset, all statistical measures improved as more classes were added, which supported the presence of multiple classes in the sample. The statistical measures values were similar up to a five-class model across the three software programs.

However, the AIC measure found no minimum in the tested number of classes. The BIC measure found no minimum in the LatentGold estimated models. In Stata the BIC based on the number of respondents (N=413) resulted in a minimum at a seven-class model while based on BIC using the number of observations (n=9,912) the minimum was at a three-class model. The RStudio 'gmnl' package also showed that estimated BIC was minimised at a three-class model.

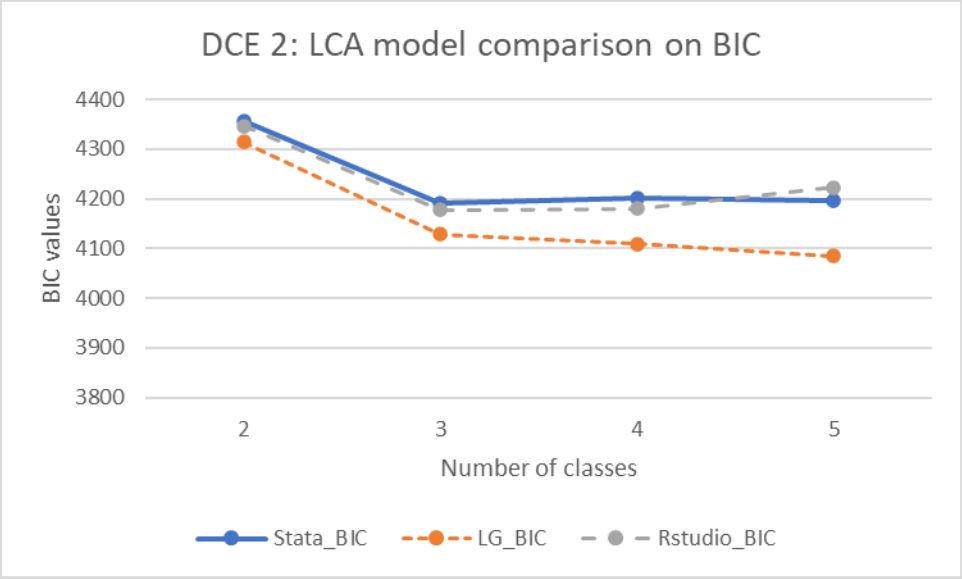
A three-class model was selected as the optimal model for this dataset based on the Stata and RStudio BIC statistical measures. The statistical measures for the DCE 2 dataset using the three software programs are presented in Table 4-9. A graphical representation of the change in the BIC with additional class across the three software is shown in Figure 4-12.

Table 4-9. Latent class model number of classes in Stata, LatentGold and RStudio, for DCE 2

Stata output					
Classes	Parameters, N	Log-likelihood	AIC	BIC (N=413)	BIC (N=9,912)[a]
2	13	−2118.14	4262.29	4314.59	4355.9
3	20	−2003.91	4047.81	4128.28	4191.8
4	27	−1975.93	4005.86	4114.49	4200.3
5	34	−1946.95	3961.89	4098.69	4197.5
6	41	−1924.03	3930.05	4095.02	—
7	48	−1899.93	3895.85	4088.98	—
8	55	−1885.8	3881.60	4102.89	—
9	62	−1874.76	3873.52	4122.97	—
LatentGold output					
Classes	Parameters, N	Log-likelihood	AIC	BIC (N=413)	
2	13	−2118.14	4262.30	4314.59	
3	20	−2003.91	4047.82	4128.29	
4	27	−1973.2	4000.40	4109.04	
5	34	−1939.64	3947.28	4084.08	
6	41	−1916.2	3914.40	4079.36	
7	48	−1897.35	3890.70	4083.83	
8	55	−1879.38	3868.76	4090.05	
9	62	−1866.29	3856.58	4096.16	
RStudio output[47]					
Classes	Parameters, N	Log-likelihood	AIC		BIC (N=9,912)
2	13	−2118.1	4262.29	—	4346.89
3	20	−2003.9	4047.81	—	4177.98
4	27	−1975.4	4004.80	—	4180.53
5	34	−1966.8	4001.53	—	4222.81

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; N: total participants in group.
Note: a: estimated using Stata command '*estat ic, n=9,912'* after each additional class model was run separately.

Figure 4-12. DCE 2 latent class comparison of BIC across three software packages



[47] A BFGS maximisation method was used in DCE 2 estimations. The Newton-Raphson did not produce estimates from a four-class model.

Abbreviation: BIC: Bayesian information criterion; LCA: latent class analysis; LG : LatentGold software.

The class membership was estimated with different shares across the classes: Class 1 (50%), Class 2 (33%), and Class 3 (17%). The results for LCA with three classes are presented in Table 4-10, and a graphic representation of the results is at Figure 4-13.

In the largest class (Class 1), respondents had a strong and significant preference for lower cost of the medicine and collecting the medicine immediately. The other attributes are not important to this class.

The second largest class (Class 2) shows that in addition to preferring lower cost and immediate collection, respondents also had strong preferences for medicine that was recommended by the pharmacist. In this class respondents appeared indifferent to the Medora branded and had a preference for the pharmacy brand generic medicine over the Megorium generic.

The preferences in Class 3 show that this class preferred the *Medora branded* and *Megorium generic* to the *pharmacy brand generic*. In addition, members of this class showed some preference for the medicine recommended by the pharmacist, compared to medicines with no recommendation.

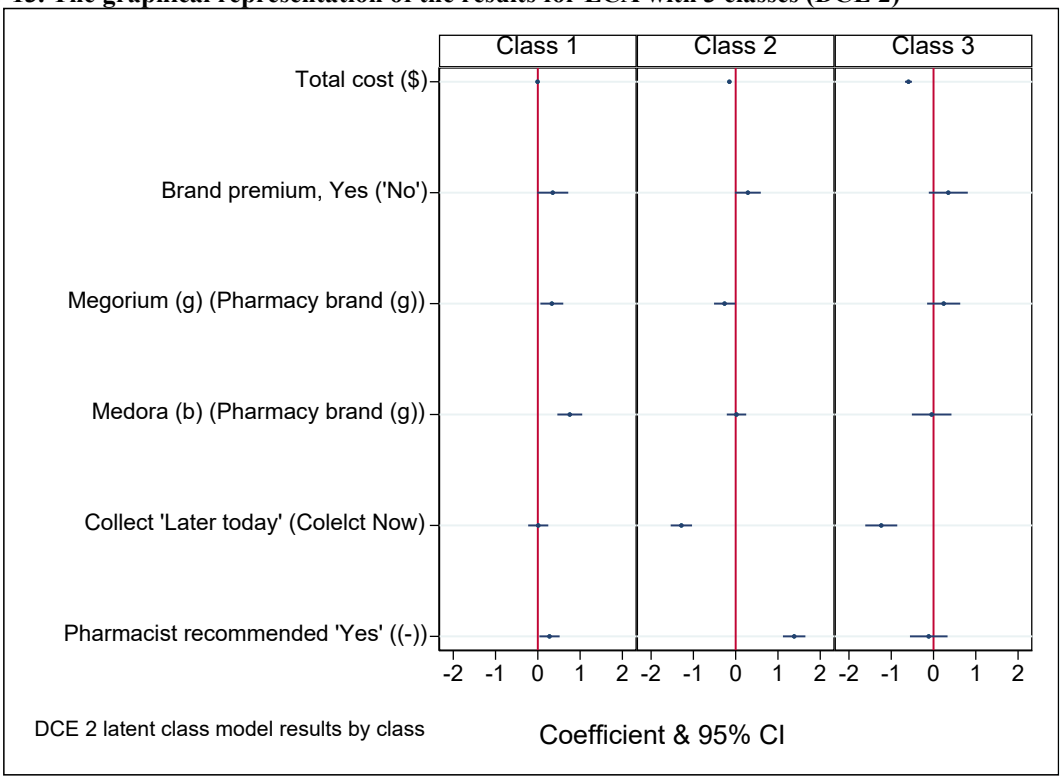
Regarding the *brand premium* attribute, the estimated results do not show any statistical significance compared to the results of the conditional logit model and MXL, where the mean of the *brand premium* attribute was positive and statistically significant, or with the MXL, also indicating a high level of heterogeneity in the preferences for brand premium.

Table 4-10. Latent class model estimates estimated in Stata.

Attributes/ attribute levels	Class 1	Class 2	Class 3
Class share	0.50	0.33	0.17
Total cost ($)	−0.592***	−0.149***	−0.006
SE	(0.042)	(0.015)	(0.010)
Brand premium	0.350	0.289	0.353
SE	(0.235)	(0.156)	(0.187)
Products ('Pharmacy brand generic')			
Megorium generic	0.241	−0.263*	0.332*
SE	(0.200)	(0.127)	(0.138)
Medora branded	−0.044	0.019	0.756***
SE	(0.239)	(0.117)	(0.150)
Collect 'Later today'	−1.236***	−1.284***	0.010
SE	(0.193)	(0.129)	(0.121)
Pharmacist's recommended 'Yes'	−0.113	1.384***	0.276*
SE	(0.227)	(0.135)	(0.122)
Constant	Base case class	−0.417**	−1.069***
SE		(0.133)	(0.155)
Observations 9,912			
Log-likelihood −2,004			

Abbreviations: p: p-value; SE: standard error.
Note: *** p<0.001, ** p<0.01, * p<0.05. Total cost is continuous variable represented in dollar values; Reference categories for the attributes: for *Brand premium* it is '*No* brand premium'; for Medicine *product* attribute is '*Pharmacy brand generic*'; for *collect* it is '*Now';* for *recommend* it is *'(-) no recommendation'.*
Note: The class shares reported represent the average shares over individuals, since the class shares are now individual-specific (Pacifico & Yoo, 2013).

Figure 4-13. The graphical representation of the results for LCA with 3 classes (DCE 2)



Abbreviations: CI: confidence interval.
Note: *** p<0.001, ** p<0.01, * p<0.05.
Note: Total cost is continuous variable represented in dollar values; Reference categories for the attributes: for *Brand premium* it is '*No* brand premium'; for Medicine *product* attribute is '*Pharmacy brand generic*'; for *collect* it is '*Now';* for *recommend* it is *'(-) no recommendation'.*

The ability of the model to make in-sample predictions of the actual choice outcomes (by estimating the class membership posterior probability and then predicting the unconditional probability of actual choice and the probability of actual choice conditional on being in specific class) is presented in Table 4-11.

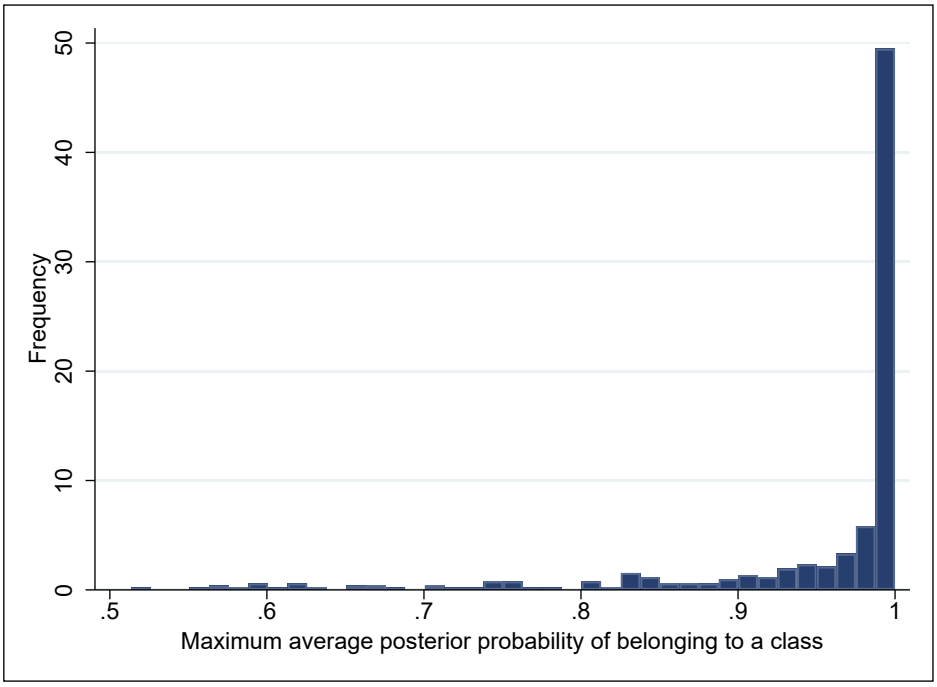
Table 4-11. The results of the class probability for latent class analysis (DCE 2)

Observations in each class	Class number	Unconditional probability	Conditional probability
2520	1	0.75	0.93
1596	2	0.64	0.69
840	3	0.47	0.57

The performance of the model was evaluated by estimating the average of the highest posterior probability of class membership, 0.95, with the majority of values falling between 0.83 and 1 (Figure 4-14). The three-class LCA does well in capturing different underlying taste patterns for the observed choice behaviour (Pacifico & Yoo, 2013). Given that there are two alternatives per choice task, the model would perform well if the prediction was higher than 0.5. The results for unconditional choice probability show two classes with higher than 0.5 probability and one class (Class 3) slightly lower than 0.5, indicating that model describes the observed behaviour well. The unconditional choice probabilities for all classes are all above

0.5.

Figure 4-14. Histogram of the maximum posterior probability for LCA, DCE 2



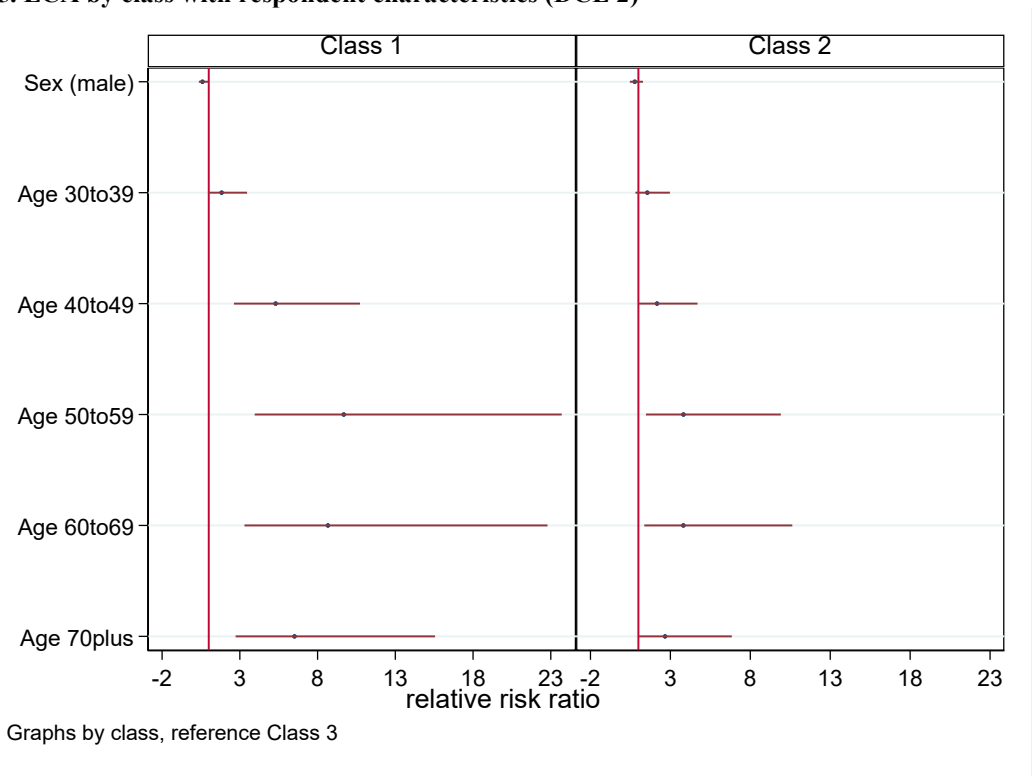
Class heterogeneity

The identification of the class composition showed no statistically significant differences between classes except for age and gender characteristics when the demographic characteristics were used together (i.e., sex, age categories, education categories, income categories etc.). Compared to the results of mixed logit model (with covariates), the age variable showed some significance. The results of the analysis are presented in Figure 4-15. Respondents identified in Class 1 (with strong preference for *Megorium generic*, *Medora branded* and *pharmacist recommended*) were more likely to be male and older than respondents in Class 3 (for whom lower *total cost* and *collecting the medicine now* were the two important factors).

Compared to Class 3, respondents in Class 2 (who had strong preferences for lower cost, collecting the medicine *now* and *pharmacist recommended* products) were more likely to be older (>50 years).

These results indicate that there are groups of consumers for whom a combination of the attributes plays a major role in selecting their prescription medicine product.

Figure 4-15. LCA by class with respondent characteristics (DCE 2)



4.5 Results DCE 3 – The *brand premium* attribute with dollar amount information

Respondents randomised to DCE 3 saw the most information on the *brand premium* attribute. The levels of the attribute included the dollar amount of the *brand premium* that was attached to the product. The other attributes were the same as those presented in DCE 2 (above) and DCE 1 (Chapter 3).

The design of the experiment imposed a number of conditions across the attributes and the levels of the *brand premium* attribute that appear in each choice task. The *Pharmacy brand generic* was set to always have a *brand premium* equal to $0, whereas the other two products presented to the respondents, *Megorium generic* and Medora branded, could take on the full range of *brand premium* levels *($0, $2, $5, $10, $15 or $20*). The difference between DCE 2 and DCE 3 is that in DCE 2 respondents were only presented with an indication attribute for brand premium (Yes/No), whereas in DCE 3 they were presented with the value of the *brand premium* (as well as the *total cost*). The additional information presented in DCE 3 was to explore changes in preference for generic and branded products and for the products with brand premium. It is important to note that this means that in DCE 3 respondents saw two attributes describing the cost of the product, but that these two attributes were linked.

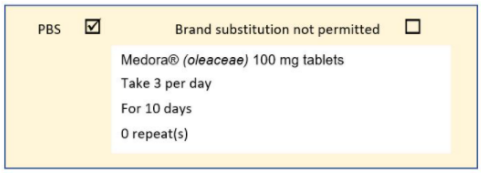
The presentation of results for DCE 3 follows the same structure as for DCE 2. The chapter also investigates the differences between DCE 2 and DCE 3 in relation to the *brand premium* attribute.

An example of the choice task shown to respondents randomised to DCE 3 is presented in Figure 4-16. In the task choice presented below, the respondent received a doctor's script for the *Medora branded* medicine; however, at the pharmacy there were only two generic brands available. The *Megorium generic* was the cheaper of the two and available to collect immediately (*collect now*). The *Pharmacy brand generic* was a little more expensive and was only available later (*collect later today*). Neither product received a pharmacist recommendation. The respondents were asked two choose one of the two alternatives.

Figure 4-16. Example of choice task presented in DCE 3.

Question 1 of 6

Imagine that you have visited your doctor for a minor health condition and your doctor gives you a prescription (below). The doctor said you should start the medicine within the next day or so.



At the pharmacy, the pharmacist offers you a choice between two medicines. Which option would you choose?

Medicine name	Megorium (*oleaceae*) - generic medicine	Pharmacy brand (*oleaceae*) - generic medicine
Total price you pay (including a Brand Premium, if any)	$30 (No Brand Premium, $0)	$35 (No Brand Premium, $0)
Available to collect	Now	Later today
Pharmacist recommended	-	-
Please choose one:		

4.5.1 DCE 3 – Randomisation into two Arms (order of scripts)

Table 4-12 shows the results of pooled and separate models for two randomised groups within DCE 3 for the order of script (as presented for DCE 1 and DCE 2 earlier). The first two columns show the results of conditional logit model for Arm 1 and Arm 2 samples respectively. A visual inspection of the results presented in the first two columns may suggest that although the results are similar across the attribute levels, there is some variability in relation to the *brand premium* and *pharmacist recommended* attributes.

Preference weights measure relative preference, which means that only changes between attribute level estimates and the relative sizes of those changes across attributes have meaningful interpretations (Hauber et al., 2016) (p. 306). However, a comparison of the two estimates can be performed by calculating the probability of each attribute level being chosen in the two models given the estimated parameters.[48] For

[48] In general form for a two-level attribute (X_1, X_2) the probability of choosing (X_1) = $Exp[\beta X_1] / Exp [\beta X_1 + Exp[\beta X_2)]$

example, in Arm 1 the expected probability of choosing a product with *brand premium* was 50.3% and in Arm 2 it was 50.5%. With respect to the product attribute the expected probabilities for choosing a level (*pharmacy brand generic*, *Megorium generic* or *Medora branded*) was similar across the two models. In both arms the expected probabilities were very similar: 27.0%, 34.1%, 38.8% in Arm 1 for each of the levels respectively, and 29.2%, 34.3%, 36.5% in Arm 2 for each of the levels respectively. Similarly, the expected probability of preferring collecting the medicine *now* compared to collecting *later today* was 61.9% in Arm 1, and 64.8% in Arm 2. For the *pharmacist recommended* attribute, the results in each arm were 53.7% and 52.4% respectively.

A formal test of the two models – the likelihood-ratio test of equal parameters across the two arms – revels a LR of 6.19 with the critical value of 11.07 at a 5% significance level in the chi-squared distribution with five degrees of freedom (the *brand premium* attribute is treated as continuous variable) Given this test statistics, the hypothesis of overall equal parameters across the two arms holds. This means that the that there were no differences in preferences across the two arms for any of the parameters.

Table 4-12. Pooled and separate estimates of DCE 3 data for two randomised groups (Arm 1 and Arm 2)

Attributes (base case)	**Active ingredient (generic) script**	**Medora (branded) script**	**Heteroskedastic conditional logit model**
	Mean (SE)	Mean (SE)	Mean (SE)
Total cost ($)	−0.131***	−0.168***	−0.098***
	(0.012)	(0.014)	(0.021)
Brand premium ($)	0.010	0.019*	0.010*
	(0.008)	(0.009)	(0.004)
Products (Pharmacy brand generic)			
Megorium generic	0.233**	0.161*	0.126**
	(0.076)	(0.071)	(0.044)
Medora branded	0.361***	0.225**	0.188***
	(0.071)	(0.078)	(0.057)
Collect later today (‘Now’)	−0.487***	−0.610***	−0.363***
	(0.076)	(0.088)	(0.080)
Pharmacist recommended ‘Yes’ (‘-‘ no recommendation)	0.148	0.096	0.078
	(0.095)	(0.097)	(0.048)
Scale term (Arm 1)			0.271*
			(0.129)
Observations	4,944	4,848	9,792
AIC	2710	2399	5105
BIC (N=413)	2749	2438	5155
Log-likelihood	−1349	−1193	−2545
LR test of equal parameters df=5, critical $\boldsymbol{X^2_{0.95}}$: 6.19 (11.07)			

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; df: degrees of freedom; LR: likelihood ratio; SE: standard error; $X^2_{0.95}$: chi-square area in upper tail at 5% critical value.
Note: *** p<0.001, ** p<0.01, * p<0.05. brand premium attributes are continuous variables represented in dollar value; Reference categories for the attributes: for Medicine product attribute is Pharmacy brand generic’; for collect it is ‘Now’; for recommend it is ‘(-) no recommendation’.

As in the analysis of data by randomisation into each arm, the analysis of the dataset by prescription presented showed that there were no significant differences in preferences for any of the estimated parameters. The results in Table 4-13 present the estimation by the type of doctor's prescription.

Table 4-13. Pooled and separate estimates of DCE 3 data for two types of doctor's script (active ingredient (generic) and Medora (branded))

Attributes (base case)	**Active ingredient (generic) script**	**Medora (branded) script**	**Heteroskedastic conditional logit model**
	Mean (SE)	Mean (SE)	Mean (SE)
Total cost ($)	−0.142***	−0.153***	−0.149***
	(0.011)	(0.011)	(0.011)
Brand premium ($)	0.017	0.014	0.015*
	(0.009)	(0.009)	(0.006)
Products (Pharmacy brand generic)			
Megorium generic	0.114	0.269***	0.200***
	(0.076)	(0.072)	(0.053)
Medora branded	0.312***	0.276***	0.298***
	(0.070)	(0.072)	(0.053)
Collect later today ('Now')	−0.646***	−0.458***	−0.555***
	(0.072)	(0.072)	(0.058)
Pharmacist recommended 'Yes' ('-' no recommendation)	0.088	0.148	0.119
	(0.084)	(0.084)	(0.070)
Scale term (Arm 1)			−0.029
			(0.065)
Observations	4,896	4,896	9,792
AIC	2551	2576	5124
BIC	2590	2615	5174
Log-likelihood	−1270	−1282	−2555
LR test of equal parameters df=5, critical $\boldsymbol{X^2_{0.95}}$: 6.84 (11.07)			

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; df: degrees of freedom; LR : likelihood ratio; SE : standard error; $X^2_{0.95}$: chi-square area in upper tail at 5% critical value.
Note: *** p<0.001, ** p<0.01, * p<0.05. Total cost is continuous variable represented in dollar value; Reference categories for the attributes: for Brand premium it is 'No brand premium'; for Medicine product attribute is '*pharmacy brand generic*'; for collect it is 'Now'; for recommend it is '(-) no recommendation'.

4.5.2 DCE 3 – Conditional logit

As with the analyses performed for DCE 2, all variables included in the model were dummy coded with the exception of the *total cost* attribute, which was included as a continuous variable. Similarly to the analysis in Chapter 3, the functional form of the *total cost* attribute was tested by adding a polynomial term and by including each cost level as a dummy variable.

The results are presented in Table 4-14 The results of the linear form (Model A) showed that respondents had a strong preference for lower levels of *cost*, and a positive but small preference for a *brand premium* cost; there was significant preference for the Medora branded medicine relative to the *Pharmacy brand (generic)*, and a strong aversion to the *collecting later in the day* attribute level. However, the estimate for the *pharmacist recommended* is not significant (p = 0.087). Similar results were seen in the *total cost*

quadratic form (Model B), and cubic form (Model C), as well as *total cost* categories presented as dummy variables (Model D). In these models, the estimated coefficients for all non-monetary attributes have the same sign and significance as those in Model A; in addition, the *pharmacist recommended* attribute level is also significant in Model B, Model C and Model D. On the other hand, the coefficient of the *brand premium* ($) is not significant in Model C and Model D, possibly indicating that the additional terms (cost) absorb the impact of the *brand premium* ($) on consumer preference. This may indicate that there is a relationship between the cost and the attribute.

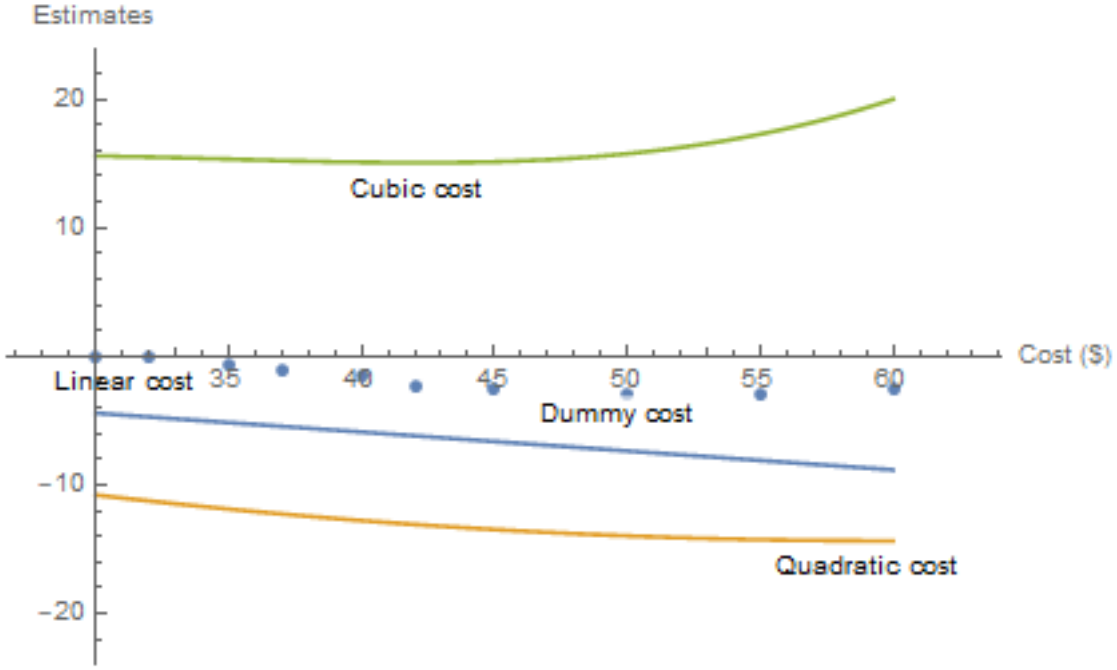
A graphic form of the *total cost* function for the three models is presented in Figure 4-17. The graph shows that the Model A, Model B and Model C functions have similar shape and slope, while the interpretation of the cubic model would complicate the interpretation of the results. Similarly to DCE 1 and DCE 2, the cost (linear) is treated as the main model.

Table 4-14. Presentation of different forms of the Total cost attribute in DCE 3 (linear, quadratic, cubic and categorical (dummy))

Attributes (base case)	**Mean (SE)** linear	**Mean (SE)** quadratic	**Mean (SE)** cubic	**Mean (SE)** dummy
Total cost linear ($)	−0.147***	−0.479***	1.4250***	
	(0.009)	(0.054)	(0.2727)	
Total cost quadratic ($)		0.004***	−0.0422***	
		(0.001)	(0.0066)	
Total cost cubic ($)			0.0004***	
			(0.0001)	
Total cost categorical (dummy, $30)				
$32				−0.055
				(0.189)
$35				−0.678***
				(0.077)
$37				−1.240***
				(0.222)
$40				−1.627***
				(0.108)
$42				−2.397***
				(0.167)
$45				−2.199***
				(0.195)
$50				−2.817***
				(0.247)
$55				−2.224***
				(0.281)
$60				−2.067***
				(0.425)
Brand premium ($)	0.015*	−0.029**	−0.0096	−0.021
	(0.006)	(0.009)	(0.0093)	(0.013)
Products				
(Pharmacy brand generic)				
Megorium generic	0.196***	0.260***	0.2512***	0.241***
	(0.052)	(0.053)	(0.0541)	(0.056)
Medora branded	0.293***	0.354***	0.3342***	0.402***
	(0.052)	(0.054)	(0.0546)	(0.059)
Collect ‘Later today’ (‘Now’)	−0.548***	−0.513***	−0.5448***	−0.613***
	(0.057)	(0.059)	(0.0607)	(0.060)
Pharmacist recommended ‘Yes’	0.117	0.244***	0.2557***	0.259***
(‘-‘ no recommendation)				
	(0.068)	(0.068)	(0.0703)	(0.073)
Observations	9,792	9,792	9,792	9,792
AIC	5122	5083	5045	5037
BIC	5165	5133	5103	5137
Log-likelihood	−2555	−2534	−2515	−2504

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; SE : standard error.
Note: *** p<0.001, ** p<0.01, * p<0.05.
total cost and *brand premium* are continuous variables; Reference categories for the attributes: for Medicine *product* attribute is ‘*pharmacy brand generic*’; for *collect* it is ‘*Now’;* for *recommend* it is *‘(-) no recommendation’.*

Figure 4-17. Results of *total cost* (polynomial forms) for DCE 3



As DCE 3 has *brand premium* attribute treated as a continuous variable in the models above, it was decided to run a model where *brand premium* is a categorial variable, with a dummy variable created for each level. Compared to Model A (*total cost* continuous and *brand premium* continuous) the AIC and the log-likelihood parameters improve, but the BIC is higher.

The estimates for the attributes other than *brand premium* have the same signs (direction) and significance as in the Model A. The pattern of estimated parameters for each level of the *brand premium* as compared to *brand premium* of $0 is non-monotonic, but only the first two levels are significantly different from the base level of $0: respondents do not want to pay a $2 *brand premium* but they prefer the $5 *brand premium* to $0. The results are presented in Table 4-15.

Table 4-15. Conditional logit model with *brand premium* attribute as a categorical variable (DCE 3)

Attributes (base level)	Mean (SE)
Total cost ($)	−0.144***
	(0.009)
Brand premium (dummy, $0)	
Brand premium $2	−0.228*
	(0.094)
Brand premium $5	0.347**
	(0.109)
Brand premium $10	−0.115
	(0.120)
Brand premium $15	0.271
	(0.150)
Brand premium $20	0.211
	(0.131)
Products	
(Pharmacy brand generic)	
Megorium generic	0.199***
	(0.059)
Medora branded	0.323***
	(0.058)
Collect 'Later today' ('Now')	−0.569***
	(0.058)
Pharmacist recommended 'Yes'	0.108
('-' no recommendation)	
	(0.067)
Observations	9,792
AIC	5110
BIC	5182
Log-likelihood	−2545

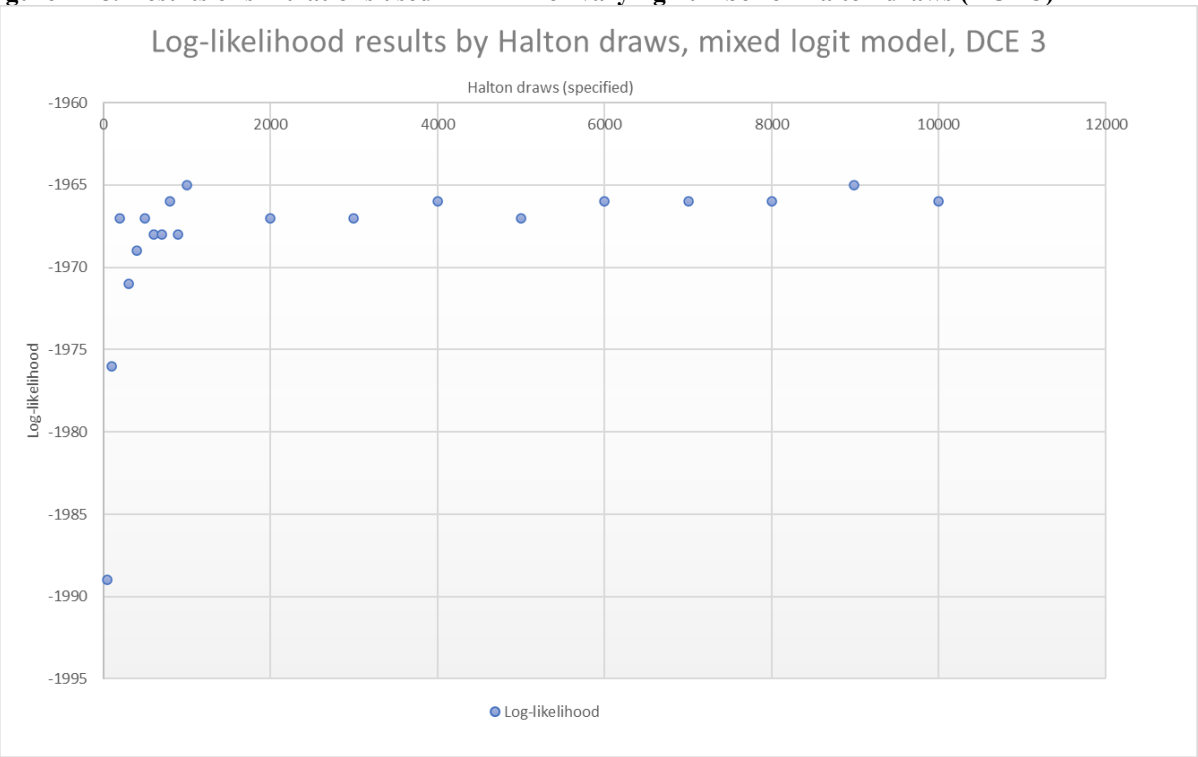
Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; SE: standard error.
Note: *** p<0.001, ** p<0.01, * p<0.05.
total cost and *brand premium* are continuous variables; Reference categories for the attributes: for Medicine *product* attribute is '*pharmacy brand generic*'; for *collect* it is '*Now';* for *recommend* it is *'(-) no recommendation'.*

4.5.3 DCE 3 – Mixed logit model (MXL)

Compared to the conditional logit model, the MXL model allows for random taste variation across the respondents. The measures of statistical fit for MXL show that the model is preferred to the conditional logit model, showing the maximised log-likelihood and minimised AIC and BIC estimates.

Figure 4-18 presents the results of log-likelihood statistics of the 20 estimations of the MXL matched to Halton draws 50 to 10,000. Based on the visual inspection of the log-likelihood, it was decided 2000 Halton draws was an acceptable number due to the observed stabilisation of the model.

Figure 4-18. Results of simulations used in MXL for varying number of Halton draws (DCE 3)



The results for the mixed logit model are presented in Table 4.6.6. These results are similar in terms of the mean values for parameters to those reported in the conditional logit but, as can be seen from the estimated standard deviations, there is significant heterogeneity in preferences.

There is strong aversion to the *collect later today* (compared to *collect now*) attribute level and a strong positive preference for *pharmacist recommended (Yes)*. These are followed by the Medora branded attribute level and Megorium generic attribute level, with respondents also showing significant preferences for cheaper medicines (*total cost* attribute). The estimated mean and standard deviation for the *brand premium* ($) attribute are not statistically significant, which could indicate that the preferences for the brand premium are uniform across the respondents.

All parameters, except for *brand premium* ($), have large and significant standard deviation, which suggests that a number of respondents are expected to have an opposite preference to the estimated value of the mean (Regier et al., 2009). The kernel density curves are presented below for each parameter to assess the distribution of the preferences.

Table 4-16. Results of the MXL for DCE 3

Attributes (base case)	Mean (SE)	SD (SE)
Total cost ($)	−0.448***	0.365***
	(0.031)	(0.027)
Brand premium (continuous variable, $0)	−0.017	0.044
	(0.013)	(0.031)
Products (Pharmacy brand generic)		
Megorium generic	0.445***	0.897***
	(0.106)	(0.157)
Medora branded	0.631***	0.987***
	(0.109)	(0.152)
Collect 'Later today' ('Now')	−1.319***	−1.493***
	(0.132)	(0.159)
Pharmacist recommended 'Yes' ('-' no recommendation)	0.826***	1.967***
	(0.149)	(0.182)
Observations	9792	
AIC	3958	
BIC	4044	
Log-likelihood	−1967	

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; SD: standard deviation; SE: standard error.
Note: *** p<0.001, ** p<0.01, * p<0.05.
total cost and *brand premium* are continuous variables; Reference categories for the attributes: for Medicine *product* attribute is '*pharmacy brand generic*'; for *collect* it is '*Now';* for *recommend* it is *'(-) no recommendation'.*

Kernel density plots for attribute levels in DCE 3

The kernel density plots for each of the estimated parameters are presented in this section. Each distribution is inspected with respect to its shape, size and location with respect to zero.

Total cost and brand premium attributes

The kernel density plot for the *total cost* attribute is shown in Figure 4-19. The shape of the distribution appears to be skewed to the right, with a high density (−1.0 to −0.5). The peak indicates that many respondents have a β_n estimate around the −1.0 mark and a tendency to skew towards the right (zero), with the tail of the plot pulled towards the positive preferences of the high *total cost*. The majority of the distribution is located to the left of zero. This shows that although most respondents preferred lower cost, there are some who saw a benefit in paying more for the prescription medicine.

Figure 4-19. Kernel density estimate for the *total cost* in DCE 3

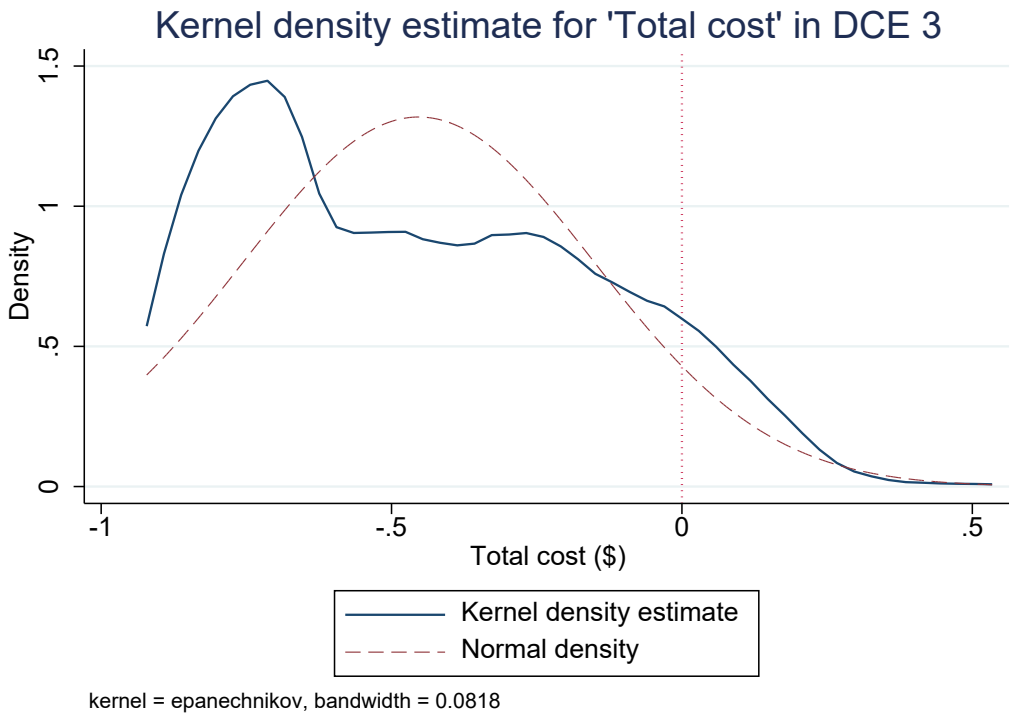
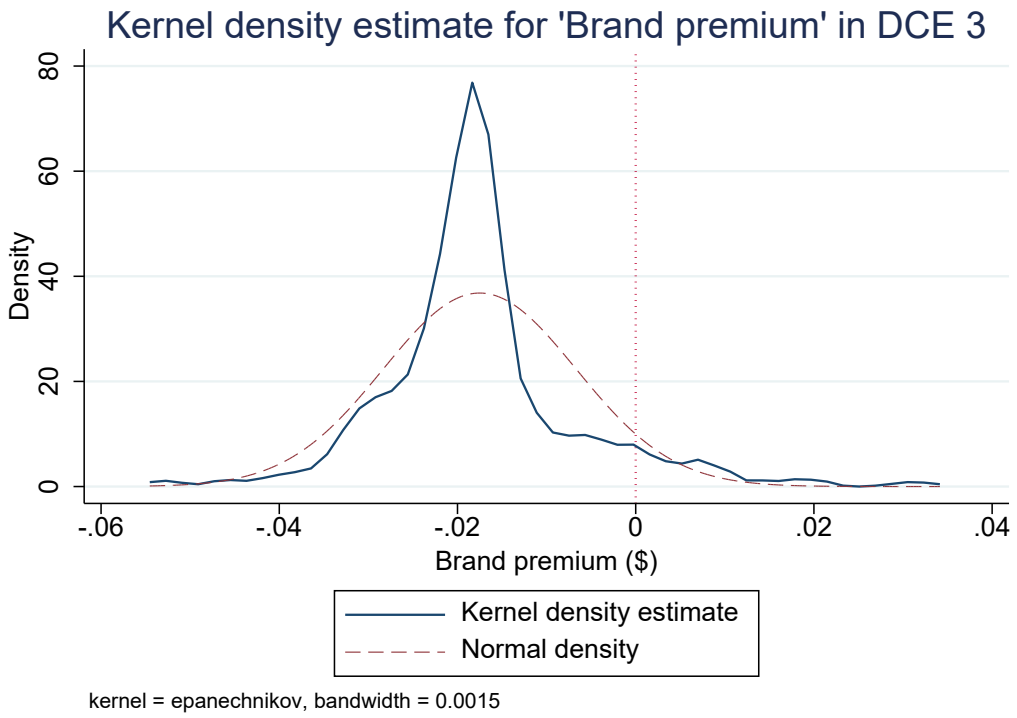


Figure 4-20 shows the kernel density curve for the *brand premium* ($) attribute. The majority of the curve is located to the left of zero, with a high density concentrated around the −0.02 value. The estimated preferences show that, although the value is not statistically significant, a majority of respondents preferred a medicine with lower brand premium.

Figure 4-20. Kernel density estimate for the *brand premium ($)* in DCE 3



To explore the brand premium, attribute a mixed logit model was estimated with *brand premium* presented as a dummy variable for each of the dollar value of the *brand premium* ($0, $2, $5, $10, $15, and $20). The results are presented in Table 4-17 The estimates for the *brand premium* show that respondents had significant preferences for zero *brand premium* compared to a $2 or a $10 premium, with negative preference shown for the $15 and $20 premiums, although not statistically significant. Interestingly, the $5 brand premium has a positive coefficient, although not statistically significant. However, the standard deviation is significant and high in relation to the estimated means for the $5 and $10 brand premium values. The estimates for the $5 *brand premium* amount indicate that there is some variation in preferences. To investigate these results further, kernel density curve was calculated for each level of the *brand premium*, and presented in Figure 4-21.

Table 4-17. Mixed logit model with *brand premium* attribute as a categorical variable (DCE 3)

Attributes (base level)	Mean (SE)	SD (SE)
Total cost ($)	−0.471***	0.392***
	(0.035)	(0.031)
Brand premium (dummy, $0)		
Bran premium $2	−0.442*	0.085
	(0.189)	(0.424)
Brand premium $5	0.156	0.876*
	(0.205)	(0.432)
Brand premium $10	−0.809*	−1.781**
	(0.378)	(0.677)
Brand premium $15	−0.248	−1.125
	(0.301)	(0.617)
Brand premium $20	−0.566	1.276
	(0.344)	(0.750)
Products		
(Pharmacy brand – generic)		
Megorium, generic medicine	0.468***	0.973***
	(0.120)	(0.176)
Medora, branded medicine	0.705***	1.031***
	(0.121)	(0.154)
Collect 'Later today' ('Now')	−1.426***	1.668***
	(0.148)	(0.184)
Pharmacist recommended 'Yes'	0.947***	2.059***
('-' no recommendation)		
	(0.160)	(0.196)
Observations	9792	9792
AIC	3957	3957
BIC	4101	4101
Log-likelihood	−1959	−1959

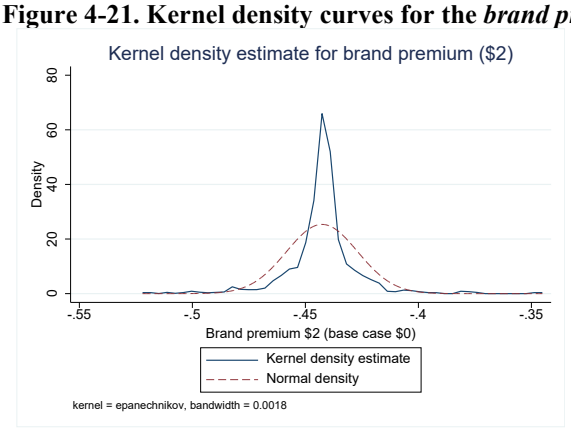
Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; SD: standard deviation; SE: standard error.
Note: *** p<0.001, ** p<0.01, * p<0.05.
total cost and brand premium are continuous variables; Reference categories for the attributes: for Medicine product attribute is 'pharmacy brand generic'; for collect it is 'Now'; for recommend it is '(-) no recommendation'.

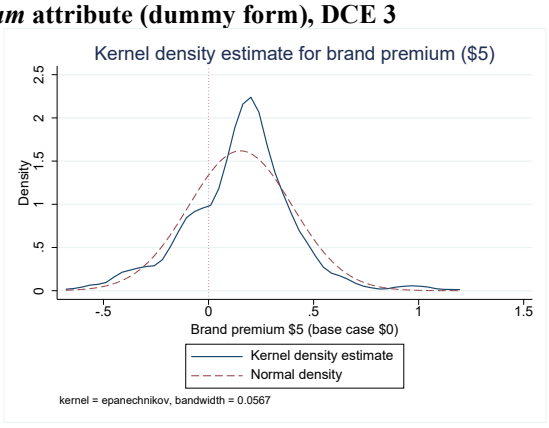
Based on the kernel density curves all levels, except *brand premium* $5, have a close to normal distribution, with highly concentrated peaks. For example, the curve for the $2 *brand premium* shows that all respondents preferred $0 to $2. The other curves show that majority of the respondents preferred the $0 level; however, some estimates fell to the right of zero, indicating a preference for the high brand premium amount.

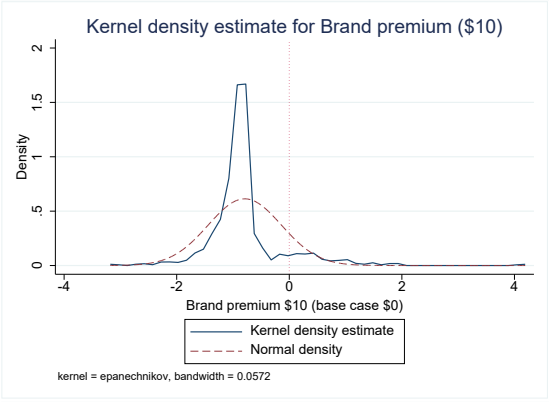
The curve for the $5 *brand premium* is skewed to the left, with the majority of the curve located to the right of zero. This indicates that respondents preferred a $5 *brand premium* to a $0. This break in pattern is not easily explained. Each level (above $0) of the *brand premium* attribute was equally represented in the choice tasks. Therefore, there may be something particular about the $5 brand premium that is attractive for majority of the respondents. Additionally, the *total cost* values with which the $5 *brand premium* was associated were $30, $40 and $45, which may be acceptable amounts close to the current PBS level of co-

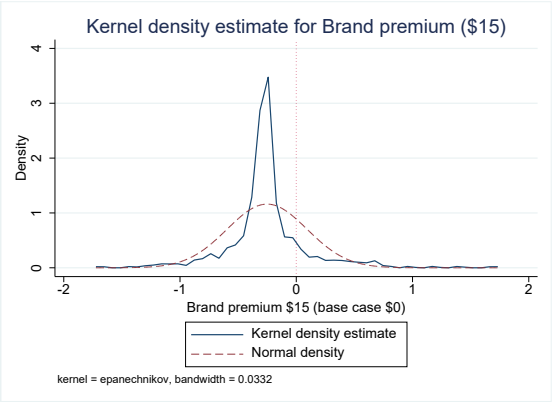
payment.

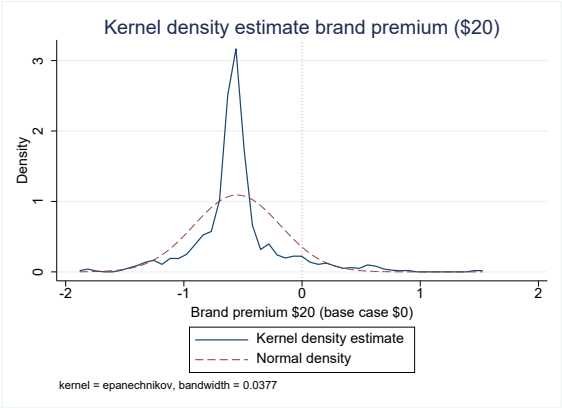
Figure 4-21. Kernel density curves for the *brand premium* attribute (dummy form), DCE 3











Medicine product attribute

Figure 4-22 shows the kernel density plot for the Megorium generic variable, and Figure 4-23 shows the plot for Medora branded. The estimated mean values for both levels in the product attribute were positive and statistically significantly different from zero, the standard deviations were large and statistically significant, indicating that there is significant heterogeneity in preferences for generic and branded products.

The shape of the distributions appears to be similar for both variables. The curves are symmetric and the majority are located to the right of zero. The high narrow peaks indicate that most respondents had very strong preferences for each of the products over the *pharmacy brand generic*.

Figure 4-22. Kernel density estimate for the *Megorium generic* in DCE 3

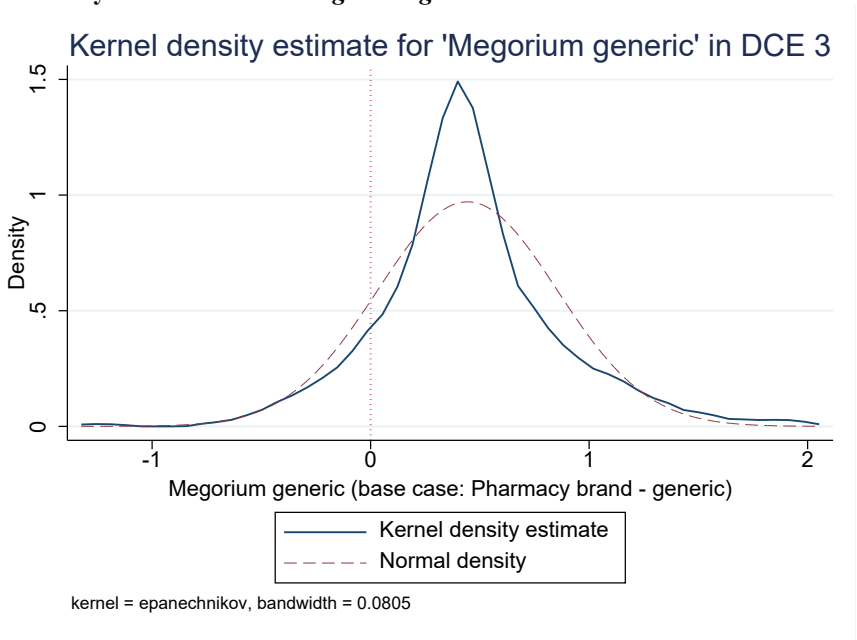
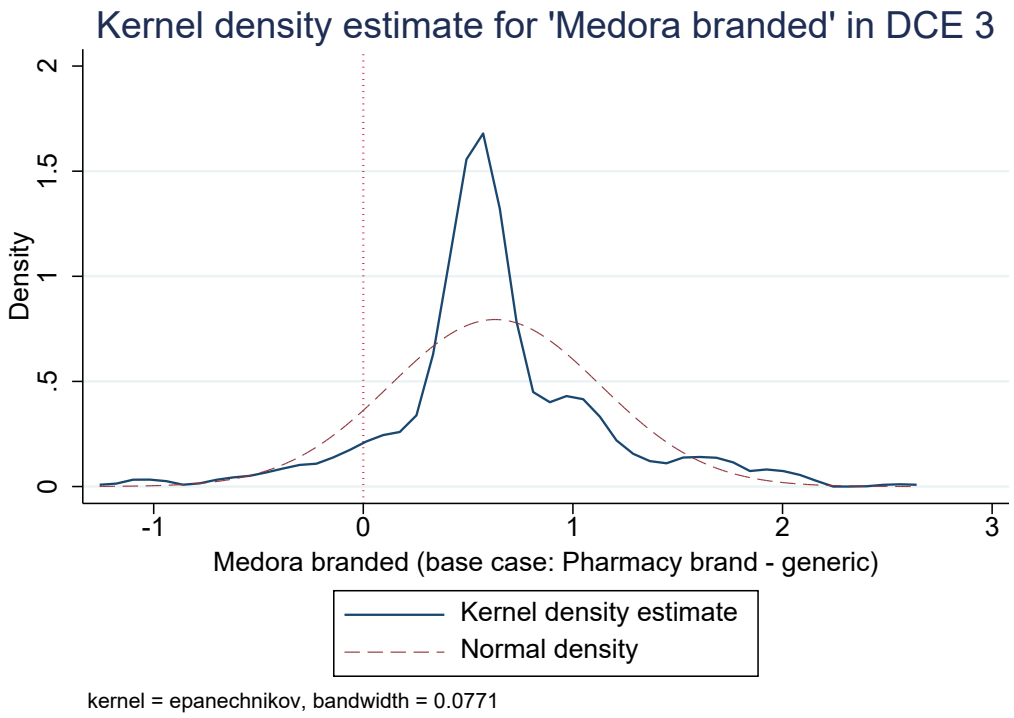


Figure 4-23. Kernel density estimate for the Medora branded in DCE 3

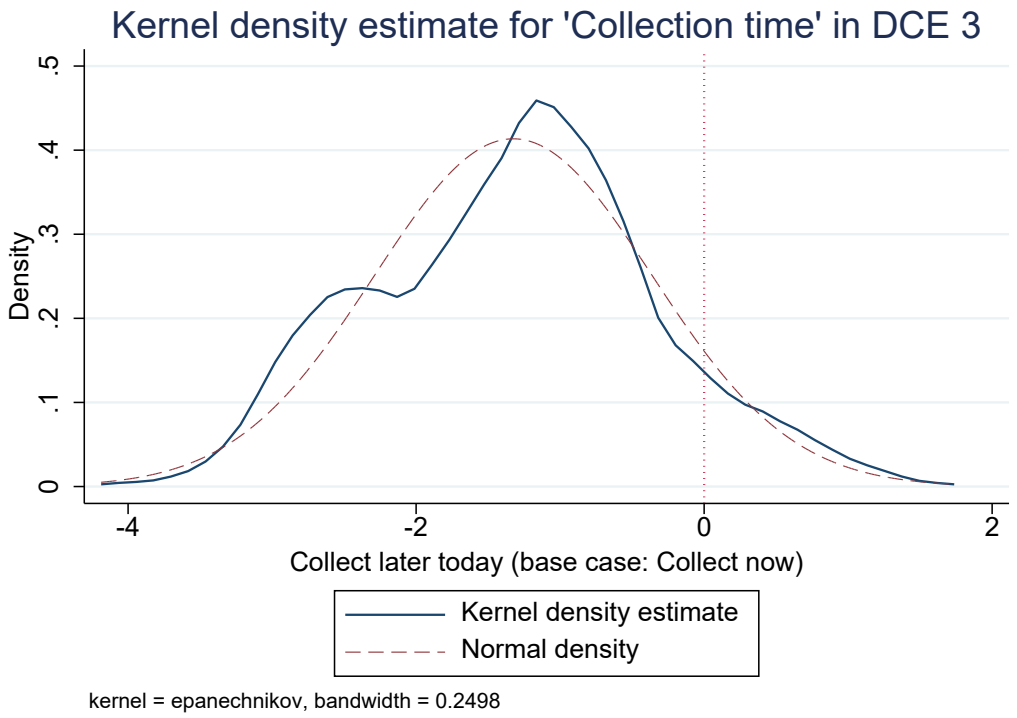


Collection attribute

Figure 4-24 shows the kernel density curve for the *collection* attribute. The curve is skewed to the left, with the majority of the curve located to the left of zero. This shows that there were strong preferences against collecting the medicine later today. This attribute can also indicate the preferences for the 'cost' of time spent collecting the medicine, with most respondents valuing their time.

The estimated mean for the *collect 'Later today'* attribute was negative and significant, showing that respondents had a strong preference for collecting the medicine '*Now'* rather than having to come back; however, 23% of the preference is estimated to be above zero, meaning respondents would be willing to come back if their preferred medicine was guaranteed to be available. While on average respondents preferred not to have to come back to the pharmacy, there is a small and significant proportion for whom this was not the case.

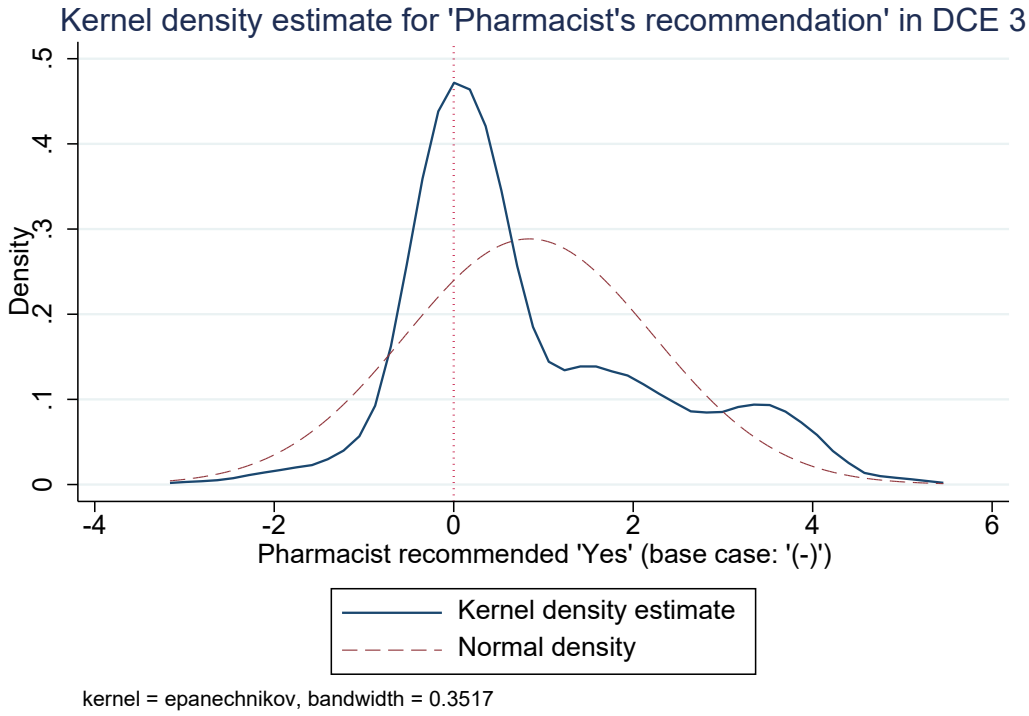
Figure 4-24. Kernel density estimate for the *collect later today* in DCE 3



Pharmacist recommended attribute

Figure 4-25 presents the kernel density curve for the *pharmacist recommended* attribute. The curve has a high density close to zero; however, the curve is heavily skewed to the right, indicating a heterogeneity in preferences. The estimated coefficient showed that respondents preferred medicine that the pharmacist recommended; however, the large and significant standard deviation showed a negative coefficient for at least 30% of the respondents, indicating that some respondents may have been indifferent to the pharmacist recommendation.

Figure 4-25. Kernel density estimate for the *pharmacist recommended (Yes)* in DCE 3



Interactions MXL

An MXL model with interaction with two demographic variables (gender and age) was run to identify whether these two covariates are significant with respect to any of the attribute levels presented in the model. As the sample population was stratified based on these two characteristics, data are available for all the respondents. The results are presented in Table 4-18. With the inclusion of covariates the product attribute levels are not significant compared with the general mixed model. Only the *total cost*, *collection* attribute and *pharmacist recommended* attributes showed statistical significance with expected signs. The standard deviations for all variables are significant and large compared to the estimated coefficients, indicating a high level of heterogeneity in the sample.

The results of interaction with the gender characteristic showed no significant difference in preferences across the two genders.

Regarding the age variable, people older than 30 years were significantly more likely to prefer a cheaper *cost* than those from the younger group (18–29 years). There was a significant preference among people aged 70+ years for the Medora branded product, while people aged 40–49 years demonstrated a positive preference for medicine that was *recommended by the pharmacist*.

The estimates for the interaction with other attribute levels were not significant. The heterogeneity present in the preferences, it is explored further in the next section estimating a latent class model.

Table 4-18. Results of mixed logit model with gender and age covariates (DCE 3)

Attributes (base case)	Mean (SE)	SD (SE)
Total cost ($)	−0.320***	0.347***
	(0.041)	(0.025)
Brand premium ($)	−0.042	0.058**
	(0.029)	(0.020)
Products ('Pharmacy brand generic')		
Megorium generic	0.460	0.861***
	(0.238)	(0.156)
Medora branded	0.390	0.941***
	(0.248)	(0.144)
Collect later today ('Now')	−1.386***	1.473***
	(0.277)	(0.162)
Pharmacist recommended 'Yes' ('-' no recommendation)	1.402***	1.938***
	(0.337)	(0.184)
Interaction with Gender (female)		
Total cost – male	0.028	
	(0.035)	
Brand premium ($) – male	0.027	
	(0.025)	
Megorium generic– male	0.217	
	(0.207)	
Medora branded – male	−0.248	
	(0.209)	
Collect later today ('Now') – male	0.327	
	(0.229)	
Pharmacist recommended 'Yes' ('-' no recommendation) – male	−0.066	
	(0.271)	
Interaction with Age		
Total cost ($) X Age (18y.o.-29y.o.)		
Age 30–39	0.016	
	(0.055)	
Age 40–49	−0.232***	
	(0.055)	
Age 50–59	−0.229***	
	(0.057)	
Age 60–69	−0.272***	
	(0.061)	
Age 70+	−0.160*	
	(0.068)	
Brand premium ($) X Age (18y.o.- 29y.o.)		
Age 30–39	−0.002	
	(0.037)	
Age 40–49	0.004	
	(0.040)	
Age 50–59	0.050	
	(0.041)	
Age 60–69	−0.011	
	(0.048)	
Age 70+	0.005	
	(0.043)	
Megorium generic		
Age 30–39	−0.466	
	(0.318)	
Age 40–49	0.185	

	(0.337)	
Age 50–59	−0.098	
	(0.354)	
Age 60–69	−0.163	
	(0.361)	
Age 70+	−0.177	
	(0.351)	
Medora branded		
Age 30–39	0.235	
	(0.320)	
Age 40–49	0.604	
	(0.345)	
Age 50–59	0.091	
	(0.349)	
Age 60–69	0.536	
	(0.375)	
Age 70+	0.905*	
	(0.371)	
Collect later today (‘Now’)		
Age 30–39	0.212	
	(0.353)	
Age 40–49	−0.338	
	(0.371)	
Age 50–59	−0.138	
	(0.385)	
Age 60–69	−0.249	
	(0.408)	
Age 70+	0.023	
	(0.399)	
Pharmacist recommended ‘Yes’ (‘-‘ no recommendation)		
Age 30–39	−0.475	
	(0.446)	
Age 40–49	−1.108*	
	(0.438)	
Age 50–59	−0.447	
	(0.454)	
Age 60–69	−0.611	
	(0.483)	
Age 70+	−0.971	
	(0.502)	
Observations	9792	
AIC	3972	
BIC	4317	
Log-likelihood	−1938	

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; N: total participants in group; SD: standard deviation; SE: standard error.
Note: *** p<0.001, ** p<0.01, * p<0.05.
total cost is continuous variable represented in dollar values; Reference levels for the attributes: for *Brand premium* it is ‘*No* brand premium’; for Medicine *product* attribute is ‘*Pharmacy brand generic*’; for *collect* it is ‘*Now’;* for *recommend* it is *‘(-) no recommendation’.*

Preferred model

The measures of statistical fit show that the MXL is the preferred model when compared to the conditional logit model, showing improvement in maximised log-likelihood (−1967 vs −2555), as well as minimised AIC (3958 vs 5122) and BIC estimates (4044 vs 5165).

The next section further explores respondents' preference heterogeneity using the latent class model.

4.5.4 DCE 3 – Latent class analysis (LCA)

The results of the LCA for DCE 3 dataset are discussed in this section. The structure of the analysis follows that of the DCE 2 in the section above.

Using three software packages (Stata, LatentGold and Rstudio) the latent class model was tested for up to nine classes to determine an optimal number of classes in the DCE 3 dataset (Table 4-19). To select the statistical measure of fit, the AIC and BIC statistics were presented for comparison across different number of classes. The BIC was used to select the optimal number of classes.

The LCA model in DCE 3 showed that all statistical measures improved as more classes were added, which supported the presence of multiple classes in the sample (although the results of the optimal number of classes are different across the three software platforms).

Based on the BIC statistical measure, there was a relatively large decrease in the value from a two-class model to a three-class model compared to other classes (Figure 4-26). In Stata-based analysis, the BIC five-class model appears to be optimal, and in LatentGold BIC is also minimised at five classes. In the Rstudio analysis, BIC is minimised at three and five classes (the six-class model did not estimate). However, the BIC value in the five-class model (Rstudio) is lower than in the three-class model.

Although the five-class model appears to have an optimal number of classes, it may not be the best number of classes to for this dataset of 408 respondents, where there potentially would be fewer than 100 respondents allocated to each class. Additionally, looking at Figure 4-26 the improvement in BIC between a four-class mode and a five-class model is minimal and would not have a major impact on the estimated results.

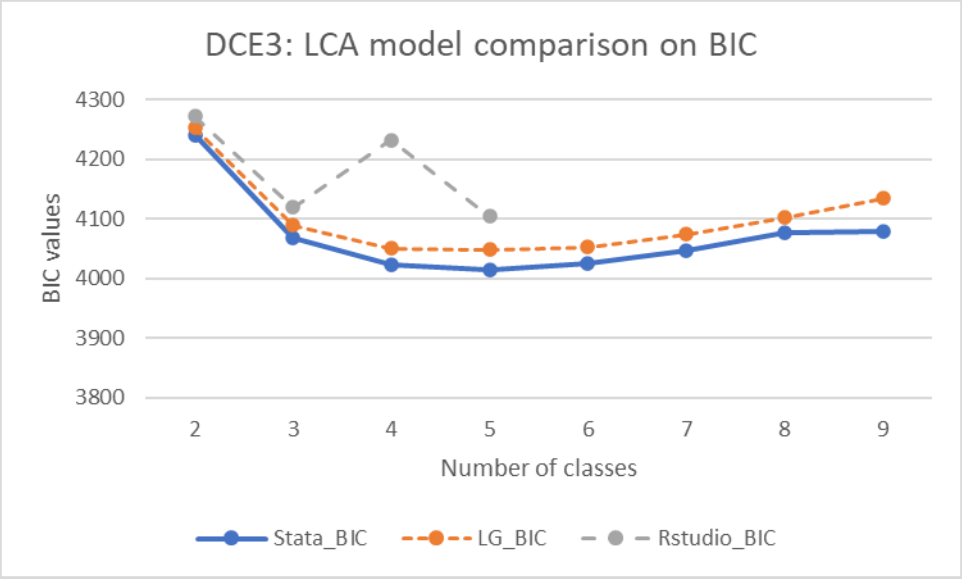
Therefore, a four-class model was selected as the main model: this provided standard errors estimates across all software packages, none of the classes had less than 10% of the sample and the classes have distinct preferences.

Table 4-19. Statistical fit for tested number of classes in Stata, LatentGold and Rstudio, DCE 3

Stata output				
Classes	Parameters, N	Log-likelihood	AIC	BIC
2	13	−2080.52	4187.045	4239.191
3	20	−1974.32	3988.641	4068.866
4	27	−1930.62	3915.242	4023.546
5	34	−1904.76	3877.526	4013.909
6	41	−1888.71	3859.42	4023.882
7	48	−1878.63	3853.264	4045.805
8	55	−1873.39	3856.787	4077.407
9	62	−1853.27	3830.535	4079.234
LatentGold output				
Classes	Parameters, N	Log-likelihood	AIC	BIC
2	13	−2080.52	4187.049	4252.196
3	20	−1974.32	3988.64	4088.866
4	27	−1930.62	3915.248	4050.553
5	34	−1904.79	3877.59	4047.973
6	41	−1882.48	3846.966	4052.428
7	48	−1868.6	3833.199	4073.74
8	55	−1858.27	3826.549	4102.169
9	62	−1849.46	3822.916	4133.614
Rstudio output				
Classes	Parameters, N	Log-likelihood	AIC	BIC
2	13	−2080.5	4187.045	4271.495
3	20	−1974.6	3989.280	4119.203
4	27	−2001.1	4056.299	4231.696
5	34	−1907.4	3882.782	4103.652

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion.
Note: highlighted cells show the best fit for each statistical measure.

Figure 4-26. DCE 3 latent class comparison of BIC across three software packages



Abbreviation: BIC: Bayesian information criterion; LCA: latent class analysis; LG : LatentGold software.

To further support the selection of a of a four-class model as the right model for this dataset, the results of the three-, four-, and five-class models were estimated in Stata; the significant parameters for each class, with class share, are presented in Table 4-20.

The results of five-class model shows that there are classes with similar preferences (i.e. total cost and *collection*) and with a smaller number of respondents the differences between the classes may not be detected. While a three-class model can be characterised by three distinct classes, it may hide the very specific class. Therefore, a four-class model was further explored as the main model.

Table 4-20. Comparison of the results of three LCA models (3- ,4- , and 5-classes)

	3-class		4-class		5-class	
Class N	Class share	Significant attribute	Class share	Significant attribute	Class share	Significant attribute
1	0.26	Total cost; Collection; Pharm. Recom.	0.16	Megorium (g); Medora (b); Pharm. Recom.	0.14	Megorium (g); Medora (b); Pharm. Recom.
2	0.54	Total cost; Collection.	0.45	Total cost; Medora (b); Collection.	0.42	Total cost; Collection
3	0.19	Megorium (g); Medora (b).	0.16	Total cost; Medora (b); Collection; Pharm. Recom.	0.17	Total cost; Medora (b); Collection; Pharm. Recom.
4			0.23	Total cost; Collection.	0.16	Total cost; Collection.
5					0.12	Total cost; Collection; Pharm. Recom.

Abbreviation: pharm.recom : pharmacist recommended.

The results of the latent class model for the preferred model, estimated with three classes are presented in Table 4-21.

The estimates in Class 1 (15.8% class share) indicate that respondents in these classes had a strong and significant preference for the two medicine products (*Megorium generic* and *Medora branded*) compared to the omitted level *Pharmacy brand generic*. This class is also characterised by a positive and significant preference for the *pharmacist recommended* medicine.

Class 2 (45.3%) is the largest class with strong and significant preferences for the lower cost of the medicine, a preference for the *Medora branded* medicine and a negative preference for *collecting the medicine later today* (compared to *collecting Now*).

Class 3 (16.4%) is characterised by statistically significant preferences for *lower cost*, *Medora branded* medicine, negative preference for *collection later today*, and a strong and positive preference the *pharmacist recommended* medicine. These preferences reflect those estimated in the conditional logit model.

Class 4 (22.5 %) is also characterised by preferences of lower *total cost* and a negative preference for the collection of the medicine later today.

The *brand premium ($)* was not significant in any of the estimated classes, while *total cost* and *collection* attributes were significant across Class 2 to Class 4.

Table 4-21. Latent class model estimates with 4 classes for DCE 3

LCA DCE 3 **Attribute level (base case)**	**Class 1**	**Class 2**	**Class 3**	**Class 4**
Class share	0.158	0.453	0.164	0.225
	Mean (SE)	Mean (SE)	Mean (SE)	Mean (SE)
Total cost ($)	0.001	−0.672***	−0.204***	−0.149***
	(0.012)	(0.082)	(0.032)	(0.024)
Brand premium ($)	−0.009	−0.018	−0.014	−0.025
	(0.016)	(0.042)	(0.025)	(0.020)
Products (Pharmacy brand generic)				
Megorium generic	0.873***	0.167	0.140	0.167
	(0.145)	(0.193)	(0.191)	(0.158)
Medora branded	0.968***	0.901*	0.629**	-0.146
	(0.148)	(0.397)	(0.234)	(0.169)
Collect ‘Later today’ (‘Now’)	−0.154	−1.680***	−1.095***	−1.097***
	(0.124)	(0.326)	(0.231)	(0.200)
Pharmacist recommended ‘Yes’ (‘-‘ no recommendation)	0.288*	0.092	3.242***	0.136
	(0.137)	(0.373)	(0.389)	(0.208)
Constant	−0.355	0.700**	−0.317	
	(0.237)	(0.251)	(0.301)	
Observations	9792			
Number of groups	4896			
AIC	3915			
BIC	4109			
Log-likelihood	−1931			

Abbreviations: BIC: Bayesian information criterion; LCA: latent class analysis; LG: LatentGold software.; SE: standard error.

The predicted unconditional probability of actual choice and the probability of actual choice conditional on being in specific class are presented in Table 4-22. The results shows that the average unconditional choice probability is higher than the 0.5 for all classes except Class 1. The average conditional probability is higher than 0.5 for all five classes.

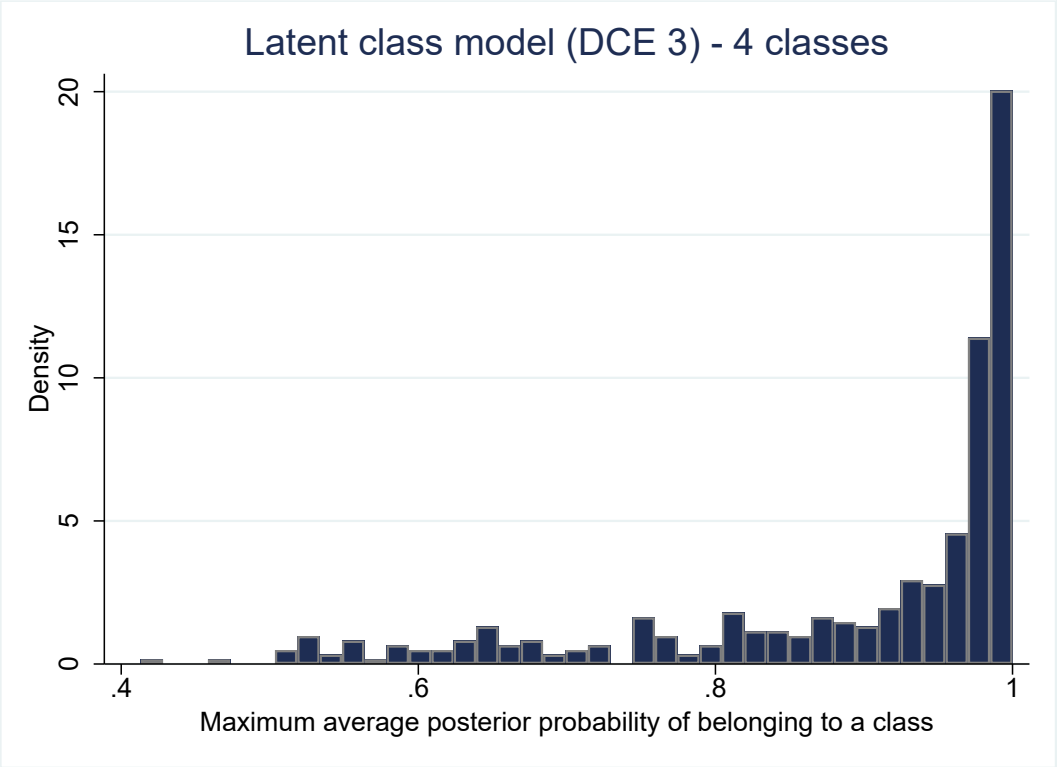
Table 4-22. The results of the class probability for latent class analysis (DCE 3)

Observations in each class	Class number	Unconditional probability	Conditional probability
756	1	0.471768	0.589592
2304	2	0.758396	0.93194
828	3	0.623758	0.792307
1008	4	0.667703	0.702714

The estimated average (over respondents) highest posterior probability of class membership is presented in Figure 4-27 . For DCE 3, the estimated average of the maximum probability of class membership is 0.89 with majority of values falling between 0.8 to 1, indicating that the model does well in capturing different

underlying taste patterns for the observed choice behaviour (Pacifico & Yoo, 2013).

Figure 4-27. Histogram of the probability of 5-class membership for latent class model in DCE 3



Class heterogeneity

The identification of the class composition showed no statistically significant differences between classes except for age and gender characteristics when the demographic characteristics were used together (i.e., sex, age categories, education categories, income categories etc.). The results are similar to the results of the mixed logit model (with covariates), in which only the age covariate showed some significance. Respondents identified with Class 2 (strong preference for lower *total cost*, *Medora branded* and *collection*) were more likely to be older (30–70 years and above) than respondents in Class 3 (preference for lower *total cost*, *Medora branded*, *collection* and *pharmacist recommended*). The difference between the classes, and the significance of age in Class 2 compared to Class 3, could indicate that older respondents do not rely on pharmacist recommendation as younger respondents do when they have other significant preferences.

4.6 Preference for *brand premium* attribute across the two information vignettes

4.6.1 Comparing DCE 2 and DCE 3

The difference between the two DCEs is in the format of the *brand premium* attribute and its levels. In DCE 2 the respondents saw the brand premium as an indicator attribute of 'Yes' (there is a brand premium attached to the product) or 'No' (no brand premium attached to the product). In DCE 3 the respondents were presented with the monetary (dollar) value of the *brand premium* attribute as well as the *total cost* of

the product, with the *brand premium* taking on the values $2, $5, $10, $15, or $20, as well as $0 which indicated that there was no *brand premium* attached to the product. As these differences were pre-designed in the experiment, it is possible to compare the responses to the DCEs. That is, the underlying design is the same for both DCEs, but with the additional information about the value of the *brand premium* provided in DCE 3.

The preferences of respondents in DCE 2 and DCE 3 are compared using two approaches, following (Payne et al., 2011): 1) identifying the impact of the scale parameter and 2) estimating and comparing their marginal willingness to pay.

To test whether it is possible to combine the two datasets together for analysis, the *brand premium* attribute in DCE 3 was re-specified as a dummy coded variable (Model 2 for DCE 3; see DCE 3 –additional results section below). It should be noted that this approach constrains the estimates for this attribute for DCE 3 to be the same across all levels (the same functional form as for DCE 2), which ignores the additional information presented in DCE 3. Taking this approach allows us to test whether the additional information has changed the estimated preferences for the other attributes, by testing a pooled model compared with the unconstrained model (in which the attributes for each DCE are estimated separately). This approach is possible because the design of the two DCEs effectively ensures that the value of the *brand premium* attribute is the same in each DCE, although the information is not presented to the respondent explicitly in DCE 2.

The log-likelihood ratio test was used to test if the two datasets can be 'pooled'. The result of the conditional logit models for DCE 2 and DCE 3 and the heteroskedastic conditional logit are in Table 4-23. The first two columns are from the conditional logit analysis of DCE 2 and DCE 3 samples.

However, the results of the LR test using the estimated heteroskedastic model and the two separate models for each dataset show that the associated chi-square statistic (13.91) is higher than the chi-square level (11.07) at 5% critical value, suggesting that the equivalence of preference, conditional upon there being different scales, must be rejected.

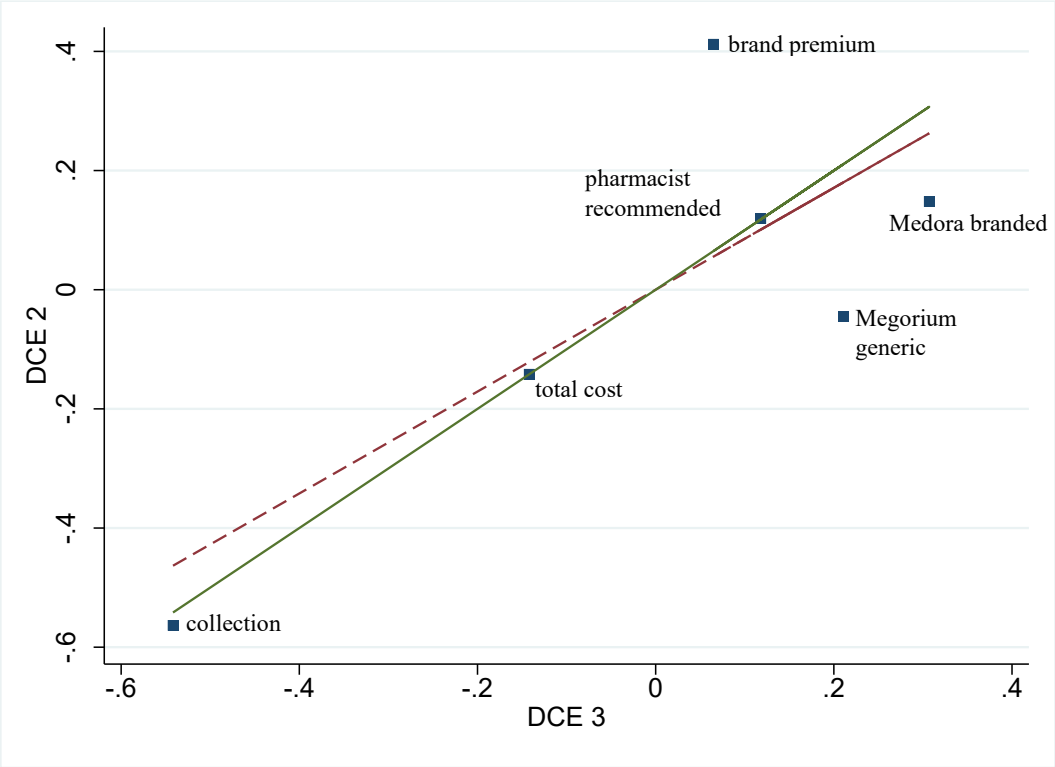
Table 4-23. Estimates of DCE 2 and DCE 3 using different model specifications.

	DCE 2 conditional logit model	DCE 3 conditional logit model	Heteroskedastic conditional logit model (DCE 2 & DCE 3)
Attributes (base case)	Mean (SE)	Mean (SE)	Mean (SE)
Total cost ($)	−0.142***	−0.142***	−0.140***
	(0.009)	(0.009)	(0.009)
Brand premium (dummy)	0.065	0.412***	0.233***
	(0.073)	(0.075)	(0.055)
Products (Pharmacy brand generic)			
Megorium generic	0.211***	−0.045	0.083*
	(0.057)	(0.061)	(0.041)
Medora branded	0.307***	0.148*	0.224***
	(0.057)	(0.060)	(0.042)
Collect 'Later today' ('Now')	−0.542***	−0.563***	−0.543***
	(0.057)	(0.057)	(0.048)
Pharmacist recommended 'Yes'	0.118	0.120	0.117*
	(0.068)	(0.066)	(0.047)
('-' no recommendation)			
Scale parameter (DCE 3)			0.030
			(0.092)
Observations	9792	9912	19,704
AIC	5127	5261	10,391
BIC	5170	5304	10,447
Log-likelihood	−2557	−2624	−5189
LR test of equal parameters df=5, critical $\boldsymbol{X^2_{0.95}}$: 13.91 (11.07)			

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; df: degrees of freedom; LR: likelihood ratio; SE: standard error; $X^2_{0.95}$: chi-square area in upper tail at 5% critical value.
Note: *** p<0.001, ** p<0.01, * p<0.05;
total cost is a continuous variable with levels represented in dollar values; Reference categories for the attributes: for *brand premium* attribute is '*No*' *brand premium*; for Medicine *product* attribute is '*Pharmacy brand generic*'; for *collect* it is '*Now';* for *recommend* it is *'(-) no recommendation'*

Additionally, a graphical representation of the estimated preferences for each sample (DCE 2 and DCE 3) of the conditional logit models in Table 4-24 are shown in Figure 4-28 (Swait & Louviere, 1993; Vass et al., 2018). The results in the graph show that the coefficients for both groups differ for half of the parameters, although they are also very similar for half (indicated by the straight line fitted through the points, which passes through the origin (Vass et al., 2018). The attributes that are different have connection to the brand name or brand premium.

Figure 4-28. 'Swait and Louvier' plot of coefficients estimated from the preferences of a sample of DCE 2 and DCE 3 groups (Hensher et al., 1998)[a].



Note: dotted line is 45 degrees for reference.
[a] (Hensher et al., 1998)

4.6.2 Marginal WTP – comparison of the effect of framing the *brand premium* attribute across the two DCEs

DCE 3 – Additional results analysing the brand premium attribute using several models.

To assess the impact of the *brand premium* information presented to the responders randomised to DCE 3, an analysis of the DCE 3 data set with five models where the *brand premium* attribute is parameterised in different ways is performed to explore the effect of the *brand premium* as it is presented in this DCE compared to DCE 1 and 2 (noting that in this DCE, the respondent saw not only that there was a *brand premium* but also the amount). The aim of this analysis is to explore whether there is a *brand premium* effect that is separate from the difference in cost. The description of each model and the list of variables is presented in Table 4-24.

Table 4-24. Summary for the five models presenting the *brand premium* attribute (DCE 3)

Model N	Description	Variables
Model 1	– removing the *brand premium* attribute from the analysis, analyse the data as if DCE 1.	Total cost ($); Product (Pharmacy brand (g) (0), Megorium (g) (1), Medora (b) (2)); Collection Pharmacist recommended.
Model 2	– presenting the *brand premium* attribute as a dummy coded variable, assigning the ($0) category a zero, and all other categories ($2, $5, $10, $15, $20) a one. Equating the model to the one similar to DCE 2.	Total cost ($); Brand premium 'Yes' (dummy); Product (Pharmacy brand (g) (0), Megorium (g) (1), Medora (b) (2)); Collection; Pharmacist recommended.
Model 3	– is the base case model, where the *brand premium* attribute is treated as continuous variable.	Total cost ($); Brand premium 'Yes' (dummy); Product (Pharmacy brand (g) (0), Megorium (g) (1), Medora (b) (2)); Collection; Pharmacist recommended.
Model 4	– specifying the *brand premium* attribute levels as categorical variable and creating a dummy variable for each category, with the ($0) level as reference level.	Total cost ($); Brand premium ($); Product (Pharmacy brand (g) (0), Megorium (g) (1), Medora (b) (2)); Collection; Pharmacist recommended.
Model 5	– allocating three sub-categories to the *brand premium* attribute levels: no BP ($0), low BP ($2, and $5), and high BP ($10, $10, $20).	Total cost ($); Brand premium (No BP (0), Low BP (1), High BP (2)); Product (Pharmacy brand (g) (0), Megorium (g) (1), Medora (b) (2)); Collection; Pharmacist recommended.

Abbreviation: b : branded; BP: *brand premium*; g: generic.

Table 4-25 shows that the results of each model show that the parameters, excluding the *brand premium*, were all statistically significant with large standard deviations, which is similar to the base case results of Model 3.

Table 4-25. MXL results for different presentation of the *brand premium* attribute, DCE 3

Attribute levels	Model 1 Model equivalent to DCE 1 (no brand premium)		Model 2 Model equivalent to DCE 2 (brand premium as a dummy variable)		Model 3 Model as DCE 3 (brand premium as a continuous $ value)		Model 4 Model with brand premium as categorical dummy variables (base case BP = $0)		Model 5 Model with brand premium split into three categories (base case BP No brand premium, $0)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Total cost ($)	−0.455***	0.353***	−0.453***	0.374***	−0.448***	0.365***	−0.471***	0.392***	−0.457***	0.376***
(SE)	(0.031)	(0.025)	(0.031)	(0.029)	(0.031)	(0.027)	(0.035)	(0.031)	(0.033)	(0.028)
Brand premium for Model 2										
Brand premium (binary)			−0.067	0.185						
(SE)			(0.048)	(0.112)						
Brand premium for Model 3										
Brand premium ($)					−0.017	0.044				
(SE)					(0.013)	(0.031)				
Brand premium for Model 4										
Brand premium $0							(reference level)		(reference level)	
Brand premium $2							−0.442*	0.085		
(SE)							(0.189)	(0.424)		
Brand premium $5							0.156	0.876*		
(SE)							(0.205)	(0.432)		
Brand premium $10							−0.809*	−1.781**		
(SE)							(0.378)	(0.677)		
Brand premium $15							−0.248	−1.125		
(SE)							(0.301)	(0.617)		
Brand premium $20							−0.566	1.276		
(SE)							(0.344)	(0.750)		
Brand premium for Model 5										
Brand premium low ($2, $5)									−0.164	0.779*
(SE)									(0.156)	(0.292)
Brand premium high ($10, $15, $20)									−0.374*	0.481
(SE)									(0.209)	(0.434)
Megorium, generic medicine	0.386***	0.898***	0.448***	0.904***	0.445***	0.897***	0.468***	0.973***	0.502***	0.813***
(SE)	(0.100)	(0.154)	(0.109)	(0.158)	(0.106)	(0.157)	(0.120)	(0.176)	(0.118)	(0.171)
Medora branded	0.569***	0.951***	0.640***	0.995***	0.631***	0.987***	0.705***	1.031***	0.691***	1.016***
(SE)	(0.101)	(0.142)	(0.112)	(0.149)	(0.109)	(0.152)	(0.121)	(0.154)	(0.119)	(0.158)
Collect ‘Later’	−1.327***	1.469***	−1.325***	1.526***	−1.319***	1.493***	−1.426***	1.668***	−1.335***	1.522***
(SE)	(0.131)	(0.157)	(0.134)	(0.165)	(0.132)	(0.159)	(0.148)	(0.184)	(0.138)	(0.167)
Recommend ‘Yes’	0.840***	1.925***	0.880***	1.928***	0.826***	1.967***	0.947***	2.059***	0.905***	1.955***
(SE)	(0.145)	(0.175)	(0.150)	(0.176)	(0.149)	(0.182)	(0.160)	(0.196)	(0.153)	(0.186)
Observations	9792		9792		9792		9792		9792	
AIC	3955		3957		3958		3957		3957	
BIC	4027		4043		4044		4101		4058	
Log-likelihood	−1968		−1967		−1967		−1959		−1965	

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; SD: standard deviation; SE: standard error. Note: *** p<0.001, ** p<0.01, * p<0.05.

Note: *total cost* is continuous variable; Reference categories for the attributes: for *Brand premium* (binary) it is ‘*No* brand premium’; for Medicine *product* attribute is ‘*Pharmacy brand generic*’; for *collect* it is ‘*Now’;* for *recommend* it is *‘(-) no recommendation’*

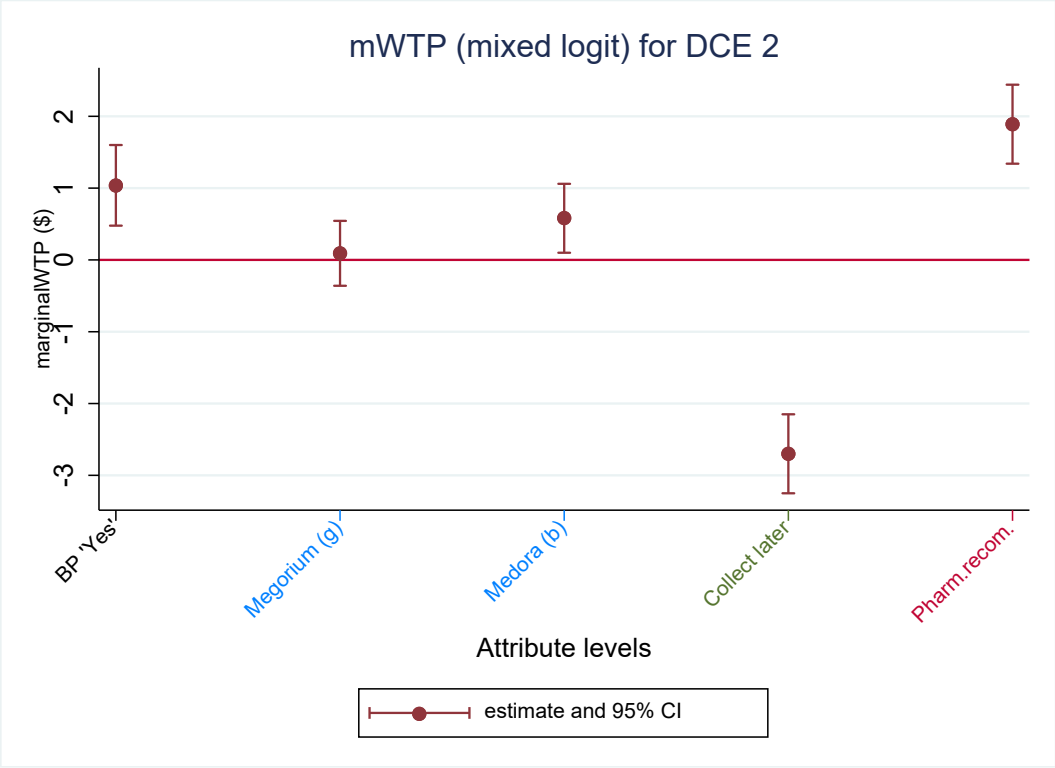
The presentation of the *brand premium* as a binary variable or a continuous variable does not change preferences for the *brand premium* attribute, as is evident from the small and non-significant estimate and standard deviation. The results in Models 4 and 5 show that respondents have stronger preferences for avoiding the brand premium. In Model 4 (categorical *brand premium*) the ($2) and ($10) levels showed statistically significant difference, but the standard deviation for ($5) and ($10) levels indicate that there is large variability in the attitudes towards brand premiums. This is also supported by the results in Model 5, where the estimated preference for *brand premium low* ($2 and $5) level is not significant but the standard deviation is large and significant.

The DCE can be used to identify the trade-offs respondents made between the presented attributes – for example, how much the respondent is willing to pay to buy the *Medora branded* medicine holding everything else equal.

The comparison of the attribute preferences between DCE 2 and DCE 3 can be done by comparing attribute WTP estimates. By estimating WTP for the DCE 2, and for the five models presented in the analysis of *brand premium* attribute for DCE 3, it can be demonstrated how the WTP is affected by the additional information on the *brand premium* attribute.

Figure 4-29 shows the estimated marginal WTP for the DCE 2 sample. The results of WTP for the *brand premium* attribute from the estimated MXL confirm that consumers viewed the brand premium attribute as a positive indicator of the product, and are willing to pay approximately $1 extra, although the wide confidence interval ($0.5–1.6) indicates that there was variation in this inclination. The results from the WTP estimates show that respondents would require a discount in price of the medicine of $2.7 (range: $2.1–3.3) if they cannot collect it immediately. Alternatively, respondents were willing to pay $1.9 (range: $1.3–2.4) more if the product was recommended by the pharmacist. The respondents were also willing to pay a little more if the medicine is *Medora branded*, approximately $0.6 (range: $0.1–1.1). The results indicate that the respondents were not interested in paying extra for another generic compared to the *pharmacy brand generic*.

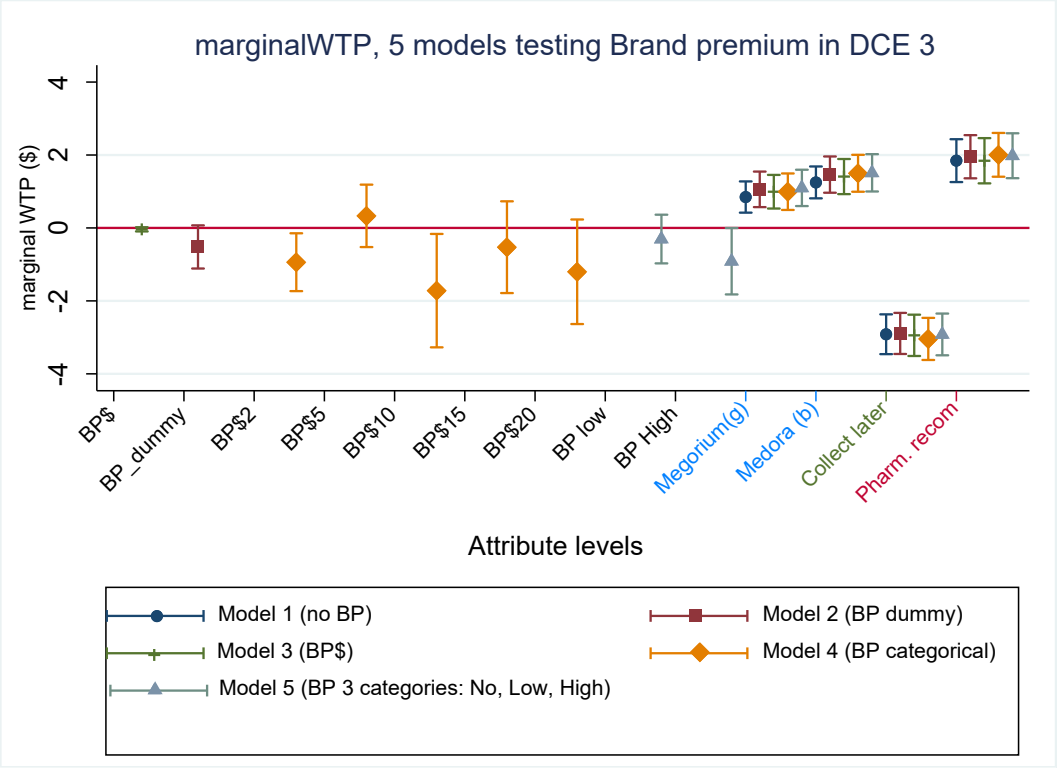
Figure 4-29. Plot of the marginal WTP, DCE 2



In Figure 4-30, the marginal WTP from the MXLs for DCE 3 population sample confirms that marginal rate of substitution are similar across the five models. Additionally, the estimates of WTP in DCE 3 for collect and pharmacist recommended attributes are similar to the estimates in DCE 2. The difference is apparent in the willingness to pay for *Megorium generic* and *Medora branded* medicine. In DCE 3, all else being equal respondents were willing to pay an additional amount, although a rather small amount, for the Megorium generic medicine, compared to respondents in DCE 2.

In the analysis of the five models it appears that the more information the respondents receive about the *brand premium*, the higher the additional amount respondents would be willing to pay for *Megorium generic* and *Medora branded* medicine rather than the *pharmacy brand generic* medicine, although the amounts are not statistically significantly different.

Figure 4-30. Plot of marginal WTP, DCE 3 (5 models)



4.7 Discussion

The aim of this chapter was to analyse two DCEs in relation to prescription medicine with a *brand premium* attribute presented in two different formats.

As with to the results in Chapter 3 (analysis of DCE 1), where respondents were randomised to the minimum amount of information (no *brand premium*), respondents of DCE 2 and DCE 3 showed preferences for lower cost of medicine and immediate collection of the medicine and were open to engaging with the pharmacist.

The DCE 2 respondents were aware only of the presence of the *brand premium* and had a strong preference for a medicine that had the *brand premium* indicator. The results showed that respondents look favourably on the label 'brand premium' and would be willing to pay extra for a medicine that had a *brand premium*. This preference can be explained by the positive associations and impact of the word 'brand premium' on consumer preferences, since the *Megorium generic* medicine was not preferred to the *Pharmacy brand generic*, although *brand premium* and *Megorium generic* would appear some of the time under the same alternative in a choice set.

Respondents randomised to DCE 3 were less likely to choose the medicine with a *brand premium* amount of $2 or $10 compared to the $0 *brand premium*. These respondents saw the amount of *brand premium*

being added to the *total cost* of the product and showed a negative preference for products with a *brand premium*. However, the breakdown analysis of the *brand premium* attribute indicates that there is high variance in the preferences for products with *brand premium*, especially of lower amounts such as $2, $5 and $10.

However, a $5 *brand premium* was more likely to be chosen by the respondents. Each level (above $0) of the *brand premium* attribute was equally represented in the choice tasks. Therefore, there may be something particular about the $5 *brand premium* that was attractive for the majority of the respondents. Additionally, the *total cost* values that the $5 *brand premium* was associated with are $30, $40 and $45, which could be acceptable amounts, close to the current PBS co-payment amounts.

The results of DCE 2 and DCE 3 show that consumers placed a value on the brand premium of the product as a label but showed adverse preferences when they saw that premium comes at a higher cost. As with the results in DCE 1 (Chapter 3), the estimated preferences and willingness to pay results support the current market distortion seen with the existence of 'brand premium' pricing in Australian pharmaceutical policy. Respondents prefer a lower cost medicine; however, they are willing to pay an additional amount for some medicines. The mixed logit and latent class analysis showed that there was significant heterogeneity in preferences for all the attribute levels in the DCEs.

The interesting results were shown in the latent class analysis, where none of the classes had a significant preference for the *brand premium* attribute. This may indicate that respondents react to the presence of the *brand premium* attribute by accepting or rejecting the medicine (depending on their preference); however, this is not the attribute that impacts choice the most.

There were common themes in the results of DCE 2 and DCE 3. First, the order of the presentation of the doctor's script did not influence the preferences for *Medora branded or Megorium generic* medicine. This is important, since the DCEs only looked at an acute medical condition; it would be expected that in a different setting (i.e. chronic condition, or when a repeat prescription is required), the preferences might change with respect to product).

Analysis of DCE 3 showed that respondents were more sensitive to the two medicine products and did show a preference for *Megorium generic* and *Medora (branded)* compared to *Pharmacy brand generic.*

The results show that respondents in both DCE 2 and DCE 3 had strong preferences for shorter wait time for collecting the medicine from the pharmacy and for the pharmacist recommendation when purchasing a product. The DCE 3 respondents had additional information about the components of the *total cost* and the dollar amount of the *brand premium* that contributed to that cost. The result also showed that respondents differentiated between the two generic medicines and the branded medicine.

CHAPTER 5. The impact of a restricted choice hypothetical PBS reimbursement policy

5.1 Overview

As previously discussed, medicines are listed on the Pharmaceutical Benefits Scheme (PBS) by their generic name (active ingredient) rather than by brand. This means that the PBS does not limit listing to a single brand of the medicine if generic brands are available. Where there are two or more brands of the same drug on the PBS Schedule, the government subsidises each brand by the same amount – up to the cost of the lowest priced brand minus the co-payment.

The brand of the medicine that is dispensed can depend on the prescription, availability at the pharmacy and the choice the consumer makes. When writing a prescription, a doctor may specify the medicine by brand name or compound name,[49] and unless the prescriber checks the 'Brand substitution is not permitted' box on the prescription, the pharmacist can dispense any available brand of the drug to the patient.

The policies in Australia provide the environment for price competition, but the structure of the market means there is relatively weak incentive for producers to lower prices, particularly when the brand premium policy allows the originator brand to maintain a higher price. The results in the previous chapters demonstrate that at least some consumers attach value to the brand and are willing to pay a higher price, which provides little incentive for price competition.

To encourage decreases in medicine prices upon the entry of generic brands into the market, the government could introduce and implement a variety of different policies as happens in many international markets in Europe, Asia and New Zealand (Godman et al., 2017; Hassali et al., 2014; Roughead et al., 2018; Vogler et al., 2017). An alternative policy approach that has been implemented in some countries is to introduce competition between the different brands for the right to supply to the market – for example, through a competitive tender process, such as that used in New Zealand (Roughead et al., 2018). The advantage for the government to subsidise only one brand of a medicine is the power to negotiate a much lower price from the supplier, as the bidders (pharmaceutical companies or suppliers) compete on price and volume. Suppliers might not be averse to such a policy, as with only one brand reimbursed by the government, it offers the opportunity for the successful bidder to capture the majority of the market.

Consumers might also benefit from such a reimbursement policy by avoiding potential brand changes

[49] At the time of carrying out this study, the new policy (2019) mandating doctors prescribe using the generic name of the medicine was not in place. Therefore, for the purpose of consistency, it is assumed that the doctor is able to choose whether to write a prescription for a generic name or brand name.

(thereby avoiding confusion) and through a potential reduction in out-of-pocket cost, although such a policy restricts the consumer to a single choice of brand if they are to benefit from the subsidisation. In New Zealand, where such a reimbursement system is used, when the government decides to fund only one brand the estimated savings to government are around NZD30–50 million per year (PHARMAC[50]).

This chapter explores the impact of a hypothetical change in policy to allow PBS listing of only one brand. Likely consumer response to such a policy was tested using the DCE method (DCE 4). There are currently no other surveys using SP methods that investigate this topic.

DCE 4 explores a hypothetical situation in which the government introduces a new subsidisation policy that allows only one brand of a medicine to be subsidised on the PBS. Other brands of the same drug could be approved for sale in Australia, and therefore available for purchase, but the prices of these other brands would not be negotiated with the government, and they could be above, the same as or lower than the agreed PBS price.

The aim of DCE 4 was to understand if consumer preferences for prescription medicines are driven by the PBS listing or whether there are other attributes that drive choice (including cost). The hypothetical policy in the DCE is designed to explore a situation in which the government approves one supplier and negotiates the price with that supplier for access to the PBS subsidy (for example, this may be through a competitive tender process). From the consumer side, the DCE was used to understand respondents' preferences when they still had a choice of several brands of drugs at different prices, but the stable cost at the PBS price was only available with one brand.

DCE 4 was conducted in conjunction with the DCEs reported in earlier chapters. All respondents who had been randomised to and completed DCE 1, DCE 2 or DCE 3 were then presented with DCE 4. The analysis presented in this chapter takes account of the DCE to which respondents were randomised in part one of the survey (and hence to the pricing information presented) through inclusion of an interaction terms.

As with the analyses presented in Chapters 3 and 4 of the DCEs in part one, the main analysis of the 'policy' DCE 4 data is based on conditional logit and random parameter logit (mixed logit) models used to estimate consumer preferences for the product attributes and the resulting preference shares. The consumers' willingness to pay analysis is also presented, as well as a WTP analysis that takes account of the DCE to which they were randomised in part one (and hence of the information about pricing that they have seen).

[50] Information extracted from PHARMAC website: https://pharmac.govt.nz/medicine-funding-and-supply/the-funding-process/the-annual-tender/ (date: 23 July 2021)

5.2 Introduction

The DCEs presented in Chapters 3 and 4 explored situations and attributes with which respondents are likely to have been familiar when purchasing a prescription medicine. In this chapter, I continue to use DCE methods to elicit respondent preferences, but this time the experiment considers a new hypothetical policy scenario. SP techniques, such as DCEs, are useful for exploring new policies, since no market data is available to observe the impact of the new policy.

As described in Chapter 2, all respondent who completed DCEs 1–3 were then asked to complete DCE 4. This was achieved by presenting the DCE 4 introduction and choice sets immediately after completion of the first DCE for each respondent. For DCE 4, the aim was to build on the previous experiments, and most attributes and levels were based on those presented in the previous DCEs. This meant that the setting and the attribute levels were familiar for respondents, although there are differences across the three previous DCEs.

Each respondent was presented with eight choice tasks in DCE 4, with two alternatives in each, and in each choice task respondents were asked to choose the alternative they preferred. Because the hypothetical policy context for the DCE only allowed for one brand of the medicine to be reimbursed by the government (i.e., listed on the PBS), the prescription given by the GP was always for the *compound (active ingredient)* name of the drug.

In the DCE 4, the respondent was asked to assume that they had been prescribed a medicine, but the hypothetical policy context meant that while there were two brands available (*Medora branded* and *pharmacy brand generic*), only one of those medicines is listed on the PBS and available at the PBS price of AUD40. The other medicine is not listed on the PBS and is available at the retail price. The medicine not listed on the PBS has market prices ranging from AUD35 to AUD120. This price range was based on the pharmaceutical pricing rules that included general patient co-payment amount of approximately AUD40, and the range of brand premiums (for the PBS-listed brands) available in Australia in 2017–2018. This price would be set by the pharmaceutical company that does not receive reimbursement from the government. Hence, the aim of the DCE is to test the impact of a potential new government policy of restricted choice, by only allowing one brand to be reimbursed on the PBS. To make this explicit, one new attribute was added to DCE 4 to indicate whether or not the medicine is listed on the PBS (*Listed on the PBS*).

As in the previous DCEs, the choice sets also included attributes that indicate respectively whether the medicine can be collected *now* or collected *Later today*, and whether the *pharmacist recommended* the brand. The presentation of these two attributes has not changed from the presentation used in DCE1, DCE2

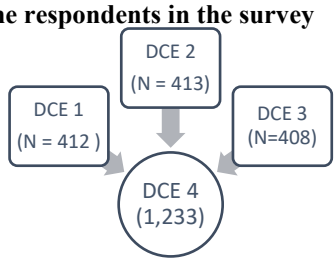
and DCE 3.

This chapter is structured as follows. Sections 5.3 and 5.4 present a brief overview of the survey and the DCE components respectively. In section 5.5 I present the raw responses to DCE 4, showing the overall response rate to some attributes. Section 5.6 presents the empirical analysis, and in section 5.7 I discuss the results. Section 5.8 presents additional analysis of the attitudinal questions towards generic and branded medicines collected during the survey. Section 5.9 presents the discussion.

5.3 The survey data

As described in Chapter 2, the survey data were collected using an online panel that is representative of the Australian population. There were 1233 respondents who completed all DCE task choices of the survey. A flow chart of the respondents in the survey is presented in Figure 5-1. These respondents were included in the final analysis of the data.

Figure 5-1. Flow chart of the respondents in the survey



Abbreviation: DCE: discrete choice experiment; N : total number of respondents in each DCE.

5.4 The DCE task choice

As presented in Figure 5-1 the respondents of DCE 4 had completed one of the versions of Part 1 of the survey (12 choice tasks in one of the three DCEs described in earlier chapters). They were then presented an introduction describing the new information to be considered for Part 2 of the survey. This introduction provided new information asking the respondents to imagine that the PBS reimbursement policy has changed and this information needs to be considered while answering the following eight choice tasks. The text of this introduction is presented below in Figure 5-2.

Figure 5-2. The information presented to the respondents at the start of DCE 4

Part 2 of the survey

Most prescription medicines are subsidised by the government via the Pharmaceutical Benefits Scheme (PBS). This means the patient only pays part of the full cost of the medicine (a co-payment), and the government pays the rest.

Some medicines on the PBS may have a brand premium, which is an additional cost above the co-payment that is charged by the pharmaceutical company.

Now consider a new Government policy.

Under the new policy the government decides to subsidise only one medicine for each condition, it may be the branded medicine or a generic version.

You still have a choice between buying the branded medicine or a generic at the pharmacy, but only one of them has the PBS subsidy.

Usually, the PBS-listed drug will be cheaper than the non-PBS-listed drug, but that is not always the case.

In each choice task, the respondent was asked to consider a situation in which they had been prescribed a medicine by their doctor and needed to get the script filled at a pharmacy. The prescribed medicine is the same across all eight choice tasks presented to them and is described by the active ingredient name rather than a brand name. An example of the choice task is shown in Figure 5-3.

Figure 5-3. Example of the task choice in DCE 4.

Imagine that you have visited your doctor for a minor health condition and your doctor gives you a prescription (below). The doctor said you should start the medicine within the next day or so.

oleaceae 100 mg tablets
Take 3 per day
For 10 days
0 repeat(s)

At the pharmacy, the pharmacist offers you a choice between two medicines. Which option would you choose?

Product	Medora® (*oleaceae*)	Pharmacy brand (oleaceae) - generic medicine
Total price you pay	$40	$90
Listed on the PBS	Yes	-
Available to collect	Now	Later today
Pharmacist recommends	-	-
Please choose one:	○	○

Each alternative in a choice task is characterised by five attributes. The attributes and levels are shown in Figure 5-4.

Figure 5-4. List of attributes and levels used in DCE 4

Attributes	Levels
Product	Pharmacy brand (oleaceae) Medora® (oleaceae) – branded
Total price	$35, $40, $50, $60, $75, $90, $100, $120
Listed on the PBS	No Yes
Collection	Now Later today
Pharmacist recommended	(-) no recommendation Yes

5.5 The data

Prior to estimating various choice models using the data, a review of the responses for listed on the PBS attribute, *Medora branded* product, and total cost are presented.

There were a total of 1233 respondents who completed all eight choice tasks in the DCE 4, resulting in responses to 9864 choice tasks (19,728 observations in the dataset, given that each choice set comprises two options (alternatives)).

The data were tabulated for each of the attribute and are presented in Table 5-1, Table 5-2 and Table 5-3. The number of times the option with listed on the PBS was chosen is summarised in Table 5-1; the number of times the choice containing the *Medora branded* attribute was chosen is presented in Table 5-2, and the number of times options that were not 'listed on the PBS at ($)40' is presented in Table 5-3.

The analysis of the listed on the PBS and the respondents' choice reveals that the option 'listed on the PBS (Yes)' was chosen most often. Of the 9864 choice tasks the option 'listed on the PBS' was chosen 7696 (78%) times.

Table 5-1 presents the distribution of the number of respondents who choose the option 'listed on the PBS' out of eight possible times. Generally, every respondent chose an option that had a 'listed on the PBS attribute' level at least once from among the eight choice tasks, while 168 (13.6%) of respondents always chose an option that had 'listed on the PBS' attribute level.

Table 5-1. Respondents choosing the option with listed on the PBS

Number of times the option was chosen across task choices	Frequency, respondents (n)	%	Chosen by respondent cluster
0	0	0.00	
1	4	0.32	
2	10	0.81	
3	25	2.03	
4	81	6.57	
5	59	4.79	
6	295	23.93	
7	591	47.93	Only one was not PBS
8	168	13.63	All were PBS
Total	1233	100.00	

Note: PBS was chosen: 7696; PBS not chosen: 1895.

Table 5-2 presents the number of times the option that included *Medora branded* medicine was chosen. Each respondent chose a task choice that had *Medora branded* medicine at least once in the eight choice tasks presented to them. In the design, there were 4932 choice tasks in which one of the options included both *Medora branded* and *listed on the PBS attribute levels*. Of these choice tasks, the option containing those two attribute levels was chosen 4086 (82.8%) times.

Table 5-2. Respondents choosing the option with *branded* attribute level

Number of task choices	Frequency, respondents (n)	%	Chosen by respondent cluster
1	11	0.89	
2	3	0.24	
3	96	7.79	
4	339	27.49	
5	259	21.01	
6	326	26.44	
7	162	13.14	Only one chosen was not branded
8	11	0.89	All chosen options had *Medora (b)*
Total	1233	100.00	

The design of the choice set was such that one of the options in each choice set always included listed on the PBS at a total cost of $40. There were 1895 times in which an option other than the one containing listed on the PBS was chosen by the respondents. Table 5-3 presents the distribution of the respondents chosen price that was not PBS ($40).

Table 5-3. Number of respondents choosing an option that was 'not' *listed on the PBS* ($)*40*

Cost $ (not listed on the PBS)	Number of times chosen (%)
$35	852 (69.1)
$40	412 (33.4)
$50	152 (12.3)
$60	120 (9.7)
$75	103 (8.4)
$90	92(7.2)
$100	86(7.0)
$120	78 (6.3)
Total	1895

Note: each respondent saw all price categories

In the majority of cases where the option chosen was one not listed on PBS and total cost was $35 (lower than the $40 PBS price), the raw responses indicate that although 69% of respondents chose the lower price, there were still almost a third of respondents who chose the option that had a listed on the PBS ($40) higher price. In the choice between PBS-listed and not PBS-listed – at an identical cost of $40, the majority of respondents chose the option that had the *listed on the PBS* attribute level.

It should be noted that these are the raw choice data, not controlling for other attributes, and so it is possible that attributes other than price and whether or not the brand was listed on the PBS may have had an impact on the choice. Thus, these raw calculations are only indicative of the respondents' preferences. Additionally, 6–12% of respondents chose the option with the higher price even when the higher price was more than $50. However, the greater the difference between the *total cost* and the *$40 (listed on the PBS*) alternative, the less likely it the option was to be chosen.

This examination of the raw data indicates that there is an overwhelming preference for options with lower cost to the consumer, as well as an inclination to purchase the medicine that was listed on the PBS, although it should be noted that the option in the choice set may often have been much more expensive. Overall, there was a slight inclination to choose the *Medora branded* medicines, but this needs to be evaluated controlling for other attributes to verify whether this was a preference of any respondents.

While these individual attribute summaries are interesting, the analysis presented in the next section can help evaluate the trade-offs people are prepared to make. In particular, it shows for which attribute(s), if any, respondents are willing to pay extra, or whether they would require a monetary compensation to choose that option.

5.6 Statistical analysis

In this section, the results of the regression analysis of the choice data are presented. All analyses were undertaken using Stata version 17 (StataCorp, 2021), with additional latent class models estimated using Latent GOLD version 6 (Statistical Innovations, Inc.) and Rstudio (Rstudio Team, 2020) packages 'gmnl'

(Sarrias & Daziano, 2017) and 'mlogit' (Croissant, 2020). The statistical models used in this chapter to analyse the respondents' choice data from DCE 4 follows the same approach as presented in Chapters 3 and 4. The dataset was analysed using the conditional logit model, the random parameters (mixed) logit model including the estimation of WTP, and latent class model.

In all of the models, the product attribute was a dummy variable, with *Pharmacy brand generic* coded as the base level and *Medora branded* results estimated in the model. The *listed on the PBS* attribute was also a dummy variable with the base level 'no'.

The *total cost* was a continuous variable. The *collection* was a dummy variable with level represented by 'Now' as the base level; and the *pharmacist recommendation* base level '(-) no recommendation' with the response level 'Yes'.

Initially, the conditional logit model is estimated for DCE 4. Then, because the respondents to the DCE 4 had each been randomised to a prior DCE (1-3), as described in the previous chapters, it was important to examine whether there are differences in preferences arising from the context of the prior DCEs. DCE 4 was tested for differences across the three DCEs (1–3).

Therefore, the first analysis looks at whether there are any statistical differences in the preferences in the DCE 4 based on the prior randomisation of the respondents to one of the three DCEs in part one of the survey. This is estimated using a heteroskedastic conditional logit (HCL) model.[51] This test is based on a log-likelihood test comparing a pooled model (across all three prior DCEs) with models based on allowing the coefficients for each prior DCE to differ.

A mixed logit model is also estimated and the marginal WTP evaluated to understand which attributes are significant in respondents' decision making.

The latent class model uses the choices of the respondents to identify whether there are groups of respondents with different preferences.

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[51] The HCL models the relationship between the error variance and a list of user-specified variables, by accounting for heterogeneity in the scale factor (Hensher et al., 1998). Compared to HCL, in a conditional logit model the scale parameter (that is inversely related to error term variance) is usually normalised to unity (Bech et al.,2011) and assumes the error term variance to be constant across individuals (Hole, 2006). The HCL model allows for unequal variances across individuals (Hole, 2006) by specifying an individual specific scale parameter as the function exp (Zn *γ) where Z_n is a vector of individual characteristics (for example, age, gender), and γ is a vector of parameters reflecting the influence of these characteristics on the error variance (Bech et al., 2011). Since the HCL model allows scale to differ, it is used as a tool to investigate the source of variance (i.e. unobserved response variability) (Bech et al., 2011). It models the relationship between the error variance and a list of user-specified variables, by accounting for heterogeneity in the scale factor (Hensher et al., 1998).

5.7 Results DCE 4

5.7.1 Conditional logit

Table 5-4 presents the estimated coefficients of the conditional logit model. Under the new hypothetical 'policy' scenario, the *collection* attribute is not statistically significant, which is different from the results described in Chapters 3 and 4 in the analysis of DCEs 1, 2 and 3.

Overall, across all models, the *listed on the PBS* and *pharmacist recommendation* attributes have the highest preference weights. The estimates for *total cost* are negative with a smaller magnitude (compared to other attributes) yet are statistically significant. This is an indication that cost of the product is important to the respondents when making a choice.

Table 5-4. The pooled conditional logit analysis for DCE 4**.**

Attribute levels	**Conditional logit model for pooled DCE 4**		
	Mean	**SE**	**95% CI**
Total cost ($)	−0.045***	(0.002)	−0.049 — −0.040
Listed on the PBS	0.508***	(0.030)	0.450 — 0.567
Medora branded	0.154***	(0.034)	0.088 — 0.220
Collect 'Later'	−0.073	(0.055)	−0.182 — 0.035
Pharmacist recommended 'Yes'	0.394***	(0.030)	0.335 — 0.452
Observations	19,728		
AIC	7946		
BIC	7985		
Log-likelihood	−3968		

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; CI: confidence interval; SE: robust standard errors; *** p<0.001, ** p<0.01, * p<0.05.
Note: total cost is continuous variable represented in dollar value; Reference categories for the attributes: for *listed on PBS* attribute is "No"; for Medicine *product* attribute is '*pharmacy generic*'; for *collect* it is '*Now';* for *recommend* it is *'(-) no recommendation'.*

To further explore the preferences and the importance of attributes in decision making, and to identify preference heterogeneity in the data, additional pooled conditional logit, mixed logit and latent class models were estimated.

Testing for differences across DCE 1, DCE 2 and DCE 3

A formal test of whether the average preferences of the respondents in the three DCEs from Part 1 of the survey can be restricted to be the same, conditional upon there being different scales, is presented in the estimated models in Table 5-5. The columns for DCE 1, DCE 2 and DCE 3 show the estimated coefficients for DCE 4 when these are allowed to differ across the samples for the three prior DCEs, and the fourth column presents the estimates when the model is constrained to have the same coefficients across all three groups (but allowing for differences in scale by estimating the HCL model[52]).

The unrestricted model has 15 parameters, since the model has five variables for each of the DCEs, and the restricted model has six parameters (five estimated variables in the DCE and scale parameter).

The test statistic is compared to the critical value of the chi-square distribution with nine degrees of freedom at a 5% significance level. (The number of degrees of freedom is given by the number of parameters in the unrestricted model minus the number of parameters in the restricted model (df: 15 – 6 = 9)).

The LR test of equal parameters across the three DCEs has a LR test statistic equal to 14.01 compared to the critical value 16.92 at a 5% significance level in the chi-squared distribution with nine degrees of freedom. Given this test statistic, the hypothesis of overall equal parameters across the three arms is not rejected. This means that there is no evidence that the preferences in DCE 4 differ across the respondents of three prior DCEs for all of the attributes. The result show that expected signs and are consistent across the models. The significance of the *Medora branded* attribute level and *collect 'later'* attribute level differs across the models. While the former has a positive sign across all models, in the model from DCE 2 the estimate is not significant. Although this is an indication of the differences in preference across the three DCE samples, the LR test showed that these differences are not significant across the three DCEs.

[52] This model was used in Chapters 3 and 4 to test the randomisation into Arms 1 and Arm2 (by order of doctor's script).

Table 5-5. Heteroskedastic conditional logit of DCE 4, allowing to differ by DCE 1, DCE 2 and DCE 3

Attribute levels	DCE 1 conditional logit model		DCE 2 conditional logit model		DCE 3 conditional logit model		Heteroskedastic conditional logit model	
	Mean	(SE)	Mean	(SE)	Mean	(SE)	Mean	(SE)
Total cost ($)	−0.044***	(0.004)	−0.050***	(0.005)	−0.041***	(0.004)	−0.046***	(0.005)
Listed on the PBS	0.517***	(0.052)	0.473***	(0.050)	0.533***	(0.053)	0.520***	(0.056)
Medora branded	0.143*	(0.058)	0.109	(0.060)	0.207***	(0.058)	0.157***	(0.037)
Collect 'Later'	−0.059	(0.089)	−0.175	(0.112)	−0.011	(0.090)	−0.075	(0.057)
Pharmacist recommended 'Yes'	0.321***	(0.052)	0.385***	(0.052)	0.476***	(0.051)	0.402***	(0.046)
Scale term (DCE)							−0.011	(0.045)
Observations	6592		6608		6528		9,728	
AIC	2686		2571		2695		7948	
BIC	2720		2605		2729		7995	
Log-likelihood	−1338		−1281		−1342		−3968	
LR test of equal parameters df = 0, critical $\boldsymbol{X^2_{0.95}}$: 14.01 (16.92)								

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; LR: likelihood ratio; SE: robust standard errors; *** p<0.001, ** p<0.01, * p<0.05.

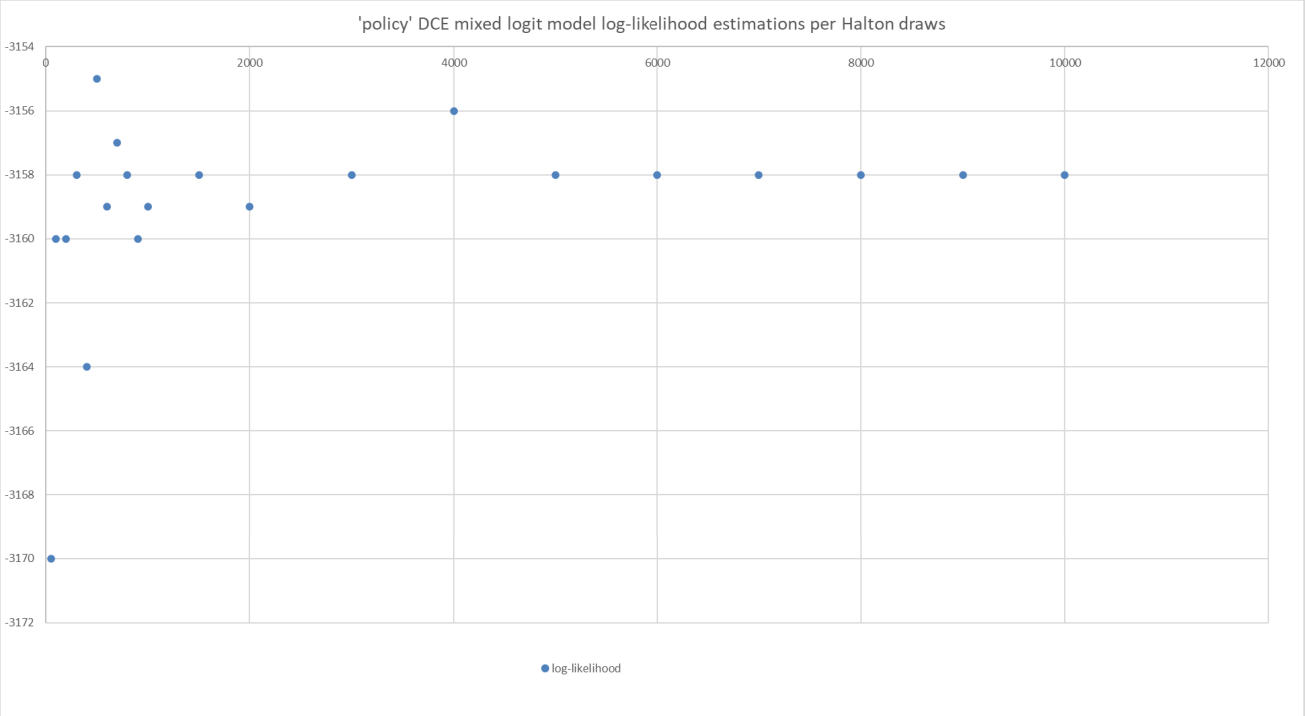
Note: total cost is continuous variable represented in dollar value; Reference categories for the attributes: for *listed on PBS* attribute is "No"; for Medicine *product* attribute is '*pharmacy generic*'; for *collect* it is '*Now';* for *recommend* it is *'(-) no recommendation'*

5.7.2 Mixed logit model

As in the previous chapters, the mixed logit model is used because it allows for random taste variation across the respondents. The mixed logit model allows us to estimate an average preference weight for each attribute for the population, but also allow for differences between individuals (that is, for a distribution of preferences around this mean preference weight).

Similarly to the procedure in Chapters 3 and 4, the model is estimated using Halton sequence methods by repeating the model with different numbers of Halton draws, ranging from 50 to 10,000, and with the first 15 elements of the sequence discarded (Train, 2000). The results of log-likelihood statistics of the 20 estimations of the MXL were matched to the Halton draws 50 to 10,000 and are reported in Figure 5-5. Based on the visual inspection of the log-likelihood, it was decided 1,00 Halton draws was an acceptable number, due to the visually observed stabilisation of the model.

Figure 5-5. Results of simulations used in the mixed logit model by varying the number of Halton draws for DCE 4.



Results in Table 5-6 show the estimated preferences using the mixed logit model. The estimated means of all attributes in the model are statistically significant.

The probability of choosing a medicine brand is a decreasing function of medicine cost and whether or not the medicine is immediately available for collection at the pharmacy. The probability increases when the medicine is listed on the PBS, if the medicine is Medora (the branded medicine) and if the pharmacist recommends the particular medicine.

Apart from the attribute *listed on the PBS* there is significant heterogeneity across the population for all attributes. The standard deviation for the attribute *listed on the PBS* is not significant, suggesting that there is much more homogeneity in preferences for this attribute.

Table 5-6. Results of the mixed logit model for DCE 4

Attribute levels	Mixed logit model (1000 Halton draws)			
	Mean	SE	SD	SE
Total cost ($)	−0.249***	(0.014)	0.167***	(0.011)
Listed on the PBS	0.522***	(0.051)	0.031	(0.228)
Medora branded	0.285***	(0.052)	0.947***	(0.082)
Collect ‘Later’	−0.235*	(0.119)	0.868***	(0.230)
Pharmacist recommended ‘Yes’	0.689***	(0.054)	0.695***	(0.103)
Observations	19,728			
AIC	6337			
BIC	6416			
Log-likelihood	−3159			

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; SD: standard deviation; SE: standard error.
Note: *** p<0.001, ** p<0.01, * p<0.05;
total cost is continuous variable represented in dollar values; Reference categories for the attributes: for *listed on PBS* attribute is "No"; for Medicine *product* attribute is '*pharmacy brand generic*'; for *collect* it is '*Now';* for *recommend* it is *'(-) no recommendation'.*

The results of the mixed logit model were used to calculate an average choice probability for each attribute.[53] Examining the results of *total cost* attribute, 93% of respondents would choose the medicine with the lower cost. A choice probability was estimated for the *product* attribute that showed that for 50% of respondents there was only 0.43 probability of choosing the cheaper medicine.

In the models presented so far the total cost attribute is treated as a continuous variable, and the results show that respondents preferred lower prices. However, it is also possible to estimate separate coefficients for each of the eight cost levels to calculate the choice probabilities for each cost presented to the respondent. The estimates were used for all costs, and not controlled for other attributes (i.e. *listed on the PBS*). The results are presented in Table 5-7.

The highest probability of being chosen is associated with the lowest price of $35 (below PBS of $40) at 0.76 with the $40 price having a probability of 0.22 of being chosen, and $50 price having a probability of only 0.02. All other cost levels have a probability of less than 0.01. This result may reflect the fact that all respondents were exposed to one of the three DCEs in part one of the survey, where the highest price unit was $60.

Table 5-7. Choice probability for total each level of the *total cost* attribute

Cost	$35	$40	$50	$60	$75	$90	$100	$120
Probability	0.76	0.22	0.02	<0.00	<0.00	<0.00	<0.00	<0.00

For the product attribute, on average respondents preferred Medora branded medicine (0.57) compared to the pharmacy brand generic (0.43). Similarly, for the collection attribute, on average respondents were moderately in favour of the collect 'Now' (0.56) compared to collect 'later' (0.44).

For the pharmacist recommended attribute, on average, respondents were strongly in favour of the pharmacist recommended product (0.67) compared to products with no recommendation. The choice probability distribution emphasises this preference, with 75% of respondents having a 0.55 or stronger probability of choosing the option where the pharmacist recommended the product, indicating the strength of the preference.

[53] Calculations performed in Wolfram Mathematica (Wolfram Research, Inc. 2021) with -normal (mean/standard deviation)-, given by $100\times\Phi(-b_k/s_k)$, where Φ is the cumulative standard normal distribution and b_k and s_k are the mean and standard deviation, respectively, of the kth coefficient (Hole, 2007).

Kernel density plots for the variables (attribute levels)

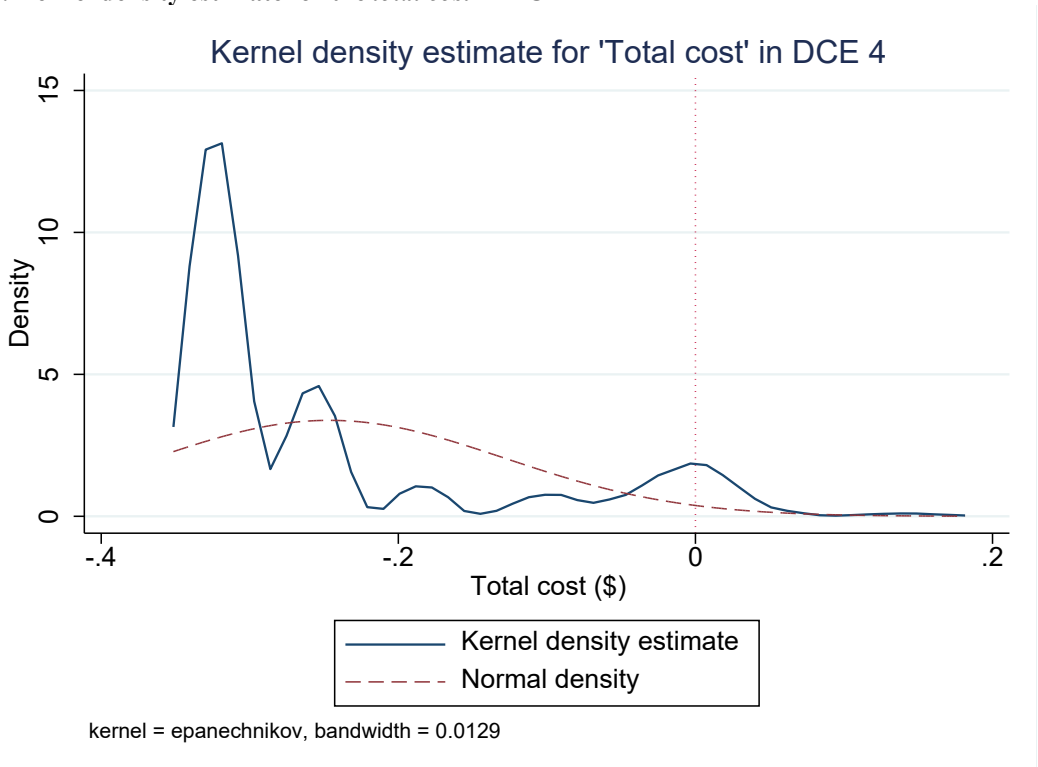
The kernel density plots for each of the estimated parameters are presented in this section. The kernel densities were estimated using the same method as in Chapter 3 and 4 for the DCE 1, DCE 2 and DCE 3 attribute levels. The derived individual-specific parameter estimates were plotted non-parametrically using kernel densities to reveal their distribution across the sampled population.

Each distribution is visually inspected with respect to its shape, size and location with respect to zero.

Total cost attribute

The kernel density plot for the *total cost* attribute is shown in Figure 5-6. The shape of the distribution appears to have a kink (break) after a peak at the far left (negative preference) area. The peak indicates that a many respondents had β_i estimates between −0.4 and −0.2) and a tendency to skew towards the right (zero), with the tail of the plot pulled towards the positive preferences of the high total cost. The majority of the function is located to the left of the zero.

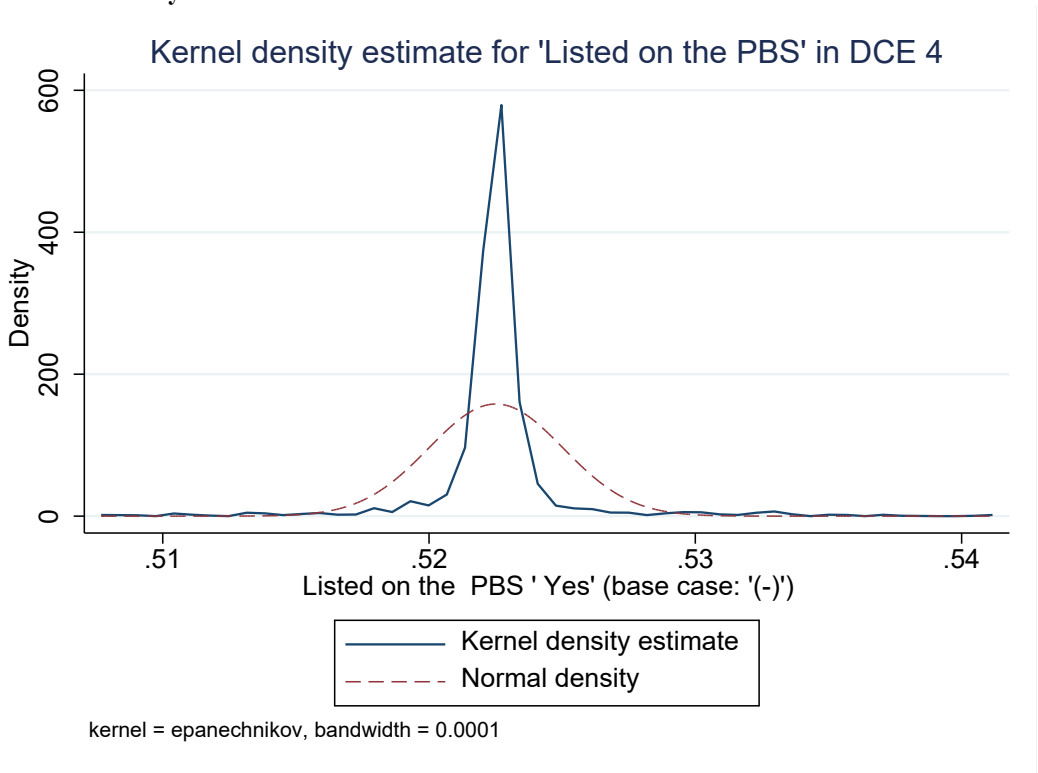
Figure 5-6. Kernel density estimate for the *total cost* in DCE 4



Listed on the PBS

The kernel density plot for the *listed on the PBS* is shown in Figure 5-7. The curve has a symmetric shape. The curves is located to the right of zero and has a high, narrow peak, indicating that most respondents had very strong preferences for the alternative of *listed on the PBS*.

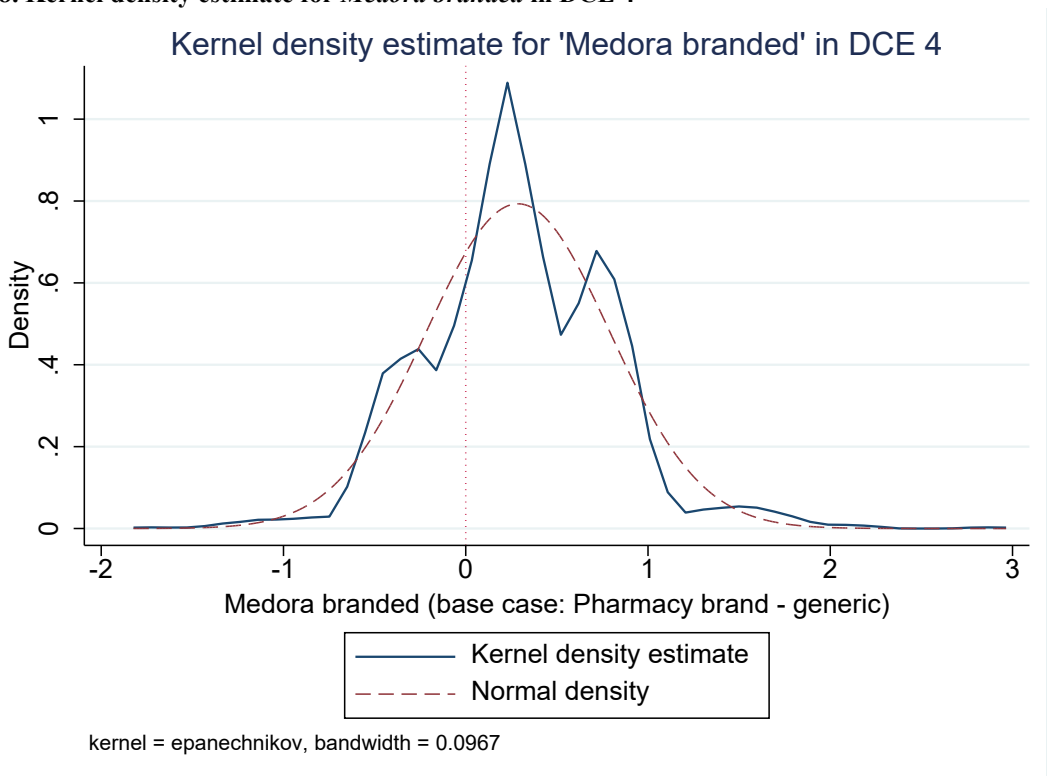
Figure 5-7. Kernel density estimate for *listed on PBS* in DCE 4



Product attribute

The kernel density plot for the *Medora branded* attribute level is shown in Figure 5-8. The shape of the distribution appears to be symmetric about the value of 0.2. The majority of the curve is located to the right of zero, indicating respondents' preference for the *Medora branded* product compared to *pharmacy brand generic*. The distribution width is wide (from −1 to +2), indicating some variation in preferences for this attribute level.

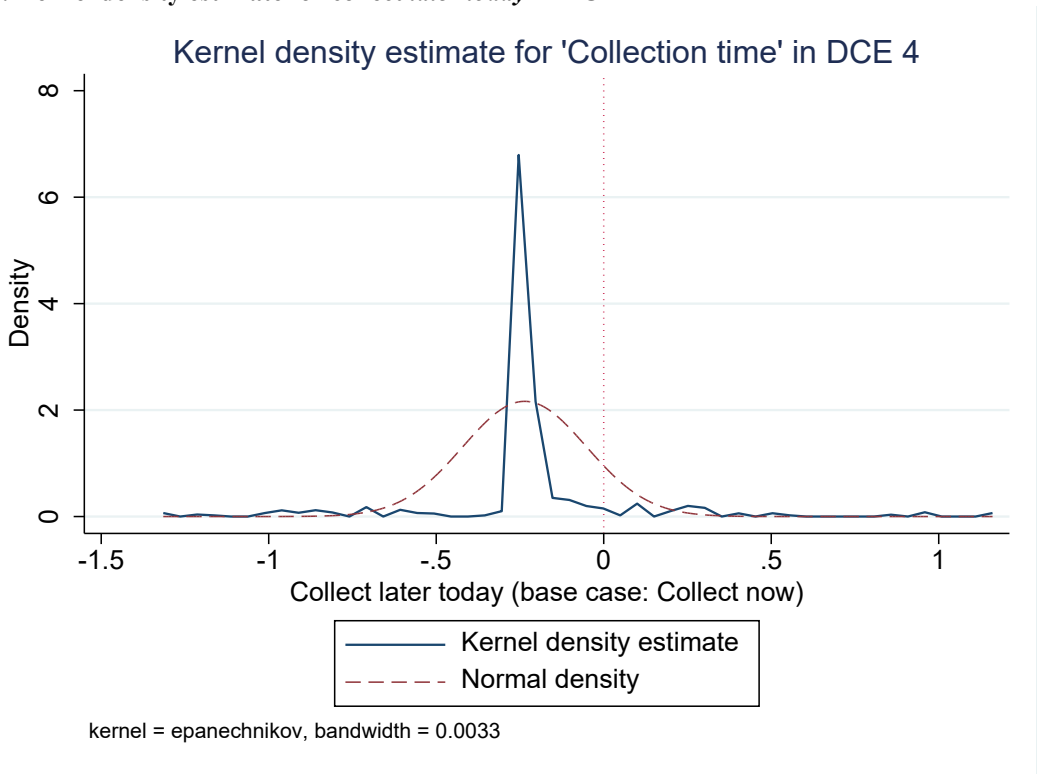
Figure 5-8. Kernel density estimate for *Medora branded* in DCE 4



Collection attribute

The kernel density plot for the *collection* attribute is shown Figure 5-9. The shape of the distribution is symmetric. The curve is located to the left of the zero, indicating respondents' aversion to having to return to the pharmacy to collect the medicine, compared to collecting it immediately. The curve has long tails on both sides, but the narrow and high peak indicated that majority of the preferences were clustered.

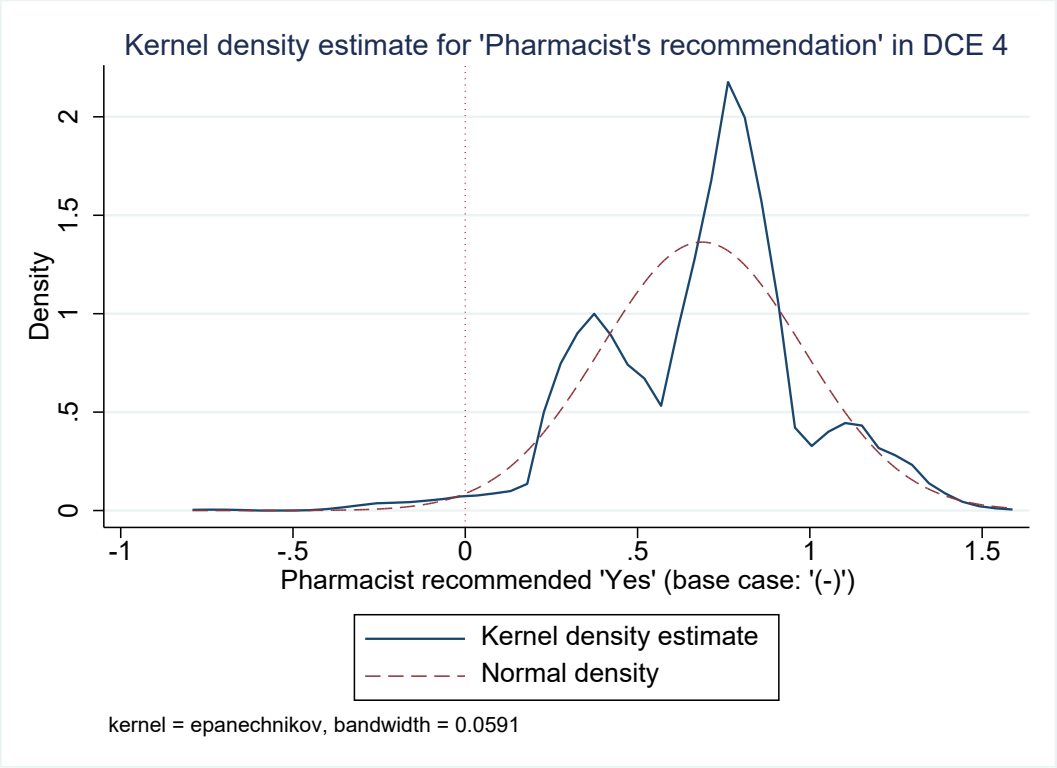
Figure 5-9. Kernel density estimate for collect *later today* in DCE 4



Pharmacist recommended attribute

The kernel density plot for the *pharmacist recommended* attribute is shown in Figure 5-10. The curve is located mostly to the right of zero, indicating positive preferences for the *pharmacist recommended* attribute level. The shape of the distribution has three peaks, indicating some variation in preferences, although the width of the curve across the three peaks is narrow (0.2–1.2). There is a long tail to the left of the curve that crosses the zero line, indicating that there are some respondents who prefer not having the pharmacist recommend a product.

Figure 5-10. Kernel density estimate for *pharmacist recommended (Yes)* in DCE 4



Interacting with DCE 1, DCE 2 and DCE 3

In Chapters 3 and 4, the analysis of DCE 1, DCE 2 and DCE 3 indicated that there was a willingness to pay for the option where the pharmacists recommended the medicine, and a willingness to pick up the medicine later only when the price was lower (or with a discount). Also, there was a general positive preference for the *Medora branded* medicine compared to the *pharmacy brand generic*, although the results were not significant across all three DCEs.

To explore whether the heterogeneity observed in this DCE is explained by the exposure to the information in the prior DCE to which respondents were randomised (DCE 1, DCE 2 or DCE 3), an additional mixed logit model was estimated that included interactions between attribute levels and a dummy variable indicating DCE group. The results of this model are presented in Table 5-8. The group with DCE 1 respondents was treated as the base case. The result showed that the interaction terms had the same sign in all estimates as they had in the general model (shown in the right-hand columns).

However, two attributes showed some differences in preferences among the three DCEs. In the *total cost* attribute, the estimates for the interaction terms were negative and statistically significant from the DCE 1 group (the base case). Recall that DCE 2 and DCE 3 each included an additional attribute shown to the respondent that indicated whether a brand premium was attached to the product, with DCE 3 also showing the monetary value of the brand premium (ranging from $0 (no brand premium) to $20). The difference in

the results (while including the three DCEs) showed that respondents in DCE 2 and DCE 3, who were shown the *brand premium* attribute, were more likely to prefer lower out-of-pocket costs than respondents in DCE 1, who were not shown the *brand premium* attribute. The magnitude of the estimated standard deviations of the total cost showed a large heterogeneity in the responses.

Preferences for the attribute *pharmacist recommendation* were also statistically significantly different across the samples (particularly, for respondents to DCE3). It is possible that the additional brand premium information available to those respondents influences the preference for additional information from the pharmacists when making a choice.

Most estimates were not statistically significant for the interaction terms for the DCE 2 and DCE 3 groups, indicating that differences in preferences for attribute levels on the whole are not related to the DCE groups.

Table 5-8. DCE 4 (mixed logit model) with interaction terms for DCE1, DCE 2 and DCE 3

	Estimates (DCE 1omitted)		Estimates for DCE 2		Estimates for DCE 3		General model (mixed logit)	
VARIABLES	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Total cost	−0.208***	0.137***	–0.107***	0.137***	–0.053**	0.122***	–0.249***	0.167***
(SE)	(0.014)	(0.009)	(0.019)	(0.013)	(0.018)	(0.017)	(0.014)	(0.011)
95%CI	(–0.236 — –0.180)	(0.120 — 0.154)	(–0.144 — –0.070)	(0.112 — 0.161)	(–0.088 — –0.018)	(0.090 — 0.155)	(–0.277 — –0.221)	(0.146 — 0.188)
Listed on the PBS (SE)	0.526***	0.173	0.013	0.131	0.027	0.191	0.522***	0.031
	(0.082)	(0.165)	(0.123)	(0.337)	(0.122)	(0.449)	(0.051)	(0.228)
95%CI	(0.366 — 0.687)	(–0.498 — 0.151)	(–0.228 — 0.254)	(–0.791 — 0.528)	(–0.211 — 0.266)	(–1.071 — 0.689)	(0.423 — 0.622)	(–0.415 — 0.477)
Medora branded (SE)	0.236**	0.915***	–0.033	0.519*	0.196	0.363	0.285***	0.947***
	(0.083)	(0.096)	(0.128)	(0.260)	(0.125)	(0.264)	(0.052)	(0.082)
95%CI	(0.073 — 0.399)	(0.728 — 1.103)	(–0.284 — 0.218)	(–1.028 — –0.009)	(–0.049 — 0.440)	(–0.155 — 0.881)	(0.184 — 0.387)	(0.785 — 1.108)
Collect ‘Later’ (SE)	–0.166	0.289	–0.170	1.740***	–0.002	1.025**	–0.235*	0.868***
	(0.171)	(0.285)	(0.319)	(0.466)	(0.273)	(0.344)	(0.119)	(0.230)
95%CI	(–0.500 — 0.169)	(–0.269 — 0.847)	(–0.794 — 0.455)	(–2.653 — –0.827)	(–0.538 — 0.533)	(–1.700 — –0.351)	(–0.468 — –0.001)	(0.418 — 1.318)
Pharmacist recommended	0.522***	0.509**	0.241	0.801***	0.353**	0.548*	0.689***	0.695***
‘Yes’ (SE)	(0.080)	(0.172)	(0.128)	(0.217)	(0.126)	(0.277)	(0.054)	(0.103)
95%CI	(0.366 — 0.678)	(–0.845 — –0.172)	(–0.010 — 0.491)	(0.376 — 1.226)	(0.105 — 0.601)	(–1.090 — –0.006)	(0.583 — 0.794)	(0.492 — 0.897)
Observations	19,728						19,728	
AIC	6362						6338	
BIC	6599						6416	
Log-likelihood	–3151						–3159	

Abbreviations: AIC: Akaike Information Criteria; BIC: Bayesian Information Criteria; CI: confidence interval; SD: standard deviation; SE: standard error.
Note: DCE 1 (no Brand premium attribute)
DCE 2 (Brand premium attribute as a bivariate (No/Yes))
DCE 3 (brand premium as a $0, $2, $5, $10, $15, $20)
Model with omitted DCE 1 – base case, showing that there is a significant effect of being in DCE 2 compared to DCE 1 with respect to ‘total cost’, and an additional significantly different effect of being in DCE 3 with respect to ‘pharmacist recommendation’.
General model represents the overall effect without interactions.
*** p<0.001, ** p<0.01, * p<0.05

Willingness to pay

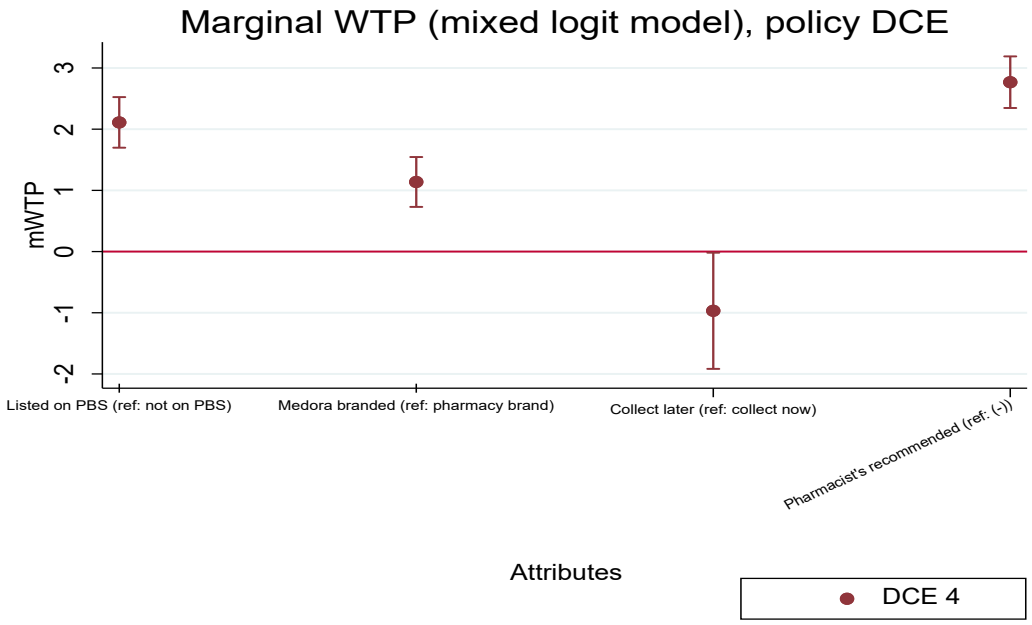
The estimated marginal WTP based on the results from the combined mixed logit model is presented in Figure 5-11. Respondents are willing to pay an additional $2 for the product that is listed on the PBS. The additional WTP for a pharmacist recommended product is $2.8 (holding everything else constant). The respondents are also willing to pay an additional $1.1 for the branded medicine compared to the pharmacy brand generic. However, the results also show that a discount of $1 would be required if the respondents cannot collect the medicine immediately and need to come back later in the day to pick it up. That said, the collect attribute has wide confidence intervals with $p < 0.05$.

Generalising these results, it can be said that respondents prefer a medicine that is listed on the PBS, compared to the other options. The preference for the branded medicine shows that there is an intrinsic value that is attached to the name (brand) of the product, either due to the branded medicine being the original or a perception that there is a difference between branded and generic medicines.

Respondents had strong preferences for the *pharmacist recommendation* attribute. The results may also indicate the trust that is placed in the profession by the respondents.

The results for the *collection* attribute are most likely an indicator of respondents valuing their time and the effort required to return to collect the medicine.

Figure 5-11. Marginal WTP for the mixed logit model of DCE 4



Abbreviations: DCE: discrete choice experiment; PBS: Pharmaceutical Benefits Scheme; mWTP: marginal willingness to pay.
Note: total cost is continuous variable represented in dollar values; Reference categories for the attributes: for *listed on PBS* attribute is "No"; for Medicine *product* attribute is '*pharmacy generic*'; for *collect* it is '*Now';* for *recommend* it is *'(-) no recommendation'*.

Latent class analysis

The latent class analysis of DCE 4 follows the same method as used in Chapters 3 and 4. The latent class analysis was explored using different software packages – Stata 17, LatentGold and Rstudio[54] – to estimate the optimal number of latent class models, starting with two classes and increasing to nine classes. The information criteria BIC (estimated for n=number of observations, and N=number of respondents), AIC and log-likelihood were used to determine the number of optimal classes; the results are presented in Table 5-9.

There are some differences in the results in terms of the optimal number of classes across the different packages. The results from Stata showed that the AIC is minimised with either five or nine classes and the BIC with five classes. The estimations run in LatentGold show that the AIC is minimised with eight classes and the BIC with four classes. The results obtained from Rstudio software indicate a four-class model as optimal.

The results show some consistency in the preferred number of classes across the software, in that the number of classes are close: four classes (LatentGold and Rstudio) or five classes (Stata). The interpretation of the models becomes more difficult as the number of classes increases; therefore the focus of the analysis is on the four- and five-class models.

Results from Stata show that a five-class model is optimal. However, the estimates of that model showed that none of the coefficients for attribute levels in a model with five classes were statistically significant. The four-class model appeared to be optimal in the LatentGold results; however, the estimated class shares were very different from the Stata and Rstudio estimates of a four-class model.

In Rstudio, the results show that a four-class model is optimal. However, for several variables only the mean estimates were produced, and the standard error and confidence interval could not be estimated.

Although a five-class model is preferred using the Stata software analysis, the model (using 'lclogit' command) reported only the estimated mean coefficient in *collection* attribute in some of the classes. The estimates for the standard error (and therefore confidence intervals) could not be computed for some of the classes[55]. Since the other two software packages estimated a four-class model as best fit, and this model also had fully estimated parameters in Stata, it was decided that a four-class model would be used as base

[54] Stata software used the user written 'lclogit' package (Pacifico & Yoo, 2013). LatentGold the embedded 'Choice' package was used. In RStudio a user written package 'gmnl' (Sarrias & Daziano, 2017)

[55] The reported point estimate for the collection attribute in some of the classes in a five-class model were possibly due to the small number of respondents allocated to that class.

case, with the final estimation of the model being performed in Stata (for consistency with previously estimated models).

Table 5-9. Estimated latent class model in Stata, Latent GOLD and Rstudio

Stata output					
Classes	Parameters, N	Log-likelihood	AIC	BIC (N=1,233)	BIC (n=19,728)
2	11	−3093.95	6209.894	6266.184	6296.682
3	17	−3011.09	6056.182	6143.174	6190.308
4	23	−2992.09	6030.169	6147.865	6201.745
5	29	−2924.36	5906.724	6055.123	6115.749
6	35	−2921.61	5913.215	6092.318	6130.019
7	41	−2919.08	5920.166	6129.972	NE
8	47	−2977.14	6048.277	6288.786	NE
9	53	−2899.59	5905.169	6176.381	NE
10	59	−2903.26	5924.523	6226.439	NE
LatentGold Output					
Classes	Parameters, N	Log-likelihood	AIC	BIC (n = 1,233)	NA
2	11	−3093.96	6209.918	6266.207	NA
3	17	−3010.07	6054.141	6141.133	NA
4	23	−2942.68	5931.353	6049.048	NA
5	29	−2924.93	5907.854	6056.253	NA
6	35	−2915.37	5900.732	6079.834	NA
7	41	−2897.47	5876.934	6086.74	NA
8	47	−2891.08	5876.153	6116.662	NA
9	53	−2879.94	5865.887	6137.099	NA
10	59	−2876.88	5871.762	6173.677	NA
Rstudio output					
	Parameters, N	Log-likelihood	AIC	NA	BIC (n=19,728)
2	11	−3094	6209.902	NA	6289.065
3	17	−3094	6075.427	NA	6197.770
4	23	−2992.9	6031.893	NA	6197.416
5	29	−2991.5	6041.096	NA	6249.799
6	35	−2978.2	6026.360	NA	6278.242

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; NA: not available; NE: not estimated.

The results of the latent class model with four classes estimated with Stata are presented in Table 5-10. The estimated Class membership shows that Class 1 contains 22% of the sample, Class 2 contains 47%, Class 3 has 14% and Class 4 17%.

The estimated coefficients for the five variables were different across the four classes and no class is like another. The estimates for Class 1 showed that the *collection* and *listed on the PBS* have the strongest preferences with *pharmacist recommendation* and *total cost* also showing some importance (statistically significant results); however, the attribute for *Medora branded* medicine was not important in this class. This class indicates that respondents would prefer to *collect later*, rather than *collect now*. The estimate and large and although statistically significant at $p < 0.1$; the large confidence intervals leave uncertainty about the magnitude of the effect. This class is the only class with a positive coefficient for the *collection* attribute.

The results for Class 2, the class with the largest class share, showed a strong preference for *pharmacist*

recommendation, *listed on the PBS* and *Medora branded*; however, *total cost* and *collection* were not important. Additionally, the estimated mean for *collection* had extremely large confidence intervals, indicating high uncertainty in the estimates.

The results for Class 3 indicated *pharmacist recommendation* and *collection* attributes were very important, with the *total cost* attribute also showing some importance. The *listed on the PBS* and the *Medora branded* attributes were not important in this class.

The results for Class 4 showed that only the *Medora branded* attribute was important in this class. The *total cost* attribute was significant; however, the mean value was very close to zero (−0.006). This shows that although the product is the most important attribute in this class, cost still plays a role when choosing the medicine.

Table 5-10. Results of the latent class model estimated with four classes for DCE 4

Class	1	2	3	4
Class share	0.22	0.47	0.14	0.17
Total cost ($)				
Mean coefficient	−0.324**	−2.002	−0.130***	−0.006**
SE	0.113	7.166	0.024	0.002
95% CI	(−0.545 — −0.102)	(−16.047 — 12.043)	(−0.177 — −0.083)	(−0.010 — −0.002)
Listed on the PBS				
Mean coefficient	1.972***	0.867***	0.938	0.020
SE	0.477	0.172	0.529	0.077
95% CI	(1.037 — 2.906)	(0.529 — 1.204)	(−0.100 — 1.976)	(−0.130 — 0.171)
Medora branded				
Mean coefficient	0.403	0.616***	0.167	0.212***
SE	0.207	0.153	0.199	0.051
95% CI	(−0.002 — 0.808)	(0.315 — 0.916)	(−0.223 — 0.556)	(0.112 — 0.313)
Collect ‘Later’				
Mean coefficient	8.291*	−56.524	−2.776**	−0.072
SE	4.069	326.109	1.010	0.071
95% CI	(0.316 — 16.266)	(−695.686 — 582.639)	(−4.756 — −0.796)	(−0.212 — 0.068)
Pharmacist recommended ‘Yes’				
Mean coefficient	0.580*	1.079***	2.820***	0.014
SE	0.271	0.184	0.567	0.074
95% CI	(0.049 — 1.112)	(0.717 — 1.440)	(1.708 — 3.932)	(−0.132 — 0.160)
Class constant	0.448	0.922***	−0.230	Reference class
SE	0.319	0.185	0.244	
95%CI	(−0.178 — 1.074)	(0.561 — 1.284)	(−0.708 — 0.248)	
Observations	19,728			
Number of groups	9864			
AIC	6030			
BIC	6211			
Log-likelihood	−2992			

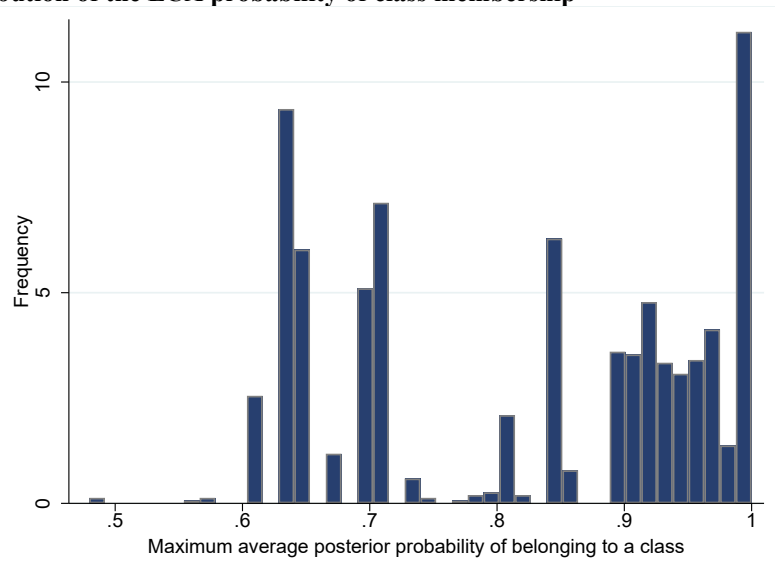
Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; CI: confidence interval; SE: standard error.

Note: *** p<0.001, ** p<0.01, * p<0.05; total cost is continuous variable represented in dollar values; Reference categories for the attributes: for *listed on PBS* attribute is “No”; for Medicine *product* attribute is ‘*pharmacy generic*’; for *collect* it is ‘*Now’;* for *recommend* it is *‘(-) no recommendation’.*

This analysis was run in Stata 17.

The individuals were assigned to one of four classes based on their highest posterior probability of class membership. The performance of the model was evaluated by estimating the average of the highest posterior probability of class membership, 0.82, with the majority of values falling between 0.6 and 1, indicating that the model does fairly well in capturing different underlying taste patterns for the observed choice behaviour (Pacifico & Yoo, 2013). A graphic presentation of the distribution of the estimated posterior probabilities across the respondents is presented as a histogram in Figure 5-12.

Figure 5-12. Distribution of the LCA probability of class membership



Additionally, the model's ability to make in-sample predictions of the actual choice outcomes (by estimating the class membership posterior probability and then predicting the unconditional probability of actual choice and the probability of actual choice conditional on being in a specific class) is presented in Table 5-11.

Table 5-11. The results of the class probability for latent class analysis (DCE 4)

Observations in each class	Class number	Unconditional Probability	Conditional probability
1416	1	0.80	0.93
5584	2	0.85	0.96
1256	3	0.78	0.91
1608	4	0.54	0.51

The assessment of the model performance shows that all probabilities are above 0.5, especially for classes 1, 2 and 3. The probabilities shown for Class 4 are closer to 0.5 and the model thus may not describe the observed behaviour as well. However, in Class 4 other than Medora branded other attributes were not significant (total cost was statistically significant, but a very small estimate), indicating that the respondents did not have strong views (at least regarding the levels chosen in the estimated model).

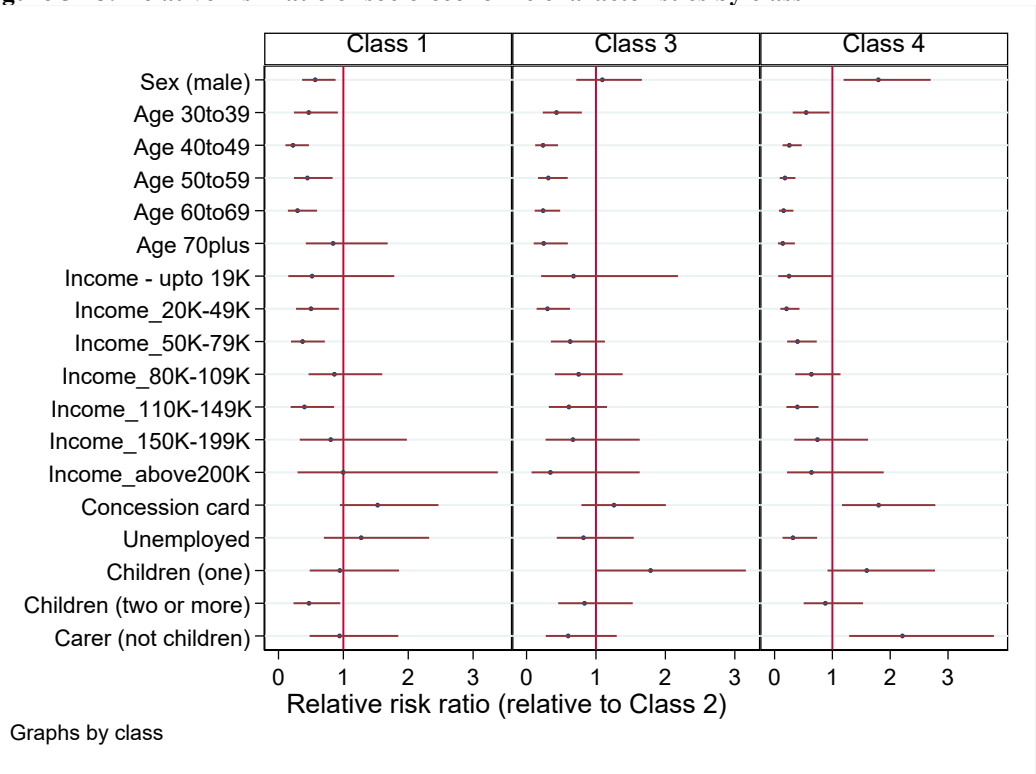
I used the multinomial logit model to investigate the socio-demographic characteristics of each class. Overall, after testing most of the available demographic and socio-economic characteristics (gender, age, country of birth, education level, marital status, household composition, number of children per household, work statis, carer status, household income level, self-reported health status, concession card eligibility, presence of chronic medical condition, and attendance at GP in the past 12 months) collected during the survey, there were seven characteristics that were significant in explaining class membership for respondents in DCE 4. The results are presented in Figure 5-13 as a relative risk ratio and 95% confidence intervals.

The results are presented relative to Class 2, where Class 1 members were less likely to be male, older and less likely to be caring for children in the household. The household income was less likely to be low to medium.

Class 3 members, with respect to Class 2, were less likely to be older and less likely to have a lower income per household. However, they were more likely to have to care for children in the household (although the confidence intervals of the estimate are wide).

Class 4 members whose main preference was for the *Medora branded* attribute level, relative to Class 2, were more likely to be male to be eligible for a concession card and to be a carer (not a child). They were less likely to be older, have a low income and less likely to be unemployed.

Figure 5-13. Relative risk ratio of socio-economic characteristics by class



Note: The base levels for characteristics variables are (shown in parenthesis): Sex (female); Age (10 to 29); Income (AUD 0); Concession card (No concession card); Unemployed (not unemployed: including full-time, part-time, studying, retired); Children (no children); Carer (no carer responsibilities).

5.8 Additional analysis based on attitude and experience questions in the survey

5.8.1 Attitudes towards generic and branded medicines

This section presents the analysis of the additional questions about the respondents' experience with prescription medicines, as well as their attitude towards generic and branded medicines, pharmaceutical companies, and the cost of the medicine.

The survey included three questions which asked respondents about their past experience with branded and/or generic medicines. The respondents were shown seven statements and asked to choose the most appropriate response based on a five-point Likert scale (ranging from Strongly Agree to Strongly Disagree). These questions aimed to assess respondents' attitude towards the branded and generic medicines. The questions are presented in Figure 5-14, as shown to the respondents in the survey.

Figure 5-14. End of survey attitudinal questions (Likert scale)

To what extent do you agree/disagree with the following statements?

Select one response from each row

	Strongly agree	Agree	Neither agree or disagree	Disagree	Strongly disagree
I would choose a generic medicine if the doctor prescribed it	○	○	○	○	○
The pharmacist's recommendation is important to me	○	○	○	○	○
Generic medicines are as effective and safe as branded medicines	○	○	○	○	○
Branded medicines are more effective and safer than generic medicines	○	○	○	○	○
A brand premium indicates better quality	○	○	○	○	○
A pharmaceutical company deserves a brand premium for discovering the medicine	○	○	○	○	○
I would always choose the lowest price medicine	○	○	○	○	○

The statements above were presented to each respondent after they completed all of the DCE 4 choice sets and received information on the meaning of branded and generic products.

Responses on a Likert scale are used to measure respondents' attitudes to a particular question or statement; the data is ordinal and the applied analysis can show that one score is higher than another but not analyse the distance between the points.

5.8.2 Summary of results

Respondents' experiences with generic and branded medicines prior to undertaking the survey

The results suggest that most respondents were familiar with the concept of branded and generic medicines before the survey. Approximately 10% of the respondents had not heard of branded or generic medicine, or were not familiar with the existence of different brands of the same medicine. A summary of the responses is presented in Table 5-12 and Table 5-13. The data presented in Table 5-12

show a summary of the respondents' experience with branded and generic medicines and by each DCE in part one of the survey. The results in Table 5-13 show the summary of responses to attitudinal questions about branded and generic medicines based on a Likert scale.

As noted in the summary of respondent demographics, a small proportion of respondents were medical doctors (3.6%) and pharmacists (2.3%). While the experience of these respondents with respect to prescription medicines is likely to be different from that of the general population, given the small proportion they are not analysed separately. The LCA estimated in the section above showed that there were no significant differences in the responses when the data was tested by including for these groups.

The majority of respondents indicated that they had prior knowledge of the terms 'branded' and 'generic' medicines, and that they had purchased both medicines in the past.

Additionally, 1058 (85.8%) respondents reported that they had consulted a GP (attended, had a GP attendance) in the 12 months prior to the survey; of those, 960 (90.7%) had been issued a prescription. The cross-tabulation of the latter and the results of those who have previously heard of branded or generic medicine, indicates that only 85 (8.9%) respondents who had received a script were not aware of the existence of both branded and generic medicines. This shows that the sample population of the survey was familiar with the Australian health system in terms of utilisation of primary health care resources and pharmaceutical resources.

Table 5-12. Respondents' experiences with branded and generic medicines.

Questions	DCE 1 (%) N = 412	DCE 2 (%) N = 413	DCE 3 (%) N = 408	Total (%) N = 1,233
Before doing this survey, had you heard of the terms "branded" and "generic" medicines?				
Yes	359 (87.4)	375 (91.2)	356 (87.2)	1,090 (88.6)
No	52 (12.6)	36 (8.8)	52 (12.7)	140 (11.4)
Missing observations	1 (0.2)	2 (0.5)	0 (0)	3 (0.2)
Have you ever bought a branded medicine?				
Yes	330 (92.4)	334 (89.3)	321 (90.7)	985 (90.8)
No	5 (1.4)	10 (2.7)	15 (4.2)	30 (2.8)
I do not know	22 (6.2)	30 (8.0)	18 (5.1)	70 (6.4)
Missing observations	55 (13.3)	39 (9.4)	54 (13.2)	148 (12.0)
Have you ever bought a generic medicine?				
Yes	336 (94.1)	338 (90.4)	331 (93.5)	1,005 (92.6)
No	13 (3.6)	14 (3.7)	14 (3.9)	41 (3.8)
I do not know	8 (2.2)	22 (5.9)	9 (2.5)	39 (3.6)
Missing observations	55 (13.3)	39 (9.4)	54 (13.2)	148 (12.0)

Abbreviation: N: total number of respondents.

Respondents' attitudes towards branded and generic medicines

This part presents the results to seven attitudinal questions in relation to generic and branded medicines based on a Likert scale. A total of 1225 (99.3%) respondents completed this part of the survey. The statements and the results by response are presented in Table 5-13.

Table 5-13. Respondents' attitudes towards branded and generic medicines, total N = 1,225[a].

Statement	Strongly agree n (%)	Agree n (%)	Neither agree nor disagree n (%)	Disagree n (%)	Strongly disagree n (%)
(1) I would choose a generic medicine if the doctor prescribed it	430 (35.1)	558 (45.5)	195 (15.9)	25 (2.0)	17 (1.4)
(2) Generic medicines are as effective and safe as branded medicines	407 (33.2)	550 (44.9)	208 (17.0)	42 (3.4)	18 (1.5)
(3) Branded medicines are more effective and safer than generic medicines	77 (6.3)	205 (16.7)	545 (44.5)	298 (24.3)	100 (8.16)
(4) The pharmacist's recommendation is important to me	211 (17.2)	568 (46.7)	367 (30.0)	60 (4.9)	19 (1.5)
(5) A brand premium indicates better quality	90 (7.3)	225 (18.4)	491 (40.1)	307 (25.1)	112 (9.1)
(6) A pharmaceutical company deserves a brand premium for discovering the medicine	87 (7.1)	368 (30.0)	552 (45.12)	162 (13.2)	56 (4.6)
(7) I would always choose the lowest price medicine	342 (27.9)	418 (34.1)	304 (24.8)	132 (10.8)	29 (2.4)

Note: a=there were 8 (0.65%) missing responses.

Respondents favoured generic medicines if the doctor prescribed them (80.2%). The majority of respondents agreed that the generic medicines are as effective and safe as branded medicines (77.6%). More than half of the respondents agreed that the pharmacist's recommendation was important when purchasing the medicine (63.2%), indicating that the pharmacist plays an essential role in the choice for the generic or branded medicine if a generic medicine is available.

Almost two-thirds of the respondents agreed that they would always choose the medicine with the lowest price. A quarter (25.5%) agreed that brand premium indicates better quality of the medicine, with a third (36.9%) also agreeing that the pharmaceutical company deserves a brand premium for discovering the medicine.

There were 12 (0.09%) respondents who always choose 'Strongly Agree', and one respondent who always choose 'Strongly Disagree' to all seven questions.

Further analyses for measure of association of the two categorical variables were performed using Kendall's tau-B[56]. In particular, for statements (2) *Generic medicines are as effective and safe as branded medicines* and (3) *Branded medicines are more effective and safer than generic medicines,* the

[56] Kendall's tau-B is used to quantify the association between ordinal nominal variables, such as Likert-type items. Analysis appropriate for ordinal scale items include the chi-square measure so association Boone, H. N., & Boone, D. A. (2012). Analyzing likert data. *Journal of extension*, *50*(2), 1-5. . The strength of relationship between variables ranges from -1 to +1, where positive sign indicates that increase in one variable leads to increases in the other and a negative sign indicates that as one variable reduces the other increases.

results show a statistically significant correlation between answers to the two statements. The test result showed that the two statements have a statistically significant negative association (Kendall's tau-B = −0.3470, p = 0.000). This shows that respondents who agreed or strongly agreed with statement (2) also disagreed or strongly disagreed with statement (3).

A similar analysis was conducted by analysis the association between statements (1) *I would choose a generic medicine if the doctor prescribed it* and (7) *I would always choose the lowest price medicine.* The prediction was that these two statements would have a degree of association, since the generic medicines would most likely be less expensive. This assumption was confirmed (Kendall's tau-B = −0.2531, p =0.000); although the relationship is weak, it is statistically significant.

Similar results with weak but significant association were seen in analysis of the association between statements (1) *I would choose a generic medicine if the doctor prescribed it* and (4) *The pharmacist's recommendation is important to me.* The prediction was that these two statements would be positively associated as consumers would receive information about the medicine from professionals such as prescribers and pharmacists. This assumption was confirmed (Kendall's tau-B = 0.3122, p = 0.000).

An analysis of associations between statements (3) *Branded medicines are more effective and safer than generic medicines*, (5) *A brand premium indicates better quality* and (6) *A pharmaceutical company deserves a brand premium for discovering the medicine*, showed that the measured association is statistically significant association between all three statements: pair (3) and (5) (Kendall's tau-B = 0.6209, p = 0.000); (3) and (6) (Kendall's tau-B = 0.3287, p = 0.000); and (5) and (6) (Kendall's tau-B = 0.4250, p = 0.00). The strongest association was between the statements (3) and (5). The positive and significant association of statements (3) and (5) with statement (6) showed that respondents answered the three questions consistently.

Comparison with the results from DCE 4 (hypothetical new policy)

In Chapter 5, the analysis of the DCE 4 showed that respondent's preferences vary across the different factors that describe the choice. From the results, it was seen that the attributes *Pharmacist recommended*, *collection*, *total cost*, *brand premium* (DCE 2 and DCE 3) and *product brand* were all important in the decision to purchase a particular prescription medicine.

The questions presented to the respondents after the DCE provide additional information to interpret and understand the results of DCEs.

The stated preferences that are revealed in the DCE differ from the results seen from the attitudinal questions (Likert scale). Each attitudinal question is answered individually as a separate general question (e.g., answering to statement (7) *I would always choose the lowest price medicine*), while in a DCE the respondent makes a choice while having to consider a specific situation based on information about several attributes and their levels. For example, although the majority of respondents indicated that they would purchase a generic brand if the doctor prescribed it (statement 1), the results from the

DCEs in part one showed that that doctor's script had no significant effect on the choice of the brand of medicine the respondents. This result could be due to the respondents not attending (respondents ignoring attributes and thinking them unimportant in that decision-making process) to the doctor's script attribute. Additionally, the responses show that the majority of respondents agreed that generic medicines have same safety and efficacy as branded medicines (statement 2), with only 23% of respondents agreeing or strongly agreeing that branded medicines are more effective and safer than generic medicines (statement 3). However, the results in Chapters 3 to 5 show that respondents preferred *Medora branded* medicine to a generic medicine, although there was a large proportion of respondents who were undecided (neither agreed nor disagreed) with the latter statement, which could also show that it was not easy for the respondents to make a choice based on a single attribute (branded vs generic).

Almost two-thirds (64%) of respondents agreed, at least to some extent, that *pharmacist recommendation* is important in their decision-making process (statement 4). This is consistent with the significant results from the DCEs that the pharmacist plays a major role in the decision-making process.

The response to the *brand premium* statements (statements 5 and 6) show some variability; the respondents in DCE 2 showed a positive preference for the *brand premium* attribute while those in DCE 3 showed a negative preference. The respondents saw different information in each of these DCEs: respondents in DCE 2 only saw an attribute for brand premium, indicating presence or an absence, while those in DCE 3 saw the dollar value attached to the presence of the attribute. Over 40% of respondents were undecided about these two statements. Assessing the results of DCE 2 and DCE3, it was observed that the significance of brand premium changed if the respondents received additional information.

The response to the cost statement had the expected results. While the majority of respondents indicated that they would only buy the cheapest product, there were approximately 13% of respondents who indicated a willingness to pay a higher amount to get the product they prefer. The results across the DCEs also showed that respondents were willing to pay additional amounts to buy *Megorium (generic)* or *Medora branded* medicines (compared to *Pharmacy brand generic*).

Comparison across the three DCEs

An overview of the responses to the seven statements by DCE (DCE 1, DCE 2 and DCE 3) shows few significant differences between the groups. As the attitude questions were presented to all the respondents, it is possible to see the impact of the information provided in each DCE on the answers. The respondents in DCE 1 saw four attributes, with a total cost attribute presented as a single value. Respondents randomised to DCE 2, saw additional information on the brand premium attached to the product; however, they were not shown the value of that brand premium, with the total cost still presented as a single value. The respondents randomised to DCE 3 saw the total cost of the product, as well as the different dollar values of the brand premium as part of the total cost.

The differences in the responses across the three DCEs were analysed using two non-parametric tests,

a Pearson chi-square test and a Kruskal-Wallis rank sum test, as presented in Table 5-14. The Pearson chi-square test helps evaluate the likelihood that the observed differences between the groups are random; the Kruskal-Wallis rank sum test tests the hypothesis that the several groups are from the same population.

Table 5-14. Results of the analysis of differences in the responses to the attitudinal statements by DCEs (in Part 1 of the survey)

Statements	Pearson Chi-square test	Kruskal-Wallis rank sum test
(1) I would choose a generic medicine if the doctor prescribed it	$\boldsymbol{X^2_{0.95}}$ = 2.6832, df = 2, p-value = 0.2614	$\boldsymbol{X^2_{0.95}}$ = 2.7758, df = 2, p-value = 0.2496
(2) Generic medicines are as effective and safe as branded medicines	$\boldsymbol{X^2_{0.95}}$ = 6.1038, df = 2, p-value = **0.04727**	$\boldsymbol{X^2_{0.95}}$4.7746, df = 2, p-value = 0.09188
(3) Branded medicines are more effective and safer than generic medicines	$\boldsymbol{X^2_{0.95}}$ = 0.10143, df = 2, p-value = 0.95	$\boldsymbol{X^2_{0.95}}$ = 0.10756, df = 2, p-value = 0.9476
(4) The pharmacist's recommendation is important to me	$\boldsymbol{X^2_{0.95}}$ = 0.32303, df = 2, p-value = 0.8509	$\boldsymbol{X^2_{0.95}}$ = 0.21339, df = 2, p-value = 0.8988
(5) A brand premium indicates better quality	$\boldsymbol{X^2_{0.95}}$ = 0.81133, df = 2, p-value = 0.6665	$\boldsymbol{X^2_{0.95}}$ = 0.50959, df = 2, p-value = 0.7751
(6) A pharmaceutical company deserves a brand premium for discovering the medicine	$\boldsymbol{X^2_{0.95}}$ = 1.7839, df = 2, p-value = 0.4099	$\boldsymbol{X^2_{0.95}}$ = 2.7552, df = 2, p-value = 0.2522
(7) I would always choose the lowest price medicine	$\boldsymbol{X^2_{0.95}}$ = 5.1271, df = 2, p-value = 0.07703	$\boldsymbol{X^2_{0.95}}$ = 4.4404, df = 2, p-value = 0.1086

Abbreviation: df: degrees of freedom. Bolded value shows statistical significance.

The Kruskal-Wallis test gives a p-value above 0.05 for all the statements, which suggests that, on average, the information in the different DCEs did not influence responses to the attitudinal statements.

However, the test for equal proportions across the three DCEs using the Pearson chi-square test showed that there was a difference across the three DCEs in the responses to statement that *generic medicines are as effective and safe as branded medicines* (statement 2) with a significant result (p = 0.47). This result shows that there was difference in opinion regarding the efficacy and safety of generic medicines compared to branded medicines. This may indicate lack of understanding of generic and branded medicines in Australian population.

The analysis of the responses to the seven statements on the attitude towards several attributes of the medicine products shows that the heterogeneity in preferences for the different attributes presented in the DCEs can be supported via these questions using ordinal responses. However, the DCE method helps elicit the preferences of the consumers with a complex aggregation of attributes, and thus provides an indication of the complex interrelationship among the attributes in the decision-making process.

5.9 Discussion

The aim of this chapter was to use a DCE to investigate the impact on consumer preferences of a hypothetical government policy changing the way medicines are subsidised. Under the hypothetical policy, only one product (per active ingredient) can be listed on the PBS, compared to the current situation where many products containing the same active ingredient can be listed on the PBS. The motivation for testing this policy is that, in theory, a single provider model would reduce the cost of off-patent medicines; the downside of such a policy is the lack of choice available to the consumer. Australia's National Medicines Policy (NMP) aims to provide access to medicines at affordable prices; however, with reimbursement for only one brand of medicine, access to different brands would be limited (or non-existent). If the out-of-pocket price is high, the suppliers of the non-PBS-listed brands would most likely withdraw from the Australian market.

This policy was tested using the DCE method, which allows respondents to state their preferences for the attributes that describe the policy. The ability to use a DCE in a purely hypothetical situation means that it is possible to elicit preferences in relation to potential policy reforms and identify which aspects of the policy would be most important.

The results of the DCE show that most respondents preferred medicines that are available on the PBS, as shown by the results for the *listed on the PBS* attribute (where no heterogeneity was found). The respondents thus indicate that they do not mind lack of choice, with PBS listing seen as a quality indicator – and, of course, price is usually lower for medicines on the PBS.

The new government policy, presented in DCE 4, does allow for some choice of product, but at a higher cost to the consumer. Approximately 50% of the responses indicated that when the non-PBS medicine was chosen, a higher price (AUD50–120) was chosen.

The hypothetical policy presented in the DCE 4 allows only one brand to be reimbursed, with the cost to consumer set at $40 (listed on the PBS). Another brand was available but (mostly) at a higher-than-PBS cost to the respondent. In DCE 4, any medicine that was not PBS-reimbursed was priced between $35 and $120 per script.

The results again show that respondents preferred products that were *listed on the PBS*; this may indicate that they prefer the security of a known price or that they infer that medicine is of higher quality. At the time of this research, there appears to be limited information about utilisation of medicines that were not listed on the PBS. Most of the available information is for those medicines that are not approved by the Therapeutic Drugs Administration, and thus cannot be purchased and administered without a special permit. These medicines were not part of this research. This lack of studies on demand for non-PBS-listed medicines is most likely due to the NMP, which subsidises all brands of approved medicines. This study thus adds to the literature on consumer preferences for medicines, generic or branded, as well as showing role of PBS listing in consumer decision making.

As presented in Chapters 3 and 4, for DCE 1 – 3 the respondents also preferred branded products over pharmacy brand generics. The non-medicine-related factors – such as convenience of collection of the medicine (now or later today) and the pharmacist's recommendation – were also important to the respondents. The marginal WTP showed robust preferences for these attributes.

Exposure to different information conditions across DCE 1-3 seems to have an influence on preferences in DCE 4. The respondents who were randomised to DCE 3 were significantly more likely to prefer to have the pharmacist's recommendation than those who were randomised to DCE 1 and DCE 2. These respondents were presented the dollar amount value of the brand premium attribute as part of the total cost. These results may indicate that, given detailed information of the cost, the respondent would still require the pharmacist's 'advice' to complete the decision-making process. This is most likely a commonsense approach, especially as medicine attributes are limited and the choice is made on factors that an average consumer is not adept at evaluating (i.e., efficacy, side effects, ease of intake).

The results demonstrate that there was a high level of heterogeneity in the sample with respect to preferences for the product. The total cost was not the most significant attribute within these preferences, with *pharmacist recommended* and *listed on the PBS* being the most significant.

The raw estimates of choice (*total cost*, *PBS-listed* and *Medora branded*), presented in section 5.5, show that respondents preferred lower cost; however, there were some for whom the cost was not important. These respondents would choose branded medicine over other attributes.

However, in a hypothetical situation where only one drug brand is reimbursed by the government, and its price is fixed, the respondents' preferences indicate that there are attributes for which they would still be willing to pay a little extra – specifically, collecting the medicine now/later, pharmacist's recommendation and branded medicine.

Therefore, in the situation where the government reimburses for only one brand of a medicine, and other brands can set their own market prices, some respondents indicated that they would pay the higher price if the PBS-listed product did not meet their preference for certain attributes. This may be an indication that consumer preferences depend on individual factors and lack awareness of the features of branded and generic brands.

The relationship between the policy, price and choice of available products is complex. The observed trend in responses shows that although respondents would generally choose lower cost (i.e., listed on the PBS), given a chance they may adapt to accepting a slightly higher price for a medicine that they prefer for other reasons.

Nevertheless, there appears limited understanding and awareness in the population about branded and generic medicines, as was highlighted in the additional analysis of the attitudinal questions presented at the end of the survey. There is also a preference for branded medicines, highlighted in the DCE, with

respondents attributing some value to the 'brand' even though, in this study, the branded and generic brand names were invented for the purpose of the research.

The strong preference for pharmacist recommendation of a product is likely an indication that consumers rely on professional opinion at the point of purchase as they lack information to distinguish between the efficacy, side effects and mode of administration of different medicines. This is a positive outcome, as the role of health professionals is a major pillar of safety and efficacy in using medicines.

There are a number of limitations attributed to DCE 4 and related to the choice of policy. The responders were presented only one policy, within which they had to indicate their preferences. A DCE can also be used to present a choice between different policies and examine the relative preferences of these policies and the attributes that describe them.

Since 2018, when this DCE was conducted, the NMP has undergone some amendments, especially with respect to 'active ingredient' prescribing, mandating that prescribers not use a brand name.

Another limitation, that is present across the DCE 1, DCE 2 and DCE 3, is that the costs presented to the respondents were based on the general patient co-payment (AUD40). However, the majority of PBS expenditure goes towards concessional patients who have a lower co-payment of approximately AUD6. This could imply that for majority of consumers who buy prescription medicines, the PBS-listed medicine is their only choice. Given this limitation, the resulting preferences of these consumers may be all homogeneous, with results of this study not applicable to them.

CHAPTER 6. Thesis discussion

6.1 Overview

Australian pharmaceutical policies have focused on improving accessibility to medicines via the Pharmaceutical Benefits Scheme (PBS) to ensure timely and affordable medicines for consumers. Policies include the subsidisation of the medicines with a fixed patient co-payment, that is lower for concession card holders, and the provision of a safety net for overall expenditure on pharmaceuticals. There have also been broader policies, such as the introduction of generic substitution (1994); the mandatory price reduction (2005) for new generic brands entering the market; and the introduction of price disclosure in the *National Health Amendment (PBS) Act 2007*. Additionally, in 2008 pharmacists were given an incentive payment for dispensing cheaper generic medicines (when appropriate) and, most recently, a mandate that doctors must prescribe using the active ingredient name (*National Health Amendment (Pharmaceutical benefits) Act 2019*) was passed. But not all pharmaceutical policies promote affordability; for example, the Brand Premium Policy (1990) allows branded medicines to be sold at a higher price, offering more choice to the consumer provided they are willing and able to pay extra for that choice.

Insofar as the general objective of Australia's National Medicines Policy is to make necessary and beneficial medicines available to Australians at a cost that is sustainable, the current policies could be seen as having had limited effect. The price disclosure system for branded and generic medicine prices has not been as effective in lowering prices as it potentially could be: when one company can still charge a higher price for its product (potentially above the patient co-payment), other companies do not have as much incentive to lower their prices. Therefore, for market forces to drive prices down, pressure must come from the consumer side. However, the challenge in this market is to understand what drives consumer demand.

While direct-to-consumer advertising of prescription medicines is not permitted in Australia, the consumer can be influenced indirectly, and thus may have a certain perception of the brand of the medicine (Mackenzie et al., 2007). The latter can potentially create demand for medicines based on familiar brand names, the fact that the medicine is branded (original brand), or that it has a brand premium attached to it and thus, for some consumers, is perceived as being better than a generic brand medicine.

This thesis used a quantitative survey method, discrete choice experiments (DCEs), to investigate the preferences of individuals in relation to the purchase of prescription medicines and the impact of particular policies in the Australian context of subsidised access to medicines. The research undertaken aimed to provide insight into issues of preferences for branded versus generic off-patent prescription medicine.

The particular issue explored with respect to the pharmaceutical policy in Australia is the availability of subsidised pharmaceuticals for the Australian population while there is a price difference for the same medicine sold under different brand names. The expiration of the patent for a medicine allows suppliers of generic brands to apply to enter the Australian market. While most medicines would be priced the same irrespective of brand, current policy allows for the original brand to charge a brand premium in addition to the regulated price. The existence of two brands of the same medicine with different price points, both subsidised by the government by an equal amount, has the potential to create further distortion in a market that is heavily regulated. In particular, since at least one brand is able to charge more for the medicine, other producers of the same medicine do not have incentives to compete for customers by lowering their prices if that first brand maintains market share. Further, in the absence of other information, consumers may use price as a signal of quality

To explore Australian consumers' preferences for medicines and the factors that can influence their purchase, a series of related DCEs were developed and implemented. The findings of the literature search were that there are few studies on the preferences for branded versus generic prescription medicines. Of those that exist, most are simple surveys that cannot be analysed using statistical probability models. Therefore, an important contribution of this thesis is to provide quantitative estimates of the impact of brand in the market for medicines.

Overall results across the four DCEs demonstrated that respondents prefer branded products, with strong preferences for non-medicine-related attributes (*collection* and *pharmacist recommended*). Surprisingly, the doctor's prescription (attribute) did not impact the preferences for branded or generic medicines across DCE 1, DCE 2 and DCE 3.

Results in DCE 4 revealed that respondents preferred the PBS-listed product, which suggests that they may prefer the security of established cost; branded products were also preferred, although the choice of the brand was not as important as other factors.

6.2 The impact of brand premium on demand for generic medicines

The presence of brand premium attached to the medicine can have different meanings for each stakeholder. The Australian Government's intention may have been to use it as a price signal to consumers, thereby encouraging the consumer to choose the cheaper (generic) brand of the same medicine, on the assumption that consumers would see all brands as the same. This assumes that the majority of consumers choose the cheaper option, even if there are still some consumers with a

> *"The policy does this by increasing prescribers' and patients' consciousness about the price of drugs. In effect, it makes both groups question whether it is necessary for the patient to pay more for the drugs when a cheaper brand is available. The policy also allows companies to establish prices taking into account competition and consumer acceptance*." (PBS website)

preference for branded medicines that attract brand premiums. The description of the brand premium policy in PBS documents states that it would affect the consumer's purchasing decision, implying that consumers would not choose the brand with a brand premium.

Three DCEs systematically investigated the framing with respect to brand premium attribute as part of the total cost of the medicine (DCE1, DCE 2 and DCE 3) to tease out the effect of price separate from the effect of the label of the brand premium, while a fourth DCE aimed to investigate the impact of only a single brand being subsidised by the government and other brands being sold at a much higher price.

The analysis revealed that all presented attributes were significant determinants of prescription medicine choice, but that there was also significant preference heterogeneity in the population. Additionally, although most respondents preferred lower cost, the strongest preferences were for two non-medicine related attributes: time of collection of the medicine and pharmacist recommendation. This demonstrates that consumers trade on factors other than price.

An important finding in relation to brand was that there was a minority that preferred branded medicines only, and for these consumers this factor was more important than cost. This is an indication that brand name carries value for some consumers, a finding that is notable because in these experiments the brand of the medicine used in the DCE was "invented" specifically for the experiment. This suggests there is a positive value attached to the word 'branded' over and above the attributes of the medicine itself (that is respondents are attributing value to the fact that the medicine has a brand.

The DCEs were also designed to investigate whether the wording and presentation of the script affected choices. The DCEs were set up to provide the information about the medicine in a way that is similar to the prescription that would be provided by the doctor either using branded medicine or a generic compound name, with the order of the prescriptions randomised. The results show that in this DCE the wording of the script did not have a significant impact on preferences for medicines, and this result held regardless of the order in which respondents saw the choice sets (ie with the branded name as the script or the generic name). This result is of interest because it suggests that the change in policy to only use compound names is unlikely to drive preferences either way for consumers.

Overall, the respondents' preference results remained consistent across the three DCEs, with respondents preferring lower cost, medicine with a branded name, a shorter wait time for collection of the medicine from the pharmacy, and pharmacist's recommendations. Consumer preferences most likely depend on individual unobserved factors and inconsistent understanding of branded and generic medicine brands.

Respondents also look favourably on the brand premium label when they are not aware of the additional cost associated with it. Results shows that respondents are willing to pay an additional $1 for the product that has a brand premium attached, when they are unaware that the brand premium is already included in the cost (with costs ranged from $2 to $20). This preference can be explained by positive responses

to the word ‘brand’. This suggests that the wording of the Brand Premium Policy may have led to unintended results.

However, when respondents are given full information about the composition of the total cost, specifically identifying the dollar amount of the brand premium, preference for the medicine with brand premium was low. Additionally, respondents did not show strong preferences for medicines with different amounts of brand premiums. This may signify that even given this information, the respondent may disregard it in their decision making.

6.3 Hypothetical scenario that limits consumer choice

The advantage of using DCEs was the ability to present respondents with hypothetical policy scenarios and to receive feedback on their preferences for goods or services that are currently not available. Collecting data for a possible variation of a policy and understanding consumer preferences is an important tool in the introduction of policy or program. The culminating piece of work in the study presented a hypothetical government policy that only provided PBS subsidisation for one brand product (rather than the current approach of subsidising multiple brands/generics). In this experiment, the cost attribute included a large range – from $35 to $120 – for non-subsidised medicines and a flat $40 for the PBS-subsidised medicine. This scenario resembles New Zealand’s medicine policy, with suppliers competing for a government tender to be the sole provider of the subsidised product.

The results showed a preference for the attribute of being listed on the PBS, indicating either familiarity with the PBS system or a preference for lower price and certainty of cost (set at AUD40). The non-medicine-related factors, such as convenience of collection of the medicine (now or later today) and the pharmacist’s recommendation, were also important to the respondents. However, total cost was not the most significant attribute within these preferences, which is expected as the PBS-listed and total cost attributes were confounded.

Additionally, since the respondents were previously randomised to one of the first three DCEs, there was a difference – a strong preference for pharmacist’s recommendation – in the group of respondents who saw the dollar amount of the brand premium attribute, indicating that given detailed information of the cost (including brand premium amount) the respondent may require the pharmacist’s ‘advice’ to make a choice on which product to purchase, holding all other attributes equal. This is most likely a commonsense approach, especially as medicine attributes are limited and the choice is made on factors that an average consumer is not adept at assessing (efficacy, side effects, type of medicine delivery).

Although the situation in DCE 4 was hypothetical and not intended to be implemented in reality, it reflects to a degree the current situation in Australia, where some brands charge higher prices (with brand premium). The results of DCE 4 show some consumers would pay the higher price if some attributes of the product that is listed on the PBS were consistent with their preferences – for example, collecting the medicine now/later, pharmacist’s recommendation and brand of medicine. This may be

an indication that consumer preferences still depend on individual factors; however, this is also likely impacted by lack of understanding the generic-branded medicine issue.

Additionally, the scenario in which other suppliers remain on the Australian market may only work if the difference in cost (between the subsidised and non-subsidised product) to consumer is minor; otherwise, it may be unreasonable to keep a supply of medicine that very few individuals would choose to buy.

Overall, across all four DCEs the strong preference for the branded medicine could be an indication of brand attachment or general preference of a brand product, which is observed in many other markets for consumer goods. However, the results in these DCEs should be interpreted in the context of current policy and practice.

Taken together, the results of these DCEs suggest that consumers do attach value to brand, and particularly to originator brand for off-patent medicines. Given that the medicines presented in these experiments were hypothetical, this is a preference that goes beyond familiarity or loyalty to the originator product. Moreover, when it was made explicit to consumers that there was a higher price attached to the originator brand (a brand 'premium') this preference persisted, suggesting a willingness to pay for the brand premium. This suggests that the existence of brand premium is likely reinforcing perceptions that there are differences between brands of generic medicines. Indeed, the brand premium policy may be having the unintended impact of signalling a difference in quality, rather than encouraging consumers to choose lower priced medicines. This has the opposite effect of the intention of the Brand Premium Policy.

During the period in which this research was undertaken, a new policy on 'active ingredient prescribing' was implemented as part of the national strategy to improve safety and quality use of medicines. The aims of this policy included equipping consumers to better understand the active ingredients in medicines; assisting conversations between consumers and pharmacists on generic and biosimilar alternatives; promoting appropriate uptake of these to decrease out-of-pocket expenses and improve the financial sustainability of the PBS and RPBS; and enhancing prescribers' PBS stewardship role and encourage more sustainable prescribing practices (Australian Commission on Safety and Quality in Health Care, 2020). The new regulation recognises that doctors' scripts may have been driving the purchase of medicines with brand premium (more expensive medicines). It is notable that this effect was not observed in the DCEs presented in this thesis, where the presentation of the script did not influence choice. However, the DCE cannot capture the effect of conversations that may occur within the consultation, which may be another factor that influences consumers to prefer a particular brand.

The new policy can be seen as being designed to provide greater capacity for the pharmacist to influence the choices that consumers make when filling a script. By using the active ingredient rather than a particular brand in the wording of the script, there is more potential for the pharmacist to engage the

consumer in a conversation about generic brands and branded medicines. This may encourage consumers to choose brands that cost the government less.

Overall, this thesis contributes to the field by providing systematic evidence of the impact of current factors in the pharmaceutical policy on consumers' choice.

6.4 Limitations and future work

An overall challenge was in the development of the DCEs' attributes and levels, with little information about consumer preferences available in this topic. Another challenge was in the development of the DCE 4 focusing on the hypothetical government policy – it was important to make it realistic enough for Australian consumers to treat it as such, yet to give it attributes that would help understand consumers' choices based on the consumer exposure within Australian health care system.

An important limitation of this research is the inability to compare the evidence collected through the DCEs with 'revealed' preference data – for example, a national database that included the doctor's script (branded or generic), the final choice made for that prescription, and the availability of alternatives to the branded medicine at the pharmacy. The DCE method is a 'stated' preference method and has the limitation of reflecting a hypothetical choice made by the respondents. However, the DCE method also has advantages: it allows the experimenter to control for specific factors and analyse their importance, as opposed to only being able to observe a final choice (from a real choice situation); it also provides a faster and less expensive way to collect a large amount of data that allows the experimenter to assess and measure preferences.

The funding of prescription medicines in Australia is multifaceted. This study focuses on the prescription medicines available to consumers under the PBS/RPBS setting. The study does not include cost for over-the-counter medicines, nor look at the medicine pricing arrangements of hospitals in Australia. Some prescription medicines can be purchased over-the-counter without a doctor's script, but these are not subsidised by the PBS.

The PBS medicine price arrangements do not apply to hospitals. Each state in Australia negotiates directly with a manufacturer for the supply of medicines used in hospitals. This has created a large price difference across Australia, with some arrangements being better than those under the PBS schedule (Duckett et al., 2013). The Grattan Institute reports that for identical PBS items (59 drugs) the price gap resulted in expenditure of AUD750 million to AUD1.2 billion for the year 2010.

This research looks at PBS medicines purchased at a general pharmacy with a prescription from a general practitioner. In particular, the conducted study was limited to the GP's prescription for an acute condition.

Future research building the findings on this thesis could test different labels for the brand premium – for example, rather than including the attribute 'brand premium', a label with a negative connotation,

such as ‘brand tax’ or ‘brand levy’, could be assigned. Repeating DCE 1-3 using different attribute labels would help disentangle the impact of the word ‘premium’, since it is plausible that a consumer would not purchase a product if they realised there was an additional tax on the product (rather than a premium)

Additionally, the extension of this work could look into developing a DCE that is more interactive and appropriate for the concession card holders (who have a lower co-payment) and include the impact of the safety net. Additionally, the focus of this thesis was on acute health conditions, while there is evidence that patients with chronic conditions are more likely to choose generic medicines (Denoth et al., 2011). Exploring various attributes in this setting could help identify principal factors that can be explored by policymakers in relation to the decision making by patients with chronic conditions. Lastly, another possible avenue to explore is other non-medicine-specific factors that may impact consumer choice, as the results of this study showed that the time of collection of the medicine and pharmacists’ recommendation where the most important attributes across all DCEs.

6.5 Conclusion

This thesis aimed to explore the impact of the Australian brand premium policy for medicine brands on consumer choice for generic medicines. The results obtained in the study using DCEs suggest that consumers are prepared to pay extra for a branded medicine compared to a non-brand generic product; however, other factors, such as being able collect the medicine immediately and having the pharmacist recommend the product, were more important than brand name.

While the original policy of allowing some brands to charge a higher price was designed to promote consumer choice and act as a signal to consumers, the results from this thesis suggest that the ‘brand premium’ name may have increased demand for branded medicines. The result of a new hypothetical policy with generic and branded medicines available at various prices, showed that generally consumers would choose a cheaper brand that was listed on the PBS. However, other policies that inform the consumer and improve medical literacy, as well as policies that impact other players (i.e. doctor and pharmacists) and their behaviour are important to take account of in this highly regulated area.

The thesis demonstrates the importance of evidence-driven policy, and that it is possible to use techniques, such as DCEs and other SP techniques, to represent the impact of future health policies in order to identify positive and negative impacts prior to roll-out of the policy. By taking an evidence-based approach we can develop and deliver more effective polices to ensure sustainable demand for medicines at a reasonable cost in Australia.

References

Alrasheedy, A. A., Hassali, M. A., Stewart, K., Kong, D. C. M., Aljadhey, H., Ibrahim, M. I. M., & Al-Tamimi, S. K. (2014). Patient knowledge, perceptions, and acceptance of generic medicines: a comprehensive review of the current literature. *Patient Intelligence*, *6*, 1-29.

Alrasheedy, A. A., Hassali, M. A., Stewart, K., Kong, D. C. M., Aljadhey, H., Mohamed Ibrahim, M. I., & Al-Tamimi, S. K. (2014). Patient knowledge, perceptions, and acceptance of generic medicines: a comprehensive review of the current literature. *Patient Intelligence*, *6*, 1-29. https://doi.org/http://dx.doi.org/10.2147/PI.S46737

Anselmsson, J., Bondesson, N. V., & Johansson, U. (2014). Brand image and customers' willingness to pay a price premium for food brands. *Journal of Product & Brand Management*.

Arons, A. M., & Krabbe, P. F. (2013). Probabilistic choice models in health-state valuation research: background, theories, assumptions and applications. *Expert Review of Pharmacoeconomics & Outcomes Research*, *13*(1), 93-108. https://doi.org/10.1586/erp.12.85

Babar, Z.-U.-D., Stewart, J., Reddy, S., Alzaher, W., Vareed, P., Yacoub, N., Dhroptee, B., & Rew, A. (2010). An evaluation of consumers' knowledge, perceptions and attitudes regarding generic medicines in Auckland. *Pharmacy world & science : PWS*, *32*(4), 440-448. https://doi.org/http://dx.doi.org/10.1007/s11096-010-9402-0

Babar, Z. U. D., Kan, S. W., & Scahill, S. (2014). Interventions promoting the acceptance and uptake of generic medicines: a narrative review of the literature. *Health policy (Amsterdam, Netherlands)*, *117*(3), 285-296. https://doi.org/http://dx.doi.org/10.1016/j.healthpol.2014.06.004

Bech, M., Kjaer, T., & Lauridsen, J. (2011). Does the number of choice sets matter? Results from a web survey applying a discrete choice experiment. *Health economics*, *20*(3), 273-286. https://doi.org/10.1002/hec.1587

Beecroft, G. (2007). Generic drug policy in Australia: a community pharmacy perspective. *Australia and New Zealand Health Policy*, *4*(1).

Ben-Akiva, M., Bradley, M., Morikawa, T., Benjamin, J., Novak, T., Oppewal, H., & Rao, V. (1994). Combining revealed and stated preferences data. *Marketing Letters*, *5*(4), 335-349. https://doi.org/10.1007/bf00999209

Ben-Akiva, M. E., Lerman, S. R., & Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel demand* (Vol. 9). MIT press.

Bhat, C. R. (1997). An endogenous segmentation mode choice model with an application to intercity travel. *Transportation science*, *31*(1), 34-48.

Blamey, R. K., Bennett, J. W., Louviere, J. J., Morrison, M. D., & Rolfe, J. (2000). A test of policy labels in environmental choice modelling studies. *Ecological Economics*, *32*(2), 269-286.

Bleichrodt, H., 2002. A new explanation for the difference between time trade-off utilities and standard gamble utilities. Health economics, 11(5), pp.447-456.Boone, H. N., & Boone, D. A. (2012). Analyzing likert data. *Journal of extension*, *50*(2), 1-5.

Breadon, P., Ginnivan, L., Duckett, S., & Venkataraman, P. (2013). Australia's Bad Drug Deal: High Pharmaceutical Prices. *Duckett, SJ with Breadon, P., Ginnivan, L. and Venkataraman, P*.

Bridges, J.F., 2003. Stated preference methods in health care evaluation: an emerging methodological paradigm in health economics. Applied health economics and health policy, 2(4), pp.213-224.Bronnenberg, B. J., Dubé, J.-P., Gentzkow, M., & Shapiro, J.

M. (2015). Do Pharmacists Buy Bayer? Informed Shoppers and the Brand Premium *. *The Quarterly Journal of Economics*, *130*(4), 1669-1726.
Bridges, J.F., Hauber, A.B., Marshall, D., Lloyd, A., Prosser, L.A., Regier, D.A., Johnson, F.R. and Mauskopf, J., 2011. Conjoint analysis applications in health—a checklist: a report of the ISPOR Good Research Practices for Conjoint Analysis Task Force. Value in health, 14(4), pp.403-413
Bulsara, C., McKenzie, A., Sanfilippo, F., Holman, C. A. J., & Emery, J. E. (2010). 'Not the full Monty': a qualitative study of seniors' perceptions of generic medicines in Western Australia. *Australian Journal of Primary Health*, *16*(3), 240-245.
Bunch, D. S., Louviere, J. J., & Anderson, D. (1996). A comparison of experimental design strategies for multinomial logit models: The case of generic attributes. *University of California Davis Graduate School of Management Working Paper*, 11-96.
Burgess, L., Street, D. J., & Wasi, N. (2011). Comparing designs for choice experiments: a case study. *Journal of Statistical Theory and Practice*, *5*(1), 25-46.
Burnham, K. P., & Anderson, D. R. (2002). A practical information-theoretic approach. *Model selection and multimodel inference*, *2*, 70-71.
Burton, B. (2003). Changing prescription software to favour generics could save Australia£ 40m a year. *BMJ: British Medical Journal*, *326*(7382), 184.
Casielles, V. R. and Álvarez, B., 2007. Consumers' characteristics and brand choice behaviour: Loyalty and consumption. Journal of Targeting, Measurement and Analysis for Marketing, 15, pp.121-131.
Cheung, K.L., Wijnen, B.F., Hollin, I.L., Janssen, E.M., Bridges, J.F., Evers, S.M. and Hiligsmann, M., 2016. Using best–worst scaling to investigate preferences in health care. Pharmacoeconomics, 34, pp.1195-1209.
Chong, C. P., March, G., Clark, A., Gilbert, A., Hassali, M. A., & Bahari, M. B. (2011). A nationwide study on generic medicines substitution practices of Australian community pharmacists and patient acceptance. *Health policy*, *99*(2), 139-148.
Clark, M. D., Determann, D., Petrou, S., Moro, D., & De Bekker-Grob, E. W. (2014). Discrete Choice Experiments in Health Economics: A Review of the Literature. *PharmacoEconomics*, *32*(9), 883-902. https://doi.org/10.1007/s40273-014-0170-x
Clarke, P. M., & Fitzgerald, E. M. (2010). Expiry of patent protection on statins: effects on pharmaceutical expenditure in Australia. *Medical Journal of Australia*, *192*(11), 633-636.
Coast, J., Al-Janabi, H., Sutton, E. J., Horrocks, S. A., Vosper, A. J., Swancutt, D. R., & Flynn, T. N. (2012). Using qualitative methods for attribute development for discrete choice experiments: issues and recommendations. *Health economics*, *21*(6), 730-741.
Coast, J. and Horrocks, S., 2007. Developing attributes and levels for discrete choice experiments using qualitative methods. Journal of health services research & policy, 12(1), pp.25-30.
Costa-Font, J., Rudisill, C., & Tan, S. (2014). Brand loyalty, patients and limited generic medicines uptake. *Health policy*, *116*(2-3), 224-233.
Croissant, Y. (2020). Estimation of random utility models in R: the mlogit package. *Journal of Statistical Software*, *95*, 1-41.
Czajkowski, M., & Budziński, W. (2019). Simulation error in maximum likelihood estimation of discrete choice models. *Journal of choice modelling*, *31*, 73-85.
Dahl, D., 2013. Social influence and consumer behavior. Journal of Consumer Research, 40(2), pp.iii-v.
De Bekker-Grob, E. W., Ryan, M., & Gerard, K. (2012). Discrete choice experiments in health economics: a review of the literature. *Health economics*, *21*(2), 145-172. https://doi.org/10.1002/hec.1697

De Bekker-Grob, E. W., Hol, L., Donkers, B., Van Dam, L., Habbema, J. D. F., Van Leerdam, M. E., Kuipers, E. J., Essink-Bot, M. L., & Steyerberg, E. W. (2010). Labeled versus unlabeled discrete choice experiments in health economics: an application to colorectal cancer screening. *Value in Health*, *13*(2), 315-323.

De Bekker-Grob, E.W., Donkers, B., Jonker, M.F. and Stolk, E.A., 2015. Sample size requirements for discrete-choice experiments in healthcare: a practical guide. The Patient-Patient-Centered Outcomes Research, 8, pp.373-384.

Deal, K. (2014). Segmenting Patients and Physicians Using Preferences from Discrete Choice Experiments. *The Patient – Patient-Centered Outcomes Research*, *7*(1), 5-21. https://doi.org/10.1007/s40271-013-0037-9

Denoth, A., Pinget, C., & Wasserfallen, J.-B. (2011). Citizens' Preferences for Brand Name Drugs for Treating Acute and Chronic Conditions. *Applied health economics and health policy*, *9*(2), 81-87. https://doi.org/10.2165/11533030-000000000-00000

DiClemente, D.F. and Hantula, D.A., 2003. Applied behavioral economics and consumer choice. Journal of economic psychology, 24(5), pp.589-602.

Dixit, S. K., & Sambasivan, M. (2018). A review of the Australian healthcare system: A policy perspective. *SAGE open medicine*, *6*, 2050312118769211.

Dobra, R.A., Boeri, M., Elborn, S., Kee, F., Madge, S. and Davies, J.C., 2021. Discrete choice experiment (DCE) to quantify the influence of trial features on the decision to participate in cystic fibrosis (CF) clinical trials. BMJ open, 11(3), p.e045803.

Dolan, P., Gudex, C., Kind, P. and Williams, A., 1996. The time trade-off method: results from a general population study. Health economics, 5(2), pp.141-154.))Duckett, S., & Breadon, P. (2015). Premium policy? Getting better value from the PBS.

Drummond, M.F., Sculpher, M.J., Claxton, K., Stoddart, G.L. and Torrance, G.W., 2015. Methods for the economic evaluation of health care programmes. Oxford university press.

Duckett, S. J., Breadon, P., Ginnivan, L., & Venkataraman, P. (2013). *Australia's bad drug deal: high pharmaceutical prices*. Grattan Institute Melbourne.

Dwivedi, A., Nayeem, T., & Murshed, F. (2018). Brand experience and consumers' willingness-to-pay (WTP) a price premium: Mediating role of brand credibility and perceived uniqueness. *Journal of Retailing and Consumer Services*, *44*, 100-107.

Dylst, P., & Simoens, S. (2010). Generic Medicine Pricing Policies in Europe: Current Status and Impact. *Pharmaceuticals*, *3*(3), 471-481. https://doi.org/10.3390/ph3030471

Dylst, P., & Simoens, S. (2011). Does the Market Share of Generic Medicines Influence the Price Level? *PharmacoEconomics*, *29*(10), 875-882. https://doi.org/10.2165/11585970-000000000-00000

Dylst, P., Vulto, A., Godman, B., & Simoens, S. (2013). Generic medicines: solutions for a sustainable drug market? *Applied health economics and health policy*, *11*(5), 437-443.

Dylst, P., Vulto, A., & Simoens, S. (2013). Demand-side policies to encourage the use of generic medicines: an overview. *Expert Review of Pharmacoeconomics & Outcomes Research*, *13*(1), 59-72. https://doi.org/10.1586/erp.12.83

Dziak, J. J., Coffman, D. L., Lanza, S. T., Li, R., & Jermiin, L. S. (2020). Sensitivity and specificity of information criteria. *Briefings in Bioinformatics*, *21*(2), 553-565. https://doi.org/10.1093/bib/bbz016

Ellis, A., de Bekker-Grob, E., Howard, K., Thomas, K., Lancsar, E., Ryan, M., & Rose, J. (2019). Number of Halton draws required for valid random parameter estimation with discrete choice data. *The patient*, *12*(4), 432-432.

Em Steenkamp, J.-B., Batra, R., & Alden, D. L. (2003). How perceived brand globalness creates brand value. *Journal of international business studies*, *34*(1), 53-65.

Fiebig, D. G., & Hall, J. (2005). 6 Discrete choice experiments in the analysis of health policy. *Quantitative Tools for Microeconomic Policy Analysis*.
Fiebig, D. G., Keane, M. P., Louviere, J., & Wasi, N. (2010). The Generalized Multinomial Logit Model: Accounting for Scale and Coefficient Heterogeneity. *Marketing Science*, *29*(3), 393-421. https://doi.org/10.1287/mksc.1090.0508
Figueiras, M. J., Cortes, M. A., Marcelino, D., & Weinman, J. (2010). Lay views about medicines: the influence of the illness label for the use of generic versus brand. *Psychology and Health*, *25*(9), 1121-1128.
Finkelman, D. P. (1993). Crossing the" zone of indifference". *Marketing Management*, *2*(3), 22.
Folland, S., Goodman, A.C. and Stano, M., 2016. The economics of health and health care: Pearson new international edition. Routledge.
Foxall, G.R., 2017. Behavioral economics in consumer behavior analysis. The Behavior Analyst, 40, pp.309-313.
Gergaud, O., & Livat, F. (2007). *How do consumers use signals to assess quality?*
Godman, B., Kurdi, A., Leporowski, A., Morton, A., Baumgärtel, C., Bochenek, T., Fadare, J., Finlayson, A., Hussein, S., & Khan, B. (2017). Initiatives to increase the prescribing of low cost generics: the case of Scotland in the international context. *Medical Research Archives*, *5*(3).
Graafland, J., 2021. Ethics and Economics: An Introduction to Free Markets, Equality and Happiness. Routledge.
Green, C., & Gerard, K. (2009). Exploring the social value of health-care interventions: a stated preference discrete choice experiment. *Health Econ*, *18*(8), 951-976. https://doi.org/10.1002/hec.1414
Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis: contrasts with mixed logit. *Transportation Research Part B: Methodological*, *37*(8), 681-698.
Gregory, J. (2007). A framework of consumer engagement in Australian health policy. *Health Issues*(91), 22-27.
Gu, Y., Hole, A. R., & Knox, S. (2013). Fitting the generalized multinomial logit model in Stata. *The Stata Journal*, *13*(2), 382-397.
Guttier, M. C., Silveira, M. P. T., Luiza, V. L., & Bertoldi, A. D. (2017). Factors influencing the preference for purchasing generic drugs in a Southern Brazilian city. *Revista de Saúde Pública*, *51*(0). https://doi.org/10.1590/s1518-8787.2017051006786
Haan, P. (2004). *Discrete choice labor supply: conditional logit vs. random coefficient models*.
Hasan, S. S., Kow, C. S., Dawoud, D., Mohamed, O., & Baines, D. (2019). Pharmaceutical policy reforms to regulate drug prices in the Asia Pacific region: the case of Australia, China, India, Malaysia, New Zealand, and South Korea. *Value in health regional issues*, *18*, 18-23.
Hassali, M. A., Alrasheedy, A. A., McLachlan, A., Nguyen, T. A., Al-Tamimi, S. K., Ibrahim, M. I. M., & Aljadhey, H. (2014). The experiences of implementing generic medicine policy in eight countries: A review and recommendations for a successful promotion of generic medicine use. *Saudi Pharmaceutical Journal*, *22*(6), 491-503. https://doi.org/10.1016/j.jsps.2013.12.017
Hassali, M. A., Kong, D. C., & Stewart, K. (2005). Generic medicines: perceptions of consumers in Melbourne, Australia. *International journal of pharmacy practice*, *13*(4), 257-264.

Hassali, M. A., Kong, D. C. M., & Stewart, K. (2010). Generic medicines: perceptions of consumers in Melbourne, Australia. *International journal of pharmacy practice*, *13*(4), 257-264. https://doi.org/10.1211/ijpp.13.4.0004

Hassali, M. A. A., Shafie, A. A., Jamshed, S., Ibrahim, M. I. M., & Awaisu, A. (2010). Consumers' views on generic medicines: A review of the literature. *International journal of pharmacy practice*, *17*(2), 79-88. https://doi.org/10.1211/ijpp.17.02.0002

Hauber, A. B., González, J. M., Groothuis-Oudshoorn, C. G. M., Prior, T., Marshall, D. A., Cunningham, C., Ijzerman, M. J., & Bridges, J. F. P. (2016). Statistical Methods for the Analysis of Discrete Choice Experiments: A Report of the ISPOR Conjoint Analysis Good Research Practices Task Force. *Value in Health*, *19*(4), 300-315. https://doi.org/10.1016/j.jval.2016.04.004

Hausman, Daniel M., "Philosophy of Economics", The Stanford Encyclopedia of Philosophy (Winter 2021 Edition), Edward N. Zalta (ed.)

Hayakawa, H., Imai, S., & Nakata, K. (2018). Empirical Analysis of Brands: A Survey. *The Japanese Economic Review*, *69*(3), 324-339. https://doi.org/10.1111/jere.12187

He, Y., 2021. A General Theory of Giffen Goods. Available at SSRN 3984159Hensher, D., Louviere, J., & Swait, J. (1998). Combining sources of preference data. *Journal of Econometrics*, *89*(1-2), 197-221.

Hensher, D. A., & Greene, W. H. (2002). *The mixed logit model: The state of practice and warnings for the unwary*. Institute of Transport Studies, the University of Sydney and Monash ….

Hensher, D. A., Rose, J. M., Rose, J. M., & Greene, W. H. (2005). *Applied choice analysis: a primer*. Cambridge university press.

Hole, A. (2009). CLOGITHET: Stata module to estimate heteroscedastic conditional logit model.

Hole, A. R. (2006). Small-sample properties of tests for heteroscedasticity in the conditional logit model. *Economics Bulletin*, *3*(18), 1-14.

Hole, A. R. (2007). Fitting mixed logit models by using maximum simulated likelihood. *The Stata Journal*, *7*(3), 388-401.

Hole, A. R. (2013, 2013). Mixed logit modeling in Stata–an overview.

Hole, A. R., & Kolstad, J. R. (2012). Mixed logit estimation of willingness to pay distributions: a comparison of models in preference and WTP space using data from a health-related choice experiment. *Empirical Economics*, *42*(2), 445-469.

Homburg, C., Koschate, N., & Hoyer, W. D. (2005). Do Satisfied Customers Really Pay More? A Study of the Relationship between Customer Satisfaction and Willingness to Pay. *Journal of Marketing*, *69*(2), 84-96. https://doi.org/10.1509/jmkg.69.2.84.60760

Hurley, J., 2000. An overview of the normative economics of the health sector. Handbook of health economics, 1, pp.55-118.

Ito, Y., Hara, K., & Kobayashi, Y. (2020). The effect of inertia on brand-name versus generic drug choices. *Journal of Economic Behavior & Organization*, *172*, 364-379.

Jiang, S., Anis, A. H., Cromwell, I., Mohammadi, T., Schrader, K. A., Lucas, J., Armour, C. M., Clausen, M., Bombard, Y., & Regier, D. A. (2020). Health-care practitioners' preferences for the return of secondary findings from next-generation sequencing: a discrete choice experiment. *Genet Med*, *22*(12), 2011-2019. https://doi.org/10.1038/s41436-020-0927-x

Johnson, F. R., Lancsar, E., Marshall, D., Kilambi, V., Mühlbacher, A., Regier, D. A., Bresnahan, B. W., Kanninen, B., & Bridges, J. F. P. (2013). Constructing experimental designs for discrete-choice experiments: report of the ISPOR conjoint analysis experimental design good research practices task force. *Value in Health*, *16*(1), 3-13.

Johnson, R. and Orme, B., 2010. Sample size issues for conjoint analysis. Getting started with conjoint analysis: strategies for product design and pricing research. Madison: Research Publishers LLC, pp.57-66.
Kleij, K.-S., Tangermann, U., Amelung, V. E., & Krauth, C. (2017). Patients' preferences for primary health care – a systematic literature review of discrete choice experiments. *BMC Health Services Research*, *17*(1). https://doi.org/10.1186/s12913-017-2433-7
Kreps. (2013). Microeconomic foundations. Princeton University Press.
Klose, T., 1999. The contingent valuation method in health care. Health policy, 47(2), pp.97-123.Kuhfeld, W. F. (2006). DISCRETE CHOICE EXPERIMENTS. *The Handbook of Marketing Research: Uses, Misuses, and Future Advances*, 312.
Kwon, H.-Y., Kim, H., Godman, B., & Reich, M. R. (2015). The impact of South Korea's new drug-pricing policy on market competition among off-patent drugs. *Expert Review of Pharmacoeconomics & Outcomes Research*, *15*(6), 1007-1014. https://doi.org/10.1586/14737167.2015.1083425
Lancaster, K., Seear, K., Treloar, C., & Ritter, A. (2017). The productive techniques and constitutive effects of 'evidence-based policy'and 'consumer participation'discourses in health policy processes. *Social Science & Medicine*, *176*, 60-68.
Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of political economy*, *74*(2), 132-157.
Lancsar, E., Fiebig, D. G., & Hole, A. R. (2017). Discrete choice experiments: a guide to model specification, estimation and software. *PharmacoEconomics*, *35*(7), 697-716.
Lancsar, E., & Louviere, J. (2008). Conducting Discrete Choice Experiments to Inform Healthcare Decision Making. *PharmacoEconomics*, *26*(8), 661-677. https://doi.org/10.2165/00019053-200826080-00004
Lancsar, E., Louviere, J., & Flynn, T. (2007). Several methods to investigate relative attribute impact in stated preference experiments. *Social Science & Medicine*, *64*(8), 1738-1753.
Lessing, C., Ashton, T., & Davis, P. (2015). New Zealand patients' understanding of brand substitution and opinions on copayment options for choice of medicine brand. *Australian Health Review*, *40*(3), 345-350.
Lines, S. (2012). Drug patent expirations and the "patent cliff.". *US Pharm*, *37*(6), 12-20.
Linnemer, L. (2002). Price and advertising as signals of quality when some consumers are informed. *International Journal of Industrial Organization*, *20*(7), 931-947.
Lofgren, H. (2004). Generic drugs: international trends and policy developments in Australia. *Australian Health Review*, *27*(1), 39-48.
Lofgren, H. (2007). Reshaping Australian drug policy: the dilemmas of generic medicines policy. *Australia and New Zealand Health Policy*, *4*(1).
Lofgren, H. (2009). Generic medicines in Australia: business dynamics and recent policy reform. *Available at SSRN 1471687*.
Louviere, J.J., Hensher, D.A. and Swait, J.D., 2000. Stated choice methods: analysis and applications. Cambridge university press.
Mackenzie, F. J., Jordens, C. F. C., Ankeny, R. A., McPhee, J., & Kerridge, I. H. (2007). Direct-to-consumer advertising under the radar: the need for realistic drugs policy in Australia. *Internal Medicine Journal*, *37*(4), 224-228. https://doi.org/10.1111/j.1445-5994.2006.01298.x
Mackrill, K., & Petrie, K. J. (2018). What is associated with increased side effects and lower perceived efficacy following switching to a generic medicine? A New Zealand cross-sectional patient survey. *BMJ Open*, *8*(10), e023667. https://doi.org/10.1136/bmjopen-2018-023667

Mangham, L. J., Hanson, K., & McPake, B. (2009). How to do (or not to do) … Designing a discrete choice experiment for application in a low-income country. *Health Policy and Planning*, *24*(2), 151-158. https://doi.org/10.1093/heapol/czn047
Mansfield, S. J. (2014). Generic drug prices and policy in Australia: room for improvement? A comparative analysis with England. *Australian Health Review*, *38*(1), 6. https://doi.org/10.1071/ah12009
Marino, A., & Lorenzoni, L. (2019). The impact of technological advancements on health spending: A literature review.
Mastrobuoni, G., Peracchi, F., & Tetenov, A. (2014). Price as a Signal of Product Quality: Some Experimental Evidence. *Journal of Wine Economics*, *9*(2), 135-152. https://doi.org/10.1017/jwe.2014.17
McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior.
McFadden, D. (1986). The choice theory approach to market research. *Marketing Science*, *5*(4), 275-297.
McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, *15*(5), 447-470.
McManus, P., Birkett, D. J., Dudley, J., & Stevens, A. (2001). Impact of the Minimum Pricing Policy and introduction of brand (generic) substitution into the Pharmaceutical Benefits Scheme in Australia. *Pharmacoepidemiology and drug safety*, *10*(4), 295-300.
Meijer, E., & Rouwendal, J. (2006). Measuring welfare effects in models with random coefficients. *Journal of Applied Econometrics*, *21*(2), 227-244. https://doi.org/10.1002/jae.841
Miguel, F. S., Ryan, M., & Amaya-Amaya, M. (2005). ?Irrational? stated preferences: a quantitative and qualitative investigation. *Health economics*, *14*(3), 307-322. https://doi.org/10.1002/hec.912
Monroe, K. B. (1973). Buyers' subjective perceptions of price. *Journal of marketing research*, *10*(1), 70-80.
Munir, S., Humayon, A. A., Ahmed, M., Haider, S., & Jehan, N. (2017). Brand image and customers' willingness to pay a price premium for female's stitched clothing. *Pakistan Journal of Commerce and Social Sciences (PJCSS)*, *11*(3), 1027-1049.
Murtaugh, P. A. (2014). In defense of P values. *Ecology*, *95*(3), 611-617.
Nardi, E. P., & Ferraz, M. B. (2016). Perception of the value of generic drugs in São Paulo, Brazil. *Cadernos de Saúde Pública*, *32*.
NhaMR, C. (2016). Statement on consumer and community involvement in health and medical research. Consumers Health Forum of Australia,
Pacifico, D., & Yoo, H. I. (2013). Lclogit: A Stata command for fitting latent-class conditional logit models via the expectation-maximization algorithm. *The Stata Journal*, *13*(3), 625-639.
Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., & Brennan, S. E. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *International Journal of Surgery*, *88*, 105906.
Parkin, Michael, and Robin Bade. Microeconomics: Australia in the Global Environment, Pearson Education Australia, 2015.
Payne, K., Fargher, E. A., Roberts, S. A., Tricker, K., Elliott, R. A., Ratcliffe, J., & Newman, W. G. (2011). Valuing pharmacogenetic testing services: a comparison of patients' and health care professionals' preferences. *Value in Health*, *14*(1), 121-134.

Potoglou, D., Burge, P., Flynn, T., Netten, A., Malley, J., Forder, J., Brazier, J.E., 2011. Best–worst scaling vs. discrete choice experiments: An empirical comparison using social care data. Social Science & Medicine 72, 1717–1727.
Probyn, A. J. (2004). Some drugs more equal than others: pseudo-generics and commercial practice. *Australian Health Review*, *28*(2), 207-217.
Productivity, C. (2005a). Economic implications of an ageing Australia.
Productivity, C. (2005b). Impacts of advances in medical technology in Australia. *Productivity Commission, Government of Australia Research Reports*.
Rao, A. R., & Bergen, M. E. (1992). Price premium variations as a consequence of buyers' lack of information. *Journal of consumer research*, *19*(3), 412-423.
Regier, D. A., Ryan, M., Phimister, E., & Marra, C. A. (2009). Bayesian and classical estimation of mixed logit: an application to genetic testing. *Journal of health economics*, *28*(3), 598-610.
Roper, C., Grey, F., & Cadogan, E. (2018). Co-production: Putting principles into practice in mental health contexts. *Melbourne: University of Melbourne*.
Roughead, E. E., Kim, D.-S., Ong, B., & Kemp-Casey, A. (2018). Pricing policies for generic medicines in Australia, New Zealand, the Republic of Korea and Singapore: patent expiry and influence on atorvastatin price. *WHO South-East Asia journal of public health*, *7*(2), 99-106.
Ryan, M., Gerard, K., & Amaya-Amaya, M. (2007). *Using discrete choice experiments to value health and health care* (Vol. 11). Springer Science & Business Media.
Sansom, L. (2004). The subsidy of pharmaceuticals in Australia: processes and challenges. *Australian Health Review*, *28*(2), 194-205.
Sarrias, M., & Daziano, R. (2017). Multinomial logit models with continuous and discrete individual heterogeneity in R: the gmnl package. *Journal of Statistical Software*, *79*, 1-46.
Shavitt, S. and Cho, H., 2016. Culture and consumer behavior: the role of horizontal and vertical cultural factors. Current opinion in psychology, 8, pp.149-154.
Simoens, S. (2007). International comparison of generic medicine prices. *Current Medical Research and Opinion*, *23*(11), 2647-2654. https://doi.org/10.1185/030079907x233395
Soekhai, V., De Bekker-Grob, E. W., Ellis, A. R., & Vass, C. M. (2019). Discrete Choice Experiments in Health Economics: Past, Present and Future. *PharmacoEconomics*, *37*(2), 201-226. https://doi.org/10.1007/s40273-018-0734-2
Soekhai, V., Whichello, C., Levitan, B., Veldwijk, J., Pinto, C. A., Donkers, B., Huys, I., Van Overbeeke, E., Juhaeri, J., & De Bekker-Grob, E. W. (2019). Methods for exploring and eliciting patient preferences in the medical product lifecycle: a literature review. *Drug Discovery Today*, *24*(7), 1324-1331. https://doi.org/10.1016/j.drudis.2019.05.001
Speckemeier, C., Krabbe, L., Schwenke, S., Wasem, J., Buchberger, B. and Neusser, S., 2021. Discrete choice experiment to determine preferences of decision-makers in healthcare for different formats of rapid reviews. Systematic Reviews, 10, pp.1-8.
Srivastava, R. K., & Wagh, S. (2020). Factors impacting consumer purchase behaviour for pharmaceutical products. *International Journal of Healthcare Management*, *13*(2), 113-121. https://doi.org/10.1080/20479700.2017.1348004
Street, D. J., & Burgess, L. (2007). *The construction of optimal stated choice experiments: theory and methods* (Vol. 647). John Wiley & Sons.
Street, D. J., & Viney, R. (2019). Design of Discrete Choice Experiments. In *Oxford Research Encyclopedia of Economics and Finance*.

Swait, J., & Louviere, J. (1993). The role of the scale parameter in the estimation and comparison of multinomial logit models. *Journal of marketing research*, *30*(3), 305-314.
Train, K. (2000). Halton sequences for mixed logit.
Train, K., & Weeks, M. (2005). Discrete choice models in preference space and willingness-to-pay space. In *Applications of simulation methods in environmental and resource economics* (pp. 1-16). Springer.
Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge university press.
Trapero-Bertran, M., Rodríguez-Martín, B., & López-Bastida, J. (2019). What attributes should be included in a discrete choice experiment related to health technologies? A systematic literature review. *PLOS ONE*, *14*(7), e0219905. https://doi.org/10.1371/journal.pone.0219905
Van den Broek-Altenburg, E., & Atherly, A. (2020). Using discrete choice experiments to measure preferences for hard to observe choice attributes to inform health policy decisions. *Health Economics Review*, *10*(1), 1-8.
Van Der Schans, S., Vondeling, G. T., Cao, Q., Van Der Pol, S., Visser, S., Postma, M. J., & Rozenbaum, M. H. (2021). The impact of patent expiry on drug prices: insights from the Dutch market. *Journal of Market Access & Health Policy*, *9*(1), 1849984. https://doi.org/10.1080/20016689.2020.1849984
Vass, C., Rigby, D. and Payne, K., 2017. The role of qualitative research methods in discrete choice experiments: a systematic review and survey of authors. Medical Decision Making, 37(3), pp.298-313.
Vass, C. M., Wright, S., Burton, M., & Payne, K. (2018). Scale Heterogeneity in Healthcare Discrete Choice Experiments: A Primer. *The Patient – Patient-Centered Outcomes Research*, *11*(2), 167-173. https://doi.org/10.1007/s40271-017-0282-4
Verma, D., & Gupta, S. S. (2004). Does higher price signal better quality? *Vikalpa*, *29*(2), 67-78.
Vermunt, J. K., & Magidson, J. (2005). Technical guide for Latent GOLD 4.0: Basic and advanced. *Belmont Massachusetts: Statistical Innovations Inc*.
Viney, R., Lancsar, E. and Louviere, J., 2002. Discrete choice experiments to measure consumer preferences for health and healthcare. Expert Review of Pharmacoeconomics & Outcomes Research, 2(4), pp.319-326.
Viney, R., Savage, E., & Louviere, J. (2005). Empirical investigation of experimental design properties of discrete choice experiments in health care. *Health economics*, *14*(4), 349-362. https://doi.org/10.1002/hec.981
Vitry, A. I., Thai, L., & Roughead, E. E. (2015). Pharmaceutical pricing policies in Australia. In *Pharmaceutical prices in the 21st century* (pp. 1-23). Springer.
Vogler, S., Gombocz, M., & Zimmermann, N. (2017). Tendering for off-patent outpatient medicines: lessons learned from experiences in Belgium, Denmark and the Netherlands. *Journal of Pharmaceutical Health Services Research*, *8*(3), 147-158.
Vondeling, G. T., Cao, Q., Postma, M. J., & Rozenbaum, M. H. (2018). The impact of patent expiry on drug prices: a systematic literature review. *Applied health economics and health policy*, *16*(5), 653-660.
Warshaw, P.R. and Dröge, C., 1986. Economic utility versus the attitudinal perspective of consumer choice. Journal of economic psychology, 7(1), pp.37-60.
Wilcox, R. (2017). Modern Statistics for the Social and Behavioral Sciences. https://doi.org/10.1201/9781315154480
Willis, E., Reynolds, L., & Rudge, T. (2019). *Understanding the Australian health care system*. Elsevier Health Sciences.

Zhou, M., Thayer, W. M., & Bridges, J. F. P. (2018). Using Latent Class Analysis to Model Preference Heterogeneity in Health: A Systematic Review. *PharmacoEconomics*, *36*(2), 175-187. https://doi.org/10.1007/s40273-017-0575-4

Zucchini, W. (2000). An introduction to model selection. *Journal of mathematical psychology*, *44*(1), 41-61.

Appendix A

Figure 0-1. Simulation results – estimated means and standard errors

Selected priors for each attributes (in order from left to right)

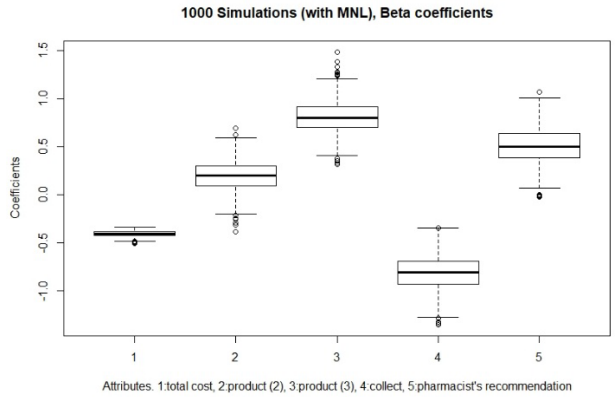
(−0.4) total cost

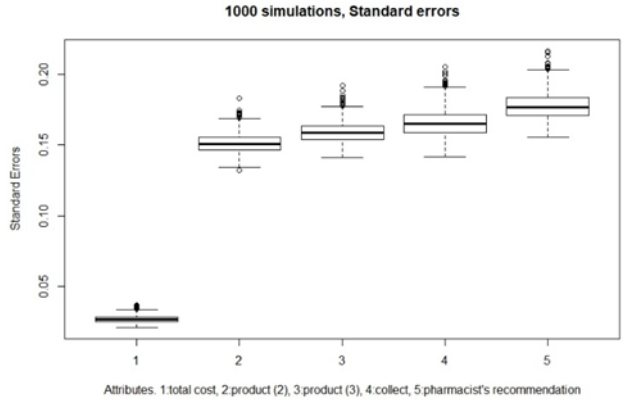
(0.2) Megorium generic

(0.8) Medora branded

(−0.8) collection

(0.5) pharmacist recommended





In the tables below, two examples of choice tasks are presented for each DCE. The information includes the attributes and levels as coded in the design. Under each level code there is the associated attribute level as it was presented to respondents.

Table 0-1. Example of DCE design of choice tasks for DCE 1

					Option A				Option B
Attributes	Product	Price	Available to collect	Pharmacist recommend	Product	Price	Available to collect	Pharmacist recommend	
					Example 1				
Levels code	1	7	1	1	0	2	0	1	
Levels text	Medora (Oleaceae)	$50	Later today	Yes	Pharmacy brand (Oleaceae) generic	$35	Now	Yes	
					Example 2				
Levels code	1	0	0	0	0	4	0	1	
Levels text	Medora (Oleaceae) branded	$30	Now	(-)	Pharmacy brand (Oleaceae) – generic medicine	$40	Now	Yes	

Table 0-2. Example of DCE design of choice tasks for DCE 2

		Option A					Option B				
Attributes	Product	Price	Brand premium	Available to collect	Pharmacist recommend	Product	Price	Brand premium	Available to collect	Pharmacist recommend	
	Example 1										
Levels coded	1	8	1	1	0	0	0	0	0	0	
Levels text	Medora (Oleaceae) branded	$55	Yes	Later today	(-)	Pharmacy brand (Oleaceae) – generic	$30	No	Now	(-)	
	Example 2										
Levels coded	2	4	0	1	1	0	2	0	1	0	
Levels text	Megorium (Oleaceae) – generic	$40	No	Later today	Yes	Pharmacy brand (Oleaceae) – generic	$35	No	Later today	(-)	

Table 0-3. Example of DCE design of choice tasks for DCE 3

		Option A					Option B			
Attributes	Product	Price	Brand premium	Available to collect	Pharmacist recommend	Product	Price	Brand premium	Available to collect	Pharmacist recommend
	Example 1									
Levels coded	2	7	3	0	1	0	0	0	1	1
Levels text	Megorium (Oleaceae) generic	$50	$10	Now	Yes	Pharmacy brand (Oleaceae) generic	$30	$0	Later today	Yes
Example	2									
Levels coded	0	2	0	1	0	1	4	3	1	1
Levels text	Pharmacy brand (Oleaceae) generic	$35	No	Later today	(-)	Medora (Oleaceae)	$40	$10	Later today	Yes

Appendix B

Choice set example (DCE 1)

In the tables below two examples of choice tasks are presented for each DCE. The information includes the attributes and levels as coded in the design. Under each level code there is the associated attribute level as it was presented to respondents.

Table 0-4. Examples of DCE design of choice tasks for DCE 1 (by code)

Attributes	**Option A**		**Option B**	
Example 1	Levels text	Levels code	Levels text	Levels code
Product	Medora (oleaceae) branded	1	Pharmacy brand (oleaceae) generic	0
Price	$50	7	$35	2
Available to collect	Later today	1	Now	0
Pharmacist recommended	Yes	1	Yes	1
Attributes	**Option A**		**Option B**	
Example 2	Levels text	Levels code	Levels text	Levels code
Product	Medora (oleaceae) branded	1	Pharmacy brand (oleaceae) generic	0
Price	$30	0	$40	4
Available to collect	Now	0	Now	0
Pharmacist recommended	(-)	0	Yes	1

Table 0-5. DCE1- Conditional logit model for the doctor's prescriptions (four types)

Attributes (base case)	generic first	generic second	brand first	brand second
Total cost ($)	−0.167***	−0.162***	−0.145***	−0.163***
SE	(0.017)	(0.016)	(0.014)	(0.016)
95%CI	(−0.200 — −0.133)	(−0.194 — −0.131)	(−0.172 — −0.118)	(−0.194 — −0.132)
Products ('pharmacy brand generic')				
Megorium generic	0.184*	0.186	0.257**	0.073
SE	(0.091)	(0.099)	(0.088)	(0.112)
95%CI	(0.006 — 0.363)	(−0.008 — 0.379)	(0.085 — 0.430)	(−0.147 — 0.293)
Medora branded	0.364***	0.399***	0.281**	0.292**
SE	(0.091)	(0.090)	(0.087)	(0.093)
95%CI	(0.186 — 0.542)	(0.222 — 0.576)	(0.112 — 0.451)	(0.110 — 0.474)
Collect later today ('Now')	−0.519***	−0.540***	−0.606***	−0.410***
SE	(0.098)	(0.102)	(0.096)	(0.108)
95%CI	(−0.711 — −0.326)	(−0.740 — −0.339)	(−0.794 — −0.418)	(−0.622 — −0.198)
Pharmacist recommended 'Yes' ('-' no recommendation)	0.334*	0.035	0.132	0.107
SE	(0.131)	(0.117)	(0.109)	(0.119)
95%CI	(0.077 — 0.591)	(−0.194 — 0.264)	(−0.082 — 0.346)	(−0.125 — 0.340)
Observations	2,576	2,516	2,580	2,522
AIC	1269	1236	1349	1236
BIC	1298	1265	1379	1265
Log-likelihood	−629.5	−613.1	−669.7	−613.0

Abbreviations: AIC: Akaike Information Index; BIC: Bayesian Information Index; CI: confidence interval; SE: standard error

Note: *** p<0.001, ** p<0.01, * p<0.05.

Additional model: G-MNL (generalised multinomial logit model)

The estimated generalised multinomial logit (G-MNL) model allows for additional investigation of the source of preference heterogeneity. Incorporation of the estimation of the scale heterogeneity allows us to identify whether sources of correlation exist in the data, with the estimated results reflecting a difference of the impact of unincluded factors in the model across the respondents (Hess & Train, 2017). The results of the G-MNL model are presented in Table 0-3. The model was estimated using a 'gmnl' user-written command in Stata (Gu et al., 2013), which accommodates both preference and scale heterogeneity (Fiebig et al., 2010). The model was estimated with all coefficients scaled and treated as random. There were 50 Halton draws used for the simulation, with 15 initial sequence elements dropped when creating Halton sequences. Attempts to fit the model with 100 and 500 and higher number of Halton draws were unsuccessful as the models did not converge. As discussed in Gu et al. (2013) the non-convergence may be overcome by trying different starting values or G-MNL model alternative specification to achieve convergence.

The signs of the mean coefficients and the ratios within attributes are consistent with those seen in the

conditional logit and mixed logit models. Responses indicate that all parameters are significant with large standard deviation ion relation to the estimated means.

The tau[57] value (standard deviation of the individual-specific scale of idiosyncratic error) was significant, showing that there is scale heterogeneity in the data.

Table 0-6. G-MNL (uncorrelated) model results for DCE 1 (with 50 draws)

Attributes (base case level))	Mean (SE)	SD (SE)
Total cost ($)	−0.803***	0.748***
	(0.185)	(0.189)
Products ('pharmacy brand generic')		
Megorium generic	0.509**	0.906**
	(0.185)	(0.344)
Medora branded	1.002***	-0.250
	(0.278)	(0.213)
Collect later today ('Now')	−2.872***	2.231***
	(0.694)	(0.568)
Pharmacist recommended 'Yes' ('-' no recommendation)	1.792***	2.920***
	(0.462)	(0.583)
Tau[a]	1.243***	
	(0.167)	
Gamma	0.007	
	(0.021)	
Observations	9,888	
AIC	3865	
BIC	3951	
Log-likelihood	−1920	

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; SD: standard deviation; SE: standard error.
Note: *** p<0.01, ** p<0.05, * p<0.1; a: tau is the standard deviation of the σ_n the individual-specific scale of the idiosyncratic error.

Table 0-7. Comparison of statistical fit

Model estimation	Log-likelihood	AIC	BIC
Conditional logit	−2462	4934	4970
Mixed logit (2000 draws)	−1890	3872	3800
G-MNL (50 draws)	−1920	3865	3951

Abbreviations: AIC: Akaike information criterion; BIC: Bayesian information criterion; G-MNL: generalised multinomial logit model.

[57] A τ of zero would imply that the G-MNL model reduces to a standard MXL specification (Fiebig et al., 2011).