UTS UNIVERSITY OF TECHNOLOGY SYDNEY

Modelling the Influence of Customer Perception on Pricing Behaviour of Banks

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Thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

under the supervision of Distinguished Professor Biswajeet Pradhan, Associate Professor Nagesh Shukla, and Professor Ghassan Beydoun

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2025

Certificate of Original Authorship

I, Muhunthan Jayanthakumaran, declare that this thesis is submitted in fulfillment of the requirements for the award of Doctor of Philosophy, in the Faculty of Engineering and Information Technology 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.

This research is supported by the Australian Government Research Training Program.

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Acknowledgements

Throughout the journey of writing this thesis, I have experienced personal and academic growth, both directly from this work and beyond it. This journey has deepened my appreciation for two key elements in academic pursuit: a supportive environment and an intrinsic desire to learn.

I am grateful to Prof. Pradhan, Assoc. Prof. Shukla, and Prof. Beydoun for providing me with the opportunity to undertake this endeavour, fostering a supportive environment, and guiding me in refining my research skills.

The desire to learn is a quality that must come from within, and I am fortunate to have gained this from my parents. My mother's encouragement and belief in my abilities have given me the confidence to pursue my aspirations. My father, through his own academic experiences, has shown me how to love thinking and learning for their own sake. His approach to life continues to be a constant source of inspiration, and I aspire to embody even a fraction of his qualities. I hope this accomplishment serves as a step forward on that path.

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Acronyms & Abbreviations

ABC	Australian Broadcasting Corporation
ACCC	Australian Competition and Consumer Commission
AML	Anti-Money Laundering
ANZ	Australia and New Zealand Bank
APRA	Australian Prudential Regulatory Authority
ARDL	Autoregressive Distributed Lag
AUC	Area Under the Curve
BART	Bayesian Additive Regression Trees
BERT	Bidirectional Encoder Representations from Transformers
BBSW	Bank Bill Swap Rate
BoW	Bag-of-Words
BPI	Banking Perception Index
CBA	Commonwealth Bank of Australia
CNN	Convolutional Neural Network
COVID-19	Coronavirus Disease 2019
CRM	Customer Relationship Management
CTM	Correlated Topic Model

ESG	Environmental, Social, and Corporate Governance
GBM	Generalised Boosting Model
GFC	Global Financial Crisis
GPT	Generative Pre-Trained Transformers
GRU	Gated Recurrent Unit
HHI	Herfindahl-Hirschman Index
HRC	Hayne Royal Commission
INVIO	Investment Interest Only
INVPL	Investment Principal and Interest
IRPT	Interest Rate Pass-Through
LDA	Latent Dirichlet Allocation
Llama	Large Language Model Meta AI
LLM	Large Language Models
LSTM	Long Short-Term Memory
MCC	Matthew's Correlation Coefficient
MGS	Monthly Growth Score
MHS	Monthly Headline Score
MRS	Monthly Review Score
NAB	National Australia Bank
NARDL	Nonlinear Autoregressive Distributed Lag
NLP	Natural Language Processing
NPS	Net Promoter Score

NSW New South Wales

OOIO Owner Occupied Interest Only

OOPI Owner Occupied Principal and Interest

OOS Out-Of-Sample

PLSA Probabilistic Latent Semantic Analysis

RBA Reserve Bank of Australia

REIT Real Estate Investment Trust

RNN Recurrent Neural Network

SBERT Sentence-BERT

SHAP SHapley Additive exPlanations

SVR Standard Variable Rate

SVM Support Vector Machine

XAI Explainable Artificial Intelligence

XGBoost eXtreme Gradient Boosting

Abstract

Mortgage pricing exerts far-reaching influence on the economy, with changes cascading from an individual's disposable income to overall aggregate demand. Traditional research has primarily focused on how changes in marginal costs drive overall pricing. In the Australian context, recent regulatory inquiries by the Australian Competition and Consumer Commission (ACCC) and Hayne Royal Commission (HRC) have highlighted the additional importance of public perception in pricing. This represents a research gap, as perception has been discussed qualitatively but not quantitatively modelled for this context.

This study extends the traditional marginal cost-based pricing framework by incorporating perception and distinguishing between pricing strategies for new (front-book) and existing (back-book) customers. The research has three key objectives: (1) to develop a measure that captures perception, (2) to build a pricing framework integrating perception and front-/back-book differentiation, and (3) to analyse how these factors influence strategic pricing decisions.

To track perception over time, this study introduces the Banking Perception Index (BPI), guided by a systematic review to inform its development. The BPI integrates factors including volume growth, customer review data, and news headlines. The resulting framework is estimated using a Nonlinear Autoregressive Distributed Lag (NARDL) approach, applied separately to front- and back-book pricing proxies to capture asymmetric and long-run dynamics. A higher BPI value corresponds to a more favourable public perception, and results show that variations in the BPI align with shifts in consumer sentiment at the organisational level.

The proposed pricing framework reveals a clear distinction in how banks treat new (front-book) versus existing (back-book) clients. Empirical evidence indicates that cost-of-funds asymmetry is significant for back-book pricing relative to front-book pricing, with banks reacting more aggressively to increases in funding costs than to decreases. Moreover, customer perception significantly affects front-book pricing compared to back-book pricing, suggesting that perception does influence rates when banks target new customers. This

finding supports the value of integrating behavioural dimensions into pricing models and helps to fill the identified research gap.

While the approach demonstrates strong empirical performance, key limitations include reliance on proxies for measuring perception and front-book and back-book pricing data. These findings offer valuable insights for policymakers, the Reserve Bank, and commercial banks by highlighting additional factors affecting price points and the more nuanced flow-on effects of central bank policy on consumers.

Chapter 1

Introduction

1.1 Background

Banks are intermediaries between depositors and borrowers. Depositors place their money in the bank and require security to know that they can take it back at a later stage. Borrowers instead require additional funds to purchase and require a bank to give them the purchasing power. One of the predominant reasons to lend is to purchase a property. As part of the 2021 Census in Australia [2], it was identified that 35% of Australians own a house with a mortgage. This is compared to 31% who own a house outright and 30.6% who rent.

Figure 1.1 shows through average loan size that for roughly one-third of the Australian population the required dependence on loans has increased [3]. In New South Wales (NSW) the average loan size has more than doubled from $300k in 2004 to roughly $750k in 2022. For reference, owner-occupied refers to loans where the purpose of the purchase is to have somewhere to live. It tends to be associated with being an essential need, with the alternative being renting. The other category is investment loans, which serve a different purpose, and the concept of loan size becomes less interesting in the context of social equity since, given it is arguably a luxury, it is less representative of the everyday customer's concerns.

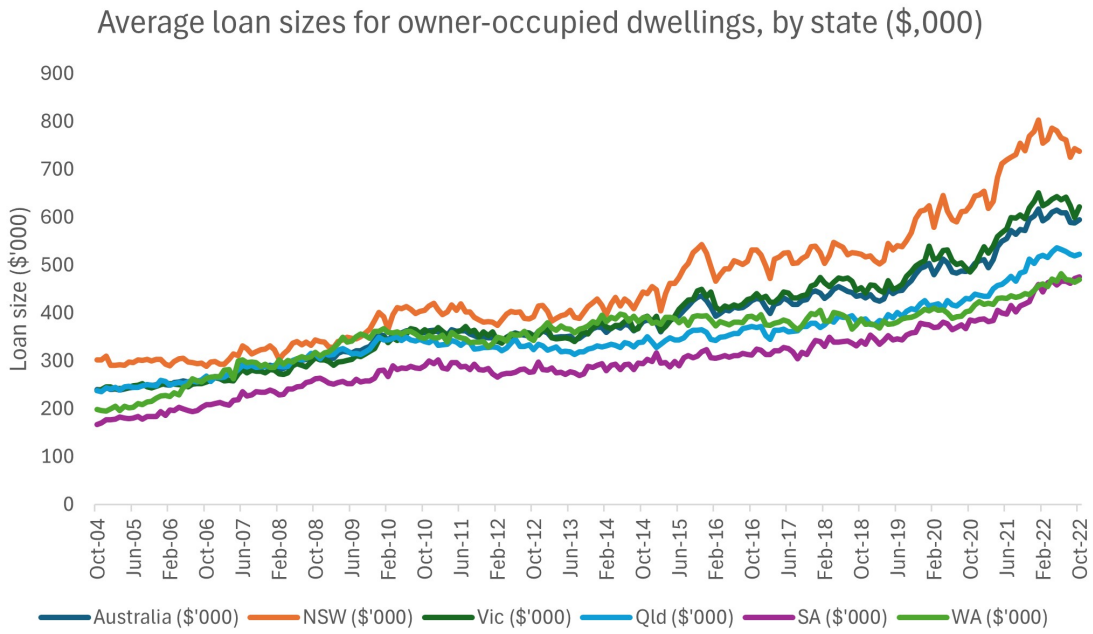

FIGURE 1.1: Average loan sizes for owner-occupied dwellings, Australian Bureau of Statistics [3]

These rising loan sizes raise questions not only about affordability but also about social equity. Certain practices in mortgage pricing and credit availability may contribute to unequal outcomes across different segments of the population. For example, due to variations in assessed credit risk, banks may apply higher interest rates or impose more restrictive lending criteria on borrowers with smaller deposits through loan-to-value ratio based pricing. These conditions can disproportionately affect lower-income households. Policies that favour property investors over owner-occupiers, such as negative gearing in Australia, which allows investors to claim tax deductions on rental losses, can also reduce opportunities for first-home buyers to enter the market even if there is rate variation such that investors pay more than owner-occupied customers. While such practices may be commercially or economically rational, they raise important questions about the role of banks and the government in promoting equitable access to housing finance and how price might act as a lever in this regard.

Changes in the banks interest rates and pricing, therefore, have a large impact on customers. For example, a 50bps increase in the cash rate, if passed onto the customer by the bank, would lead to roughly a \$3.8k ($50bps \times \$750k$) increase in repayments per year. For

reference, the median taxable income for an Australian in 2019-20 is $48.4k [4]. Note that over the course of 2022, the cash rate increased by 300bps. This is equivalent to $22.5k increase in annual repayments in 2022 for the average NSW balance of $750k.

Given the magnitude of impact that rate changes can and have had on customers, it makes sense to understand how banks price mortgages in greater detail. Are banks influenced predominantly by the cash rate, or is there an underlying behavioural aspect that motivates pricing strategy? If we assume the banks goal is a combination of volume and marginal revenue growth, would it make sense to forego a price increase in some scenarios? On the other hand, if a customer is sticky and unlikely to refinance would they instead choose to focus on revenue growth?

1.1.1 Complexity 1: Asymmetric Pricing Concept

This topic has complexities because of the nature of how banking products function and these will be addressed in the thesis. For example, the concept of asymmetric pricing will be referenced significantly [5–7]. The idea is if a bank observes an increase in the cost-of-funds, which in turn has the potential to hurt their margins if the price does not increase, they will likely match the cost-of-funds increase with a price increase. For simplicity, note that the cost-of-funds from a banking perspective will be proxied by the Bank Bill Swap Rate (BBSW) as a representation of the bank's short-term borrowing costs. In contrast, however, if the banks see a decrease in the cost-of-funds, they are less likely to reduce their rates and instead preserve margin. This leads to a greater disconnect between the rates banks charge and the cash rate set by the Reserve Bank of Australia (RBA).

1.1.2 Complexity 2: Front-Book vs Back-Book Pricing Concept

The concept of front-book and back-book can be complex. Front-book is what a bank charges new customers and these rates are usually advertised on the bank's website. The rate charged to new customers is calculated by applying a discount to a standard rate. If the bank changes the standard rate with RBA, the customer rate will also change. The

discount applied to get the front-book rate could be based on the perceived credit risk of the customer or the risk of the customer choosing another bank.

Back-book refers to what the bank charges its existing customers who have been with the bank for some time, say five years. This distinction is important for pricing strategy because a customer on the front-book is more likely to receive better treatment than a customer on the back-book [8].

The strategic reason is likely due to the split of the front-book population and the back-book population. For example, from September 2022 to October 2022, the loan book for the biggest four banks of Australia increased from $1.00tn to $1.01tn. Note that this $0.01tn movement is a combination of attrition from customers leaving and new settlements from front-book customers. However, for simplicity, the front-book movement can easily be seen to be roughly around 1% compared to the rest being back-book. So, if the banks changed their back-book rate, it could have massive profitability implications, while a movement in front-book rate could be absorbed by a strong back-book rate position. This allows banks to be more generous on price movements for front-book and potentially less so on the back-book. From a customer perspective, refinancing between banks regularly provides them with the leverage to get deals from banks that offer a better price point.

1.1.3 Complexity 3: Perception Pricing Concept

This thesis focuses on the concept of perception. This section explains how it is defined in the context of the study. A classic contribution by Zeithaml [9] helps to conceptualise the link between perception and pricing through the concept of perceived value. This concept is shaped by multiple attributes, as shown in Figure 1.2.

Perception can therefore be influenced by a wide range of sources. Notably, Figure 1.2 distinguishes between objective price and perceived monetary price. This suggests that objective price may be viewed as perceived price excluding the influence of perception. This thesis explores the magnitude of that perception component and how it may vary over time.

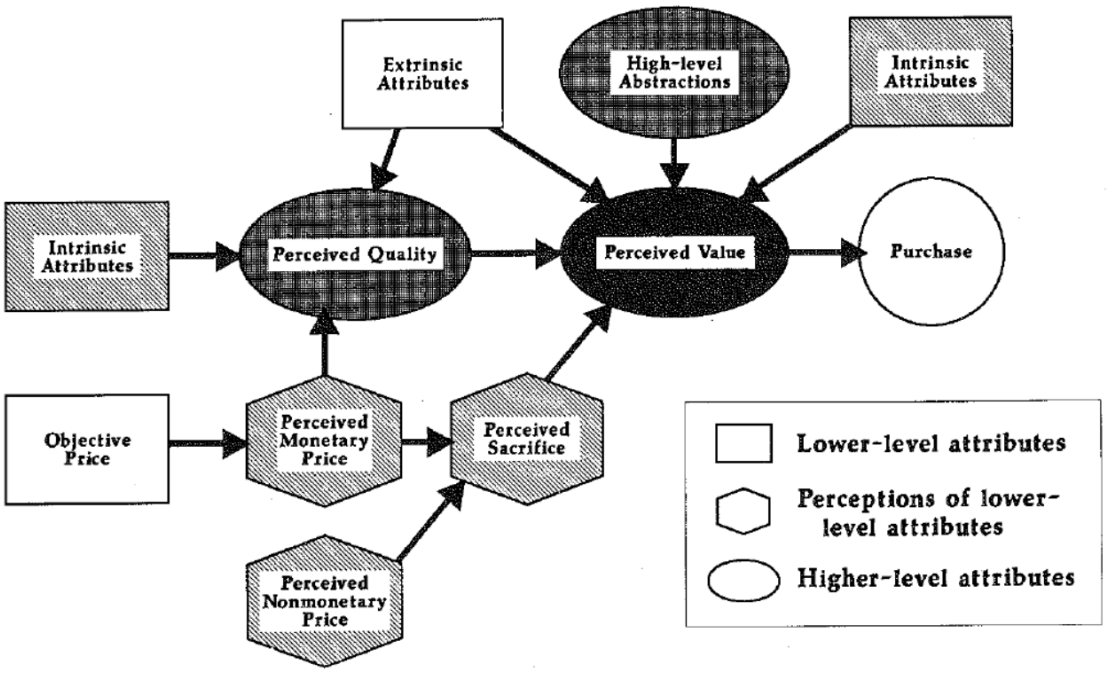

FIGURE 1.2: A means-end model relating price, quality, and value, Zeithaml [9]

A more recent study by Wang et al. [10], based on a survey of cross-border e-commerce users, found that consumer perception plays a crucial role in shaping purchasing behaviour. They reference buyer's value theory, which defines customer value from the customer's own perspective—that is, as a mental assessment, or perception. Similarly, Dey et al. [11] argue that shifts in perception can arise from both direct and indirect stimuli, including advertisements, promotions, customer reviews, social media commentary, and company responses. Capturing perception effectively in a model therefore requires synthesising these diverse sources.

A bank focused on long-term growth must be perceived positively in the eyes of consumers. However, sustainable growth also requires covering costs and generating profit. In financial services, price is a particularly important mechanism for managing this trade-off, given that pricing changes often receive significant media attention and influence public perception. For example, public scrutiny is common when a bank responds adversely to an RBA cash rate change.

This thesis incorporates perception into its pricing framework through three observable data sources: customer reviews, media headlines, and historical growth patterns. Drawing

on the above literature and this operationalisation, perception is defined as the customer's interpretation of a financial institution's value and intentions, informed by indirect signals such as media coverage, customer reviews, and observable business performance. This aligns with prior literature, which conceptualises perception through brand image, trust, fairness, and sentiment [9–11].

Analysing perception and pricing dynamics together in this way serves multiple purposes. It can help the RBA anticipate how policy rates translate into consumer-facing rate changes, assist banks in evaluating and adjusting their pricing strategies, and improve customer and academic understanding of bank behaviour and responsiveness.

1.1.4 Complexity 4: Australian Market Characteristics

The Australian banking sector exhibits distinctive market characteristics, making it a unique case for analysis. A primary feature is the oligopolistic nature of the Australian mortgage market. As of October 2022, data from the Australian Bureau of Statistics (ABS) indicates that approximately 75% of owner-occupied mortgage loans were held by the biggest four banks (Big-4), comprising Commonwealth Bank of Australia (CBA), Westpac, National Australia Bank (NAB), and Australia and New Zealand Bank (ANZ). This concentration is significant as it suggests that pricing dynamics in this imperfect market are heavily influenced by these dominant players. For instance, a change in the cash rate by the Reserve Bank of Australia (RBA) followed by a corresponding move by one of the Big-4 banks could set a precedent for others. If a Big-4 bank alters its rates by a certain number of basis points (bps), other banks are likely to mimic this change. Deviating significantly from this norm could lead to strategic disadvantages: reducing margins more than the set benchmark might trigger a price war, detrimental to the banks' financial interests, while setting higher rates could damage customer perceptions and flows. Thus, by adhering to this implicit benchmark, banks can maintain or even enhance their margins while preserving their market reputation.

A distinct feature of the Australian mortgage market is its predominant use of variable-rate home loans. As of 2017, 85% of home loans in Australia were variable-rate, in stark contrast to the United States, where, since 2009, 93% of home loans have been at fixed

rates [6]. This difference significantly impacts the dynamics of front-book and back-book rates in Australia.

In the case of fixed-rate loans, at the end of the term, customers typically face a decision point as their loans roll over, usually into variable-rate products with pre-established discounts. This rollover often prompts customers to reassess their options, such as refinancing or entering into a new fixed-rate agreement. The change in their rate at this juncture can be noticeable, driving them to consider alternatives.

Conversely, customers with variable-rate loans might experience a more static discount level, unless they actively negotiate with their bank. While the base variable rate may fluctuate based on bank decisions, this does not automatically translate into improved discount offers for existing variable-rate customers. Banks might advertise attractive discounts on their websites for new customers, but these offers are not typically extended to the existing variable-rate book. The absence of clear information about new customer rates on the banks' websites means that existing customers may remain unaware of potentially better offers. This lack of transparency affords banks greater control over margins, particularly with customers who are less inclined to shop around.

This scenario aligns with the findings of the ACCC inquiry [8]. The inquiry highlighted these market dynamics, underscoring the complexity and the significant impact of loan structure on both customer decision-making and bank pricing strategies in Australia.

1.2 Motivation

1.2.1 Academic Interest

This thesis develops a behavioural mortgage pricing model for Australian banks that incorporates customer perception as a measurable input. While mortgage pricing has received significant attention, there are four areas—outlined in Section 1.1—where the existing literature remains underdeveloped. Addressing these areas is critical for establishing a perception-aware framework for pricing, with implications for regulators, banks, and consumers.

1. **Asymmetric Pricing (Section 1.1.1)**: While asymmetric interest rate pass-through is well documented [5, 7], prior studies do not account for customer perception as a potential explanatory factor. This limits the ability to distinguish behavioural pricing motives from responses to cost pressures.

2. **Front-Book vs Back-Book Pricing (Section 1.1.2)**: Despite its policy relevance, limited empirical work has explored differential pricing strategies between new and existing customers. Aggregate data masks bank-level differences, and few studies have linked such pricing behaviour to competitive dynamics or perception.

3. **Perception and Pricing (Section 1.1.3)**: Although marketing and behavioural economics literature highlights the role of perception in shaping consumer behaviour [9, 10], this concept has not been operationalised in the context of Australian mortgage pricing. There is currently no framework for quantifying banking perception using structured and unstructured data sources.

4. **Australian Mortgage Market Structure (Section 1.1.4)**: Much of the international literature assumes more transparent or competitive settings. Australia's concentrated, variable-rate driven market—with a history of opacity and inertia—requires a context-specific pricing model that accounts for behavioural nuance.

By addressing these four complexities, this thesis contributes to a more complete understanding of mortgage pricing behaviour. Specifically, it proposes a new quantitative measure of banking perception, applies it to historical pricing behaviour, and investigates how perception interacts with asymmetric and segmented pricing strategies in the Australian context.

1.2.2 Government Level Interest

Recently there has been a spotlight on banking behaviour in Australia on the back of the HRC (2017 - 2019) and the ACCC (2019) examination into the pricing behaviour of banks. Additionally, there has been greater scrutiny of the RBA in relation to its management of the cash rate (2022). This highlights how important this topic because

a bank's behaviour, whether in pricing or general conduct, has massive implications for the livelihoods of customers (35% with mortgages as suggested in Section 1.1) and the performance of the economy.

The HRC focused on the misconduct in the Banking, Superannuation and Financial Services Industries. It was established following concerns in the media on greed being demonstrated by several Australian financial institutions. The topics examined included links with money laundering, terrorism financing and ignored statutory reporting. Among other topics, HRC, for example, had identified Westpac and ANZ as implicated in a BBSW rigging scandal.

ACCC examined home loan pricing specifically. The topics they examined included home loan switching in Australia, bringing the benefits of switching to the borrower's attention, transparency in ascertaining and assessing home loan prices, complexities in discharging discouraging switching and ensuring continuous monitoring of prices and competition in the home loan market [8]. Some key elements relevant to this research include ACCC suggesting the problems associated with having a distinction between front and back-book pricing by calling out the switching costs associated with refinancing for the purpose of a new rate and the lack of transparency for back-book customers on how much other customers are being charged.

The RBA also has a keen interest in banking pricing because the cash rate is a key factor in influencing interest rates charged by banks by altering the cost of funds. In 2022, the RBA changed the cash rate a total of 8 times. There has been greater scrutiny on the RBA on how they manage the cash rate given how much impact it has on the daily lives of customers [12]. Of particular note, it was called out that the RBA should examine lessons learnt from its approach to forecasting. Given the mechanism by which the cash rate translates to interest rate movements, there is further value in this thesis examining that interaction.

1.2.3 Bank and Customer Level Interest

As highlighted, there is an obvious interest in how banks price from a government level. This naturally translates into an interest in the variations of banking strategy. In other words, do all banks follow the same or different approach when it comes to pricing? With the advent of government scrutiny on banking behaviour and on the back of basic marketing principles such as the customer is always right, to what extent are banks motivated by how they themselves are perceived when they change rates? As an example, if RBA increased the cash rate by 25bps and a bank choose to increase rates by 50bps, there would most certainly be large media backlash. However, if they engage in cartel behaviour, and all banks increase their prices at the same time, it becomes harder to have negative perceptions of a particular bank relative to other banks. This is because the customer does not have a choice to vote with their wallet and choose another bank.

What this example highlights is that there is a clear behavioural intent behind pricing. It is not entirely driven by how much the RBA moves the cash rate, and as it will be highlighted in the later sections of the thesis — there is historical data to suggest deviations between RBA movements and bank price movements on both the front-book and the back-book. As such, this thesis hypothesises that it would only be natural to consider not just the cost of funds movements but also to consider this behavioural aspect. This behavioural aspect could be a representation of a deeper underlying behaviour or a situational one dependent on the current market; for example, banks are more concerned about scrutiny during the period of the HRC. For reference and further motivation, past studies on the HRC focused on actions taken by the HRC and talked about the industry as a whole [13–16] rather than the quantitative impact of the HRC on individual bank performance. Analysis of behavioural pricing provides the opportunity to examine this quantitative impact.

It is important to note that this concept of perception of banks has not been explored as a holistic component; however, there are studies that tackle specific elements typically performed through surveys or Roy Morgan[1] customer satisfaction measures [17–20]. This thesis suggests a quantitative resource that combines publicly available information such

[1]Roy Morgan is an independent Australian market research company.

as news, reviews, and growth data would be a useful resource for banking-related analysis. This study would derive such a resource and utilise it to understand pricing strategy.

1.3 Research Questions and Scope

This section will break down the research question into subject areas that align with the motivation of the thesis. The first three research questions (1-3) are focused on the concept of banking perception and how to measure it. The background of what it refers to is highlighted in Section 1.1.3, and the motivation and importance of including it in this study are highlighted in Section 1.2. Note that this set of research questions does not consider pricing directly but rather how to actually obtain the concept of perception. These questions include:

- **Research Question 1: Banking Perception Measurement**: How can banking perception be measured quantitatively?
- **Research Question 2: Banking Perception and the HRC**: Does banking perception vary due to the HRC?
- **Research Question 3: Idiosyncratic movements in Banking Perception**: Do individual banks experience different movements in perception over time, and if so, what drives them?

The second set of three research questions requires the first three to be completed. This is because there is now a derived quantitative representation of perception. This can be used to inform how banking pricing strategy is influenced by perception. The nature of these three questions emphasises asymmetric pricing, front and back-book pricing, and behavioural pricing, effectively closing the loop on all of the issues suggested in Section 1.1 and Section 1.2. The questions are as follows:

- **Research Question 4: Asymmetric Pricing**: Is pricing asymmetric to the cost of funds movements for the period analysed?

- **Research Question 5: Front and Back-Book Pricing**: Do banks have different strategies regarding the cost of funds and perception of front-book pricing relative to back-book pricing?
- **Research Question 6: Behavioural Element of Pricing**: Is pricing a function of cost-of-funds and perception?

The study focuses on Australian data and examines pricing strategies only for residential mortgages. The time period considered is from 2012 to 2020 to account for the post-Global Financial Crisis (GFC) period and pre-Coronavirus Disease 2019 (COVID-19) periods.

While this study is focused on Australian data and addresses market-specific characteristics, as outlined in Section 1.1.4, the analytical framework is intended to be broadly applicable. The key contextual difference, particularly for pricing strategy, lies in the mix of variable- and fixed-rate mortgage products. This difference has important implications for how pricing should be interpreted, especially in distinguishing strategies for new versus existing customers. Before applying these techniques to other markets (outside Australia), the underlying product mix, in particular, should be carefully considered.

1.4 Research Aims and Objectives

The overall aim is to be able to explain the influence of perception on the pricing behaviour of banks. The hypothesis is that current research focuses on the cost of funds and the influence on pricing. However, this might lead to an omitted variable bias in the analysis, given the importance placed on market perception of pricing. The nature of incorporating perception is more common in the literature of other industries. By undertaking this analysis, it is possible to expand the nature of pricing analysis and identify if there are any changes required to the strategic side of pricing. In order to achieve this, it is necessary to break this down into objectives. The objectives can be summarised as follows:

- Objective 1: To develop a quantitative index model of banking perception labelled BPI and validate this index through application to Haynes Royal Commission.

- Objective 2: To develop a better pricing behaviour model by incorporating the developed BPI and capturing the differences between front and back-book pricing.
- Objective 3: To evaluate the quantitative impact of BPI on pricing for front/back-book by assessing model coefficients and conducting statistical tests to identify practical implications.

In summary, this thesis aims to expand the understanding of pricing behaviour in the banking industry by introducing perception as a key factor and developing a comprehensive framework for analysing pricing decisions.

1.5 Contributions

1.5.1 Contribution to Knowledge

Past literature [17–20] has examined the concept of perception. However, this was using survey data and was limited in scope. In conjunction, prior research in the more general area of sentiment analysis has been relatively limited when focused on the banking sector and analysing shorter-form headline data. This thesis uses novel data sources to derive an index with publicly available information, allowing for more length of time of the data allowing for trend analysis.

Prior pricing studies focused on pricing in general [5–7, 21] without differentiating between the concept of front-book and back-book pricing. By creating this distinction, it is possible to directly model the concerns from the ACCC on a difference in pricing approach for front-book and back-book. This would mean prior research would need to be re-examined to determine whether it is more applicable to new or existing customers.

Existing pricing studies have not considered perception in the context of mortgages. It has been incorporated as a concept in other areas, although the modelling used was quite different to the concept of asymmetric pricing, and these studies measured perception through data that had already existed for the corresponding areas [22, 23]. This would

change how the framework for determining price is approached to necessitate value in incorporating perception.

1.5.2 Contribution to Practice

The perception index derived from this study allows for a unique perspective on the HRC compared to existing studies. Existing research on HRC used qualitative information [13–16]. Notably, using qualitative information has limited prior studies to look at the impacts on the banking industry holistically [13–16]. This study believes that an individual bank level analysis is necessary to examine a thesis hypothesis that the HRC had a larger negative impact for certain banks than others, and this might act as an incentive for banks most adversely impacted to emulate aspects of banks less impacted.

Prior research has examined the asymmetry of bank interest rates for mortgages in Australia [5–7]. However, this research was more focused on the GFC. If the nature of pricing has been altered due to market developments since then, it would be valuable to present this from a perspective with practical implications.

The examination of how perception influences pricing provides alternative means by which the government can influence banking behaviour beyond the cash rate changes done by the central bank. With the recent report on the effectiveness of the RBA [24], this type of analysis has practical implications. Additionally, it highlights the importance of transparency and information from not only a legislative angle but also a behavioural angle.

1.6 Thesis Outline

Chapter 2 presents a comprehensive literature review, exploring pricing models in banking and delving into perception as it applies to the problem statement. This chapter identifies key trends and gaps in the field, setting the stage for further exploration.

Subsequently, Chapter 3 conducts a focused, systematic review of sentiment analysis in banking headlines. It examines how this analysis helps understand customer perceptions and its potential impact on banking pricing strategies.

Building upon these foundational chapters, Chapters 4 and 5 delve into the practical applications. Chapter 4 discusses the creation of the Banking Perception Index (BPI), and Chapter 5 addresses the modelling of pricing dynamics within banks, integrating insights gleaned from customer sentiment. These chapters are designed to directly address the Research Questions and Aims outlined in Sections 1.3 and 1.4, as detailed in Table 1.1.

Chapter	Research Questions
4	1, 2, 3
5	4, 5, 6

TABLE 1.1: Thesis outline

Chapter 7 synthesises the findings from each chapter and discusses future research directions.

Chapter 2

Literature Review

2.1 Introduction

The purpose of this literature review is to examine the existing research on pricing mortgages in the banking industry, focusing on the role of asymmetric pricing and the impact of the cost of funds. To achieve the goal of the thesis, the review begins by exploring models that investigate how perception affects pricing in banking. From there, questions arise about the drivers of perception and pricing strategy, as well as the distinctive features of the banking industry. This analysis, identifies potential gaps in the literature, and the research question is formulated.

The section is divided into several parts: Section 2.2 presents the existing literature on the subject, including a discussion on the different types of drivers considered in traditional pricing models and a key stylised pricing model. This section also demonstrates the concept of asymmetry and how it has been used in past literature, as well as the statistical approach to model estimation. Following this, Section 2.3 highlights the research gaps in the literature. To address these gaps, Section 2.4 proposes a new state of literature, which becomes the basis for proposing what will be discussed in the following chapters of the thesis. This proposed state of pricing models is represented at a conceptual level in Figure 2.3. Finally, the Conceptual Framework is discussed in Section 2.5, which overviews

the gaps identified and showcases what the contributions targeted by this thesis are using Figure 2.3 as a basis. Chapter 3 follows with a deep-dive into the measurement of perception through a systematic review.

2.2 Current State of Pricing Modelling

There are two key theoretical frameworks [6] for determining pricing models for bank interest rates: the marginal cost pricing model of De Bondt [25] and the industrial organisation approach of Freixas and Rochet [26]. The empirical literature on bank price-setting tends to employ both approaches to determine the retail interest rates, for example, Gambacorta [27]. In its most fundamental form, the pricing model would typically take the form of Equation 2.1.

$$Y_{i,t} = \alpha_i + \beta^{'} X_{i,t} + \epsilon_{i,t} \tag{2.1}$$

where, i refers to a bank and t refers to a time period. $Y_{i,t}$ is the interest rate charged by the bank, α_i is the constant and $\epsilon_{i,t}$ is the error term. The exogenous factors are captured in $X_{i,t}$ with the coefficient $\beta^{'}$ corresponding to the impact.

Equation 2.1 is a straightforward yet insightful equation that aligns with common intuition. As the interest rate is essentially determined by exogenous factors, the question that follows is which factors could be utilised as exogenous variables. The subsequent section of this study provides an overview of the existing literature that expounds upon this simplified pricing model and the various types of exogenous variables that have been applied within the context of the marginal cost pricing approach.

2.2.1 Explanatory Variables in the Literature

The literature is varied in what comprises $X_{i,t}$. One such example within the context of banking is van Leuvensteijn et al. [28] who suggest the inclusion of a factor to measure the level of competition known as the Boone Indicator [29, 30]. This is based on the concept

that when differences in bank performance become more determined by marginal cost differences, then there is an increase in competition. The Boone Indicator is presented below with the key explanatory variable of marginal cost.

$$ln(ms_{i,t}) = \alpha + \beta_t ln(mc_{i,t}) + \sigma\gamma_t d_t + \epsilon_{i,t} \tag{2.2}$$

where ms refers to market share, i is the bank, t is year, mc is the marginal cost with coefficient β and time dummy d_t with coefficient γ. $\epsilon_{i,t}$ is the error term. The Boone indicator is β_t and is notably at an industry level rather than a bank level. Since it is not at a bank level it does not contribute as effectively to discussing heterogeneity at a firm level in the banking industry. While the Boone index is a representation of performance to measure competition in the form of rivalry, there is also the Herfindahl-Hirschman Index (HHI) which instead focuses on the concept of concentration [31–33]. The HHI arrives at a similar conclusion to the Boone index, where a higher concentration leads to a higher lending rate and margin. In addition, De Graeve et al. [34] used market share in place of a Boone index or HHI and arrived at the same finding relating to stronger market share, providing a basis for more control over pricing.

Gambacorta et al. [35] suggest another example of variables incorporated in $X_{i,t}$. The study references delinquency rates[1] as an industry-level variable with the expectation that the greater risk of customers being unable to repay their loans is matched with higher rates than expected. Similarly, Fungáčová and Poghosyan [31], Ehrenbergerová et al. [33] incorporate non-performing loan ratios to capture the risk of the loan. Furthermore, Gambacorta et al. [35] refer to a variable more suited to the European market than the Australian market at the time in the form of the level of central bank assets divided by GDP. It is intended to be a representation of unconventional monetary policies. This is an industry-level variable rather than a firm-level variable. Ehrenbergerová et al. [33] extend the concept of $X_{i,t}$ with the consideration of capital regulation impact. In particular, it assesses whether a change in capital requirements leads to a change in pricing policy using a bank-level supervisory dataset for the Czech Republic.

[1]The percentage of loans where payments are due.

Ehrenbergerová et al. [33], Basten and Casanova [36], Benetton et al. [37] incorporate borrower-based macro-prudential measures in the context of mortgage pricing. For example, the loan-to-value ratio, debt-service-to-income ratio, and debt-to-income ratio. Note that these measures are correlated with a greater risk to the bank as the debt increases. Concepts like loan-to-value change over the course of the loan as the loan get repaid. Ehrenbergerová et al. [33], Martin-Oliver et al. [38], Dagher et al. [39], Šútorová and Teplỳ [40] all suggest using macroeconomic controls such as GDP growth, consumption, disposable income and the house price index. Notably, these types of variables are likely to be interrelated with a number of previously suggested variables. For example, default rates could easily be seen as a function of GDP growth with a weakened economy leading to more vulnerable customers. There is also consideration of concepts such as loan maturities and reference rates Brož and Hlaváček [41], Bruuha [42], which have an impact on price points as well. Notably, different lengths of loans are tied to different cost of funds measures. For example, a fixed loan of 3 years might be better linked to a swap rate of a similar magnitude rather than a shorter-term rate.

2.2.2 Marginal Cost Pricing Model

Section 2.2.1 showcased an approach that requires all the potential control factors to apply to the model. As suggested previously in Section 2.2.2, an alternative approach exists in the form of a marginal cost pricing model. This model is more parsimonious and, therefore, requires fewer variables. Rousseas [43] suggested this model where banks charge a margin based on their cost-of-funds. Naturally, if the banks were facing larger costs, they would tend towards increasing their rates to ensure that their overall profit margin is not harmed. De Bondt [25] converted this into a now widely used model with a long-term Interest Rate Pass-Through (IRPT), as demonstrated in Equation 2.3.

$$br = \lambda_0 + \lambda_1 mr \tag{2.3}$$

Intuitively, the bank makes a constant markup on lending in the case of mortgages to account, for example, the risk of default as seen by λ_0 and is expected to be positive. λ_1

is representative of demand elasticity. This elasticity is reflective of the level of market power allowing for deviations from market rates [44], asymmetric information on risk [45] and switching costs making it harder for customers to change banks [46]. Note that this means that this theory, does not ignore the variables shown in Section 2.2.1, instead, it encompasses these elements as part of the markup or constant in Equation 2.3.

A λ_1 of 1 would imply that market rate changes are perfectly translated to bank rate movement; less than 1 would suggest the bank rates tend to lag relative to market rates, while greater than 1 would imply bank rates move faster than market rates. In perfect competition, one would expect λ_1 to have a value of 1; however, in oligopolistic cases, this would differ. Of key interest is to what extent the λ_1 benefits the bank, i.e. if cost-of-funds reduce, to what extent do banks hold onto the rate to maintain their margin? However, there is a limitation with a single λ_1 coefficient; it implies that banks that lag when cost-of-funds drops would also lag when cost-of-funds increase. In practice, this would be unusual as it is more representative of a slow reaction time when, in reality, these movements in prices are reflective of margin and volume related decisions.

2.2.3 Asymmetric Marginal Cost Pricing Model

The line of argument towards the end of Section 2.2.2 focused on variations in pricing behaviour between increases and decreases in marginal costs. This concept drives asymmetric mortgage IRPT studies. These types of studies are done at both a single-country level analysis [47, 48] and multiple-country comparative analysis [5, 25, 49], highlighting that this concept of asymmetry is not limited to an individual region or particular market. However, it is worth noting that the direction of the asymmetry varies by study. One view is referred to as the "rockets-and-feathers" by Bacon [50], where when costs rise, firms react fast as a rocket shooting into the sky, and when costs fall, firms react slowly as a feather falling to the ground. This was in reference to the reaction of the United Kingdom's gasoline prices to cost changes.

Lowe et al. [51] examine different lending products and conclude the level of stickiness varies suggesting mortgages tend to have a more significant coefficient on downward movements of cost of funds relative to upward movements, however, the difference in speed with

which rates are adjusted is small. In contrast, for overdrafts and credit cards, Lowe et al. [51] suggested there were no significant differences. One of the primary reasons for mortgage asymmetry was suggested to be the concept of switching costs or the cost of moving from one bank to another. Outside of banking, Peltzman [52] used a large sample of 77 consumer and 165 producer goods to show that output prices tend to respond faster to an increase in input prices than a decrease. Like Lowe et al. [51], one of their arguments was that this is driven by search or switching costs. Search or switching costs relate to the effort required to find a cheaper product, acting as a deterrent to switching. This means, firms are able to increase prices with lower repercussions and, therefore, may exploit this.

Allen and McVanel [53] examine the Canadian mortgage market and divide their analysis into posted rates and discounted rates. This is similar but different to the concept of front vs back-book pricing suggested in this thesis (please see Section 1.1.2 for a high-level overview). This brings to the fore a unique element of the Australian market relative to other markets in that it is heavily focused on variable products as opposed to fixed-rate mortgages. A fixed-rate mortgage would imply, as soon as the term ends, a natural point for the price to change. A variable-rate mortgage, on the other hand, would not allow for a fixed time-point for change in price point. Regardless, the concept highlighted by Allen and McVanel [53] showcases that sometimes there is a differential between what rate the public sees and the rate a customer actually pays. Given the lack of transparency, the latter is hard to attain data for, suggesting the lack of literature in the area. Overall, Allen and McVanel [53] conclude that there is adjustment asymmetry when controlled for discounting, such that prices were adjusted quicker upwards than downwards.

Tacit collusion is a driver that might lead to more asymmetry in the long-run. Damania and Yang [54] suggest that within an oligopoly, there is reason to believe that there is punishment for deviating from expected movements. For example, if one bank were to reduce its rates significantly more than other banks, it would face an initial upsurge in the volume of loans sold. However, if other banks were to inevitably follow and therefore reduce their own rates to avoid the outflow of their own customers to the bank that reduced their rate, it would lead to a situation where all banks now have a lower rate, but the volume distribution change would likely not compensate for the drop. Since the revenue from a mortgage is based on the loan amount and the interest rate, and only if the

interest rate has shifted significantly, then the overall revenue would decrease. They go on to suggest that there is little evidence of menu costs for adjusting prices. This means, that banks don't experience significant costs when they change the price, and therefore, this does not discourage them from changing the price in either direction. The combination of tacit collusion having an influence and menu costs not having an influence suggests tacit collusion is a primary cause for asymmetric price movements.

Roufagalas [55] showed this concept of asymmetry by recognising the economic concept of a budget constraint. If prices increase, it may breach a budget constraint; however, if prices decrease, it would not. This means there is more urgency associated with a price increase from a consumer perspective than a price decrease. As a result, given that re-optimising the budget requires additional effort, connecting to the concept of search or switching costs, a consumer may choose not to change immediately. The conclusion is this further provides firms with less incentive to reduce prices than to increase prices post a cost of funds change since a reduction in prices may not lead to additional flows given that this may be an inelastic component of a kinked demand curve.

In more recent Australian studies, Valadkhani and Anwar [7], Valadkhani and Worthington [48] observed that for mortgage rates of the biggest four banks in Australia, banks immediately pass on 120% of any rate rise but only 85% of any rate cut looking at the period of 2001 to 2012. They suggest the value this would have for the RBA monetary policy transmission mechanism and the effectiveness of cash rate upward and downward movements.

In contrast to "rocket-and-feathers" [50], Neumark and Sharpe [56] applied and found the opposite phenomenon when looking at consumer deposits. They determined that banks in concentrated markets are slow to raise rates rather than increase them. It is worth noting that while the asymmetry is in the opposite direction, the underlying driver is likely the same. When a bank increases its deposit rate, it takes a margin hit, while when it increases a lending rate, it takes a margin gain. As such, it is not unexpected for the asymmetry to be different depending on the banking product in question as a function on whether the movement harms or benefits the margin. Apergis and Cooray [5] examined the United States, United Kingdom and Australian banking markets between 2000 and

2013 and identified the existence of positive asymmetry for lending rates and negative asymmetry for deposit rates, confirming this perspective.

Notably, though, there are studies in the lending space that suggest a contrasting perspective. One such example is Liu et al. [57], who determined that in the New Zealand market, mortgage rates' initial response to funding cost changes is greater for decreases than for increases, which they suggest is due to higher competition between banks for market share. Supporting this line of thinking, Haan and Sterken [58] observed the same phenomenon in the Dutch mortgage market, where they suggest due to competitive pressures, banks adjust their rates more as a result of funding costs decreasing rather than increasing.

Overall, this suggests a strong literature base regarding asymmetric pricing. Conceptually, Equation 2.3 can be updated to Equation 2.4. Note that this is a stylised model that is foundational to the representation of asymmetry but does not reflect the statistical estimation technique applied.

$$br_{i,t} = \lambda_i + \beta_i^{+} mr_{i,t}^{+} + \beta_i^{-} mr_{i,t}^{-} + \epsilon_{it} \tag{2.4}$$

Within this equation i refers to bank or country and t refers to time period. The $+$ and $-$ indicate whether or not mr is increasing or decreasing. For example in relation to $+$, if the value is decreasing it would be set to 0. This makes it representative of the concept of a 'shock' to the cost of funds.

2.2.4 Model Estimation

The literature on how to estimate the degree of asymmetry is quite varied. Holland et al. [6] summarised current techniques applied and weaknesses associated with them. Included was consideration that a number of studies consider the dependent variable to be based on aggregate mortgage rates at a country level. Valadkhani and Anwar [7], Liu et al. [57]. Holland et al. [6], De Graeve et al. [34] suggest that there might be heterogeneity issues if you average out mortgage interest rates across banks. As a practical example within the Australian market, one might expect banks with greater market share, such as the biggest

four banks, to act differently from challenger banks, considering that greater market share provides greater price leadership potential by the nature of imperfect competition. In an ideal world, it would be possible to measure the asymmetry at a bank level. However, this data is hard to obtain as it is confidential. Studies that have used some degree of bank-level data include Valadkhani and Worthington [48] for Australia, Fuertes et al. [47] for the UK, Allen and McVanel [53] for Canada and Haan and Sterken [58] for the Netherlands. With the exception of Fuertes et al. [47], it was not possible for these studies to have a comprehensive look at a large number of banks.

Notably, the vast majority of studies consider the asymmetry of how long it takes for rates to adjust rather than the rates movements themselves. The ones that consider rate movements, which is the predominant interest of this thesis, include Valadkhani and Anwar [7], Valadkhani and Worthington [48], Allen and McVanel [53], Haan and Sterken [58]. Holland et al. [6] suggest this is driven by methodologies that do not allow for the rate point-of-view. They follow a two-step approach, which is useful for the purpose of co-integration of interest rate asymmetry, but it does not distinguish as effectively short-term relative long-term asymmetry. This concept of short-term vs long-term asymmetry is the idea that the banks might react instantaneously to a cost-of-fund shock today differently from how the rates look multiple years in the future. If there is long-term asymmetry, then the deviation between prices charged by banks and cost-of-funds could theoretically become quite large a century from now, for example. For example, Valadkhani and Worthington [48] showed that in Australia banks pass on 120% of any rate rise relative to 85% of any rate decrease. Without a deviation between short and long-run in modelling methodology, if this trend continued, rates would be unfeasibly higher in the future relative to cash rate than they are now.

The NARDL model proposed by Shin et al. [59] provides one such option to estimate Equation 2.4, a single-equation co-integration technique. Apergis and Cooray [5] applied this methodology when analysing selected large banks in the United States, the United Kingdom, and Australia. Holland et al. [6] applied the methodology at a panel data level. Equation 2.5 showcases an application of Shin et al. [59]'s approach in a panel data form for banking.

$$\begin{aligned}\Delta br_{i,t} = \mu_i + \rho_i br_{i,t-1} + \delta_i^+ mr_{i,t}^+ + \delta_i^- mr_{i,t}^- + \sum_{j=1}^{p-1} \lambda_i j \Delta br_{i,t-j} \\ + \sum_{j=0}^{q-1} (\pi_{ij}^+ \Delta mr_{i,t-j}^+ + \pi_{ij}^- \Delta mr_{i,t-j}^-) + \epsilon_{it}\end{aligned} \tag{2.5}$$

$$\Delta mr_{i,t}^+ = \sum_{j=1}^{t} \Delta mr_{ij}^+; \Delta mr_{i,t}^- = \sum_{j=1}^{t} \Delta mr_{ij}^- \tag{2.6}$$

$$\Delta mr_{ij}^+ = max(\Delta mr_{ij}, 0); mr_{ij}^- = min(\Delta mr_{ij}, 0) \tag{2.7}$$

The market rate or cost of funds in equation 2.7 is represented by mr and is equivalent to the 1 month Bank Bill Swap Rate. Banks are represented by i and time point is represented by t. A cumulative sum of these asymmetric shocks is applied to obtain Equation 2.6. This is then substituted into Equation 2.5 where bank rate is represented by br.

The NARDL approach is applied when variables are integrated of order 0 and integrated of order 1, separation of long-run relationship and short-run dynamics is desired, and co-integration is feature of the variables and incorporates asymmetry. These are all valuable characteristics of the marginal cost pricing model. It is expected that rates are integrated of order 1, and therefore, to ease modelling, the first difference needs to be taken to turn it into order 0. The long-run parameter on the impact of change in the cost of funds is represented as $\beta_i^+ = -\delta_i^+/\rho_i$ and $\beta_i^- = -\delta_i^-/\rho_i$. The short-run parameters for the impact of cost of funds are represented by the symbols π_{ij}^+ and π_{ij}^-. The NARDL model estimates unbiased long-term coefficients and is expected to be a positive value. The short-term coefficients are more complex to assign an expected sign to given it depends on a combination of the long-run parameters, the error correction coefficient (ρ_i) and the model dynamics [59].

From an economic perspective, the coefficients in the NARDL model offer insight into how banks adjust mortgage rates in response to changes in the cost of funds. Most importantly:

- β_i^+ and β_i^- represent the long-run response of bank i's mortgage rate to a positive or negative shock in the cost of funds, respectively. If $\beta_i^+ > \beta_i^-$, this implies that banks pass on cost increases more fully than cost decreases in the long run—an indication of asymmetric pricing behaviour. For example, if banks raise rates quickly when funding costs increase, but delay or reduce rate cuts when funding costs fall, this results in upward pricing rigidity.

- ρ_i is the error correction coefficient. It reflects how quickly the mortgage rate returns to the mean. A larger (absolute) value of ρ_i indicates faster adjustment, while a value close to zero implies sluggish correction.

Together, these parameters allow the model to differentiate between short- and long-run behaviours, and between rate increases and decreases—offering a richer view of how pricing decisions are made over time.

2.3 Gaps in Banking Pricing Modelling

Overall, the current state of pricing modelling can be summarised in Figure 2.1. This assumes the concept of Marginal Cost Pricing as opposed to the Industrial Organisation Approach, as Holland et al. [6] termed the two options. A potential element of note is the period of analysis considered.

Figure 2.1 is a stylised view where the inputs of Asymmetric Pricing and Cost of Funds are what are explicitly stated as the drivers in the model. The constant in the equation captures other elements that come into play, such as the risk of the loan, since it is representative of the margin. This focus on Marginal Cost Pricing is driven by the hypothesis stated in the thesis; the interest is in how perception influences pricing behaviour rather than finding all the individual drivers. Furthermore, the model for Marginal Cost Pricing has the advantage of applying a statistical approach that effectively splits out short-term and long-term impacts, where behaviour or perception might similarly deviate on both horizons. Additionally, the method, as highlighted in the literature in Section 2.2.4, has been used in a similar context of banking previously. In past literature, the focus has been

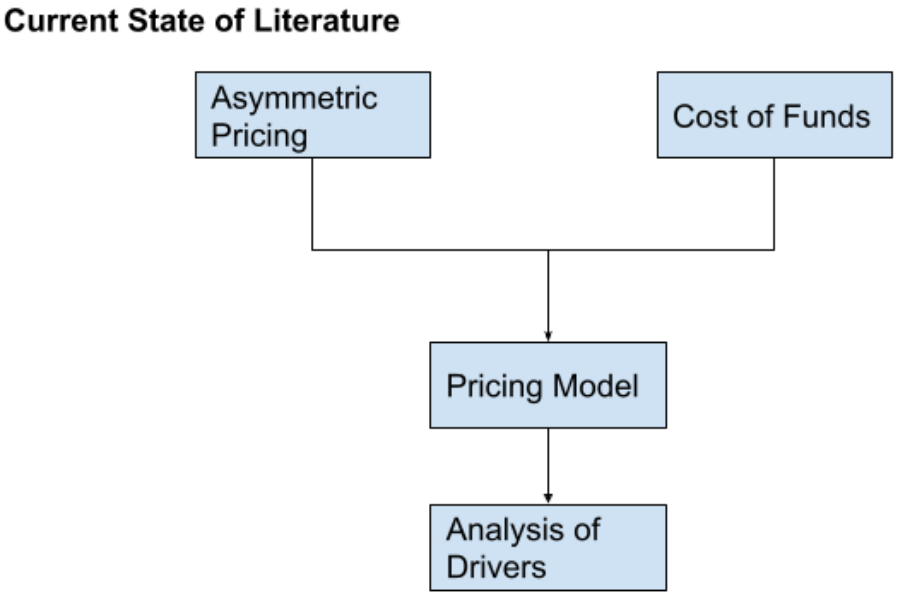

FIGURE 2.1: Current approach for pricing modelling based on literature

up to the mid-2010s. Holland et al. [6] is one of the most recent studies on the Australian market and uses data up to 2015. However, aside from that, there are a number of other elements lacking in current literature that need to be covered to answer the thesis question.

One of the key elements to note is that the current approach to pricing modelling, based on what has been observed in the literature, lacks an explicit treatment of perception. While perception is conceptually important, prior models do not incorporate it in a quantitative way. This is due in part to several challenges: (i) the dominant modelling approaches—such as marginal cost frameworks or error correction models—focus primarily on internal financial variables like cost of funds; (ii) measuring perception is inherently interdisciplinary, requiring the integration of data science and economic theory; and (iii) the data sources needed to capture perception have only recently become prominent, with the rise of social media, online reviews, and news scraping techniques. As a result, perception is typically treated as part of the residual term or absorbed within time-fixed effects, rather than as an observable explanatory variable. Furthermore, the traditional datasets used in these models, such as aggregated interest rate series, lack the temporal and organisational granularity necessary to reflect dynamic shifts in sentiment. Techniques from sentiment analysis or natural language processing have not been widely applied in

this context, meaning that real-time external data—such as customer reviews or media headlines—have rarely been used to measure perception directly. This highlights a clear methodological gap and helps explain why perception, although frequently discussed qualitatively, has not been incorporated into pricing models in this context in a systematic, empirical way.

There are other benefits to the concept of perception than the inclusion into the context of pricing. HRC occurred during 2017–2019. As a result of the Commission, it is reasonable to ask how that influences people's views on banks in general and also of each bank relative to other banks. For example, whether or not customers have larger expectations out of the biggest four banks relative to challenger banks and if this might influence perception. As such, Section 2.4.3 will examine what type of analysis has been performed for the HRC. In turn the HRC could feed into pricing as well through the form of how perception is measured. This is just one example of an event, but generally speaking, what did the perception of banking look like prior to the HRC and whether or not this was a leading indicator on the commission? Section 2.4.1 will consider what type of trend analysis on perception has been performed.

An important aspect to consider is the concept of front and back-book pricing in the banking sector. Section 2.2.3 references a study by Allen and McVanel [53] which explored the differential between posted rates and the actual discounted rates offered to customers. This study shed light on the transparency, or lack thereof, in pricing strategies, specifically within the fixed-rate mortgage market. However, as identified in Section 1.1.4, the Australian mortgage market predominantly operates with variable interest rates. This variable rate market is particularly prone to issues of transparency. Unlike fixed-rate loans, where customers are periodically prompted to reconsider their rates (typically at the end of a fixed-term period), variable-rate customers may not encounter such clear decision points. This lack of a natural juncture for rate reassessment can lead to less transparency, as customers on variable rates may continue with their existing terms without actively seeking better discounts or rates.

From a banking perspective, there is generally little incentive to proactively offer better rates to these existing variable-rate customers, especially if it means reducing the bank's

profit margins. The main exception occurs when there is a risk of the customer switching to another lender, highlighting the influence of customer retention strategies. Furthermore, the concept of switching costs, as discussed by Lowe et al. [51], introduces an additional hurdle for customers considering changing their banking arrangements. This dynamic between front and back-book pricing, especially in a market dominated by variable-rate loans, has not been extensively explored in academic literature.

2.4 Addressing Perception within Pricing

2.4.1 Defining Perception

2.4.1.1 Perception within Banking

The concept of perception is not straightforward to measure. A philosophical lens would suggest everything is a function of perception. This study considers the sentiment of customers towards the bank as one element that might drive it. However, it suggests that the scope of perception extends beyond this. To highlight this, it is important to first see how the literature connects banking and perception in its current state. An example of an Australian study using online survey data was performed by Tucker and Jubb [17]. They asked students how they determined which bank they would choose and what would make them want to 'shop' with a particular bank. They determined from this analysis that students consider bank competence, word of mouth, pricing of the products, services offered and where the bank is located. An example of bank location could be a digital bank relative to a branch-based bank.

Hedley et al. [60] used a combination of survey data and interviews with industry executives to conclude that there is a preference or expectation that banks that are either large or small will perform better than banks that are in the middle in terms of size. The justification is that larger banks have economies of scale, and smaller banks can target particular niches. In contrast to the concept of focusing on niches, Lees and Winchester [18], Lees et al. [19] used Roy Morgan data to suggest customer composition is not quite so clear for each bank. This implies banks do not target particular segments; instead, they opt

for a one-size-fits-all approach. This suggests an opportunity from a marketing perspective as banks could incorporate greater market segmentation into their strategy. Saxena and Khandelwal [20] also look at the concept of consumer perception of banks by measuring it through Customer Relationship Management (CRM) techniques. They conclude that banks that apply the "3 Cs" are preferred. These are Convenience in terms of being easily accessible, Confidentiality in terms of being secure and Customer Relationship in terms of making the customers have positive interactions.

Notably, these studies do relate to the concept of perception by suggesting what customers like from there bank. The studies utilise a more survey-based marketing approach than quantitative analysis. As a result, it cannot be incorporated into a pricing model to represent perception since it is a point in time. It does, however, provide inspiration of what elements a quantitative measure should consider if it were to satisfy current marketing principles.

2.4.1.2 Link between Perception and Pricing

Existing empirical models that used equation 2.3 as a base focused on marginal cost and pricing links for mortgages. Notably, outside of banking, the concept of perception was included in pricing models that were similarly structured to De Bondt [25]. One example of this is Ruscheinsky et al. [22], who applied sentiment to the context of Real Estate Investment Trust (REIT) returns. For estimation, they instead applied a Vector Auto-Regressive method with two endogenous variables of REIT index and media sentiment indices. They were able to show that media sentiment was an important variable to incorporate into the model. Similarly, Qadan and Nama [23] looked at the impact of investor sentiment on the price of oil. They modelled oil prices as a function of economic factors and sentiment factors and suggested these are rational and irrational factors respectively. Despite the "irrationality" of sentiment as a driver, it was shown to be a predictive variable. Both Ruscheinsky et al. [22], Qadan and Nama [23] showcase sentiment to have a relationship with the dependent variable of price/return in a different context to banking.

2.4.2 NLP and Text Mining to Identify Public Perception

2.4.2.1 Sources of Unstructured Data and Deriving Value

With quantification at the forefront of mind an overview of different analysis techniques that could be applied in the context of banking is presented. The articles referred to range from different industries and disciplines as this is required in order to address the thesis question. The reason for examining the area of Natural Language Processing (NLP) and Text Mining is as will be discussed, that this is a common source of data for the concept of perception. In layman's terms and related to the context of this thesis, NLP provides a method to gain key information from text that is freely entered. For example it could read a review of a product and determine what emotions the author appeared to portray based on how they articulated themselves.

Extracting key information and ultimately deriving value from free text is a growing research area. As such, this section highlights a sample of data sources and techniques used by researchers. This is a worthwhile area to explore since using such data and techniques helps translate qualitative information into a more quantitative view. The goal of doing so is to ultimately incorporate such information into a model and to have a more simplistic way to analyse large magnitudes of information.

One example of this is a study by Li and Li [61] that shows how to use data-analytical techniques to take market intelligence out of micro-blogs such as Twitter and use this information to support decision-makers and marketing campaigns. They developed a framework that achieves this goal, and the framework is structured systematically. The conclusion was that Support Vector Machine (SVM) is good for sentiment classification and emotions are a good proxy for expressed sentiments. The main research problem faced by Li and Li [61] was the difficulty in synthesising a large amount of data available through social media for decision-making. Their framework to solve this includes: trend topic detection, opinion classification, sentiment classification, credibility assessment and numeric summary using SVM and a variety of equations.

This study focused on an application to Twitter data for predominantly helping with marketing. The techniques applied do not need to be restricted to the context of Twitter and

could work with any text data. The focus on SVM and Naïve Bayes could be extended to consider other techniques. Later studies, such as Li et al. [62], suggest using a technique they call SMeDA-SA. The purpose of this approach is to mine Twitter data, apply sentiment analysis and then use this to predict how stock prices will move. This technique utilises emotional phrases to better classify sentiments in the tweets, leading to an increase in average accuracy.

Deng et al. [63] proceed further with examining how to overcome domain-specific quirks of social media, as suggested by Li et al. [62]. In particular, the method proposed by Deng et al. [63] looks at a developing corpus (structured set of texts), a seed lexicon and a dictionary. Their developing corpus allowed a domain-relevant sentiment indicator; the seed considered the polarity of sentiment words while the dictionary helped filter out spelling errors. They were limited by not being able to determine the optimal threshold between candidate words; any frequently co-occurring words are assumed to have similar sentiment orientation, and they ignored hashtags that tend to have strong sentiment expression (e.g. #feelsgoodman). The main takeaway was the value of domain-specific social media analysis, which suggests the importance of a tailored approach relative to a general approach to get overall bank perception when using unstructured data. Similar to Deng et al. [63], this study could involve using variables specific to the context; in the case of this thesis, that could include mortgage or banking-related variables.

Jain et al. [64] perform a systematic literature review of 68 papers that use machine learning and online reviews to analyse consumer sentiment. A common recurring theme in the articles they reviewed is to use the review scores themselves as predictors. They identified the application of this method in a wide range of areas such as hotel, airlines and restaurant reviews. Note that review scores range from 0% to 100%, and therefore, a higher value is associated with a positive perception of the organisation. This is more organic than analysing free text without a score, where it might be necessary to manually label a portion of the sample points in order to have a variable to model outcome on, which would naturally have a degree of author subjectivity.

To further support the argument on using review data, Arbore and Busacca [65] suggested that reviews are capable of acting as a proxy for the importance of a positive image. They

did this by performing a survey analysis of publicly available review data which reflected satisfaction through interpersonal relationships with the organisation, understanding individual customer sophistication in relation to product variety and the perception of belonging to a reputable bank as key factors of importance. Reichheld [66] suggested that these review scores could be translated into a Net Promoter Score (NPS). NPS is the percentage difference between promoters and detractors. They found that NPS and business growth are directly proportional. Anselmsson and Bondesson [67] further examined the link between customer mindset metrics such as NPS and market performance data, implying a link between growth data and perception. Notably, business growth could be seen as a representation of a positive perception. Marsden et al. [68] suggest that NPS is one of the best measure of consumer satisfaction and predictive consumer recommendation decisions. Not all research in the area has been so positive, with Zaki et al. [69] suggesting that the NPS is not sufficient for measuring customer loyalty and instead encouraging a multidimensional approach in its place.

The use of review and social media data are not the only examples of unstructured data present in the literature. Another example is Faheem et al. [70] analysis of headlines during the COVID-19 outbreak in relation to positive, negative, and neutral sentiments. They concluded that this form of headline analysis is useful for understanding the implications of emotional well-being and the economic perspective of this event. Similarly, Narayan and Narayan [71] examined headlines and their impact on oil prices and demonstrated another case where a headline data source was used. However, a problem to solve is that these are examined more on the content of the headlines themselves, and the desire is to quantify the perception that there is not a review score equivalent for headlines. The methodology section will provide a solution for this by leveraging knowledge gained from the review space. The concept of headlines for the context of banking is considered to be strongly linked to events such as HRC. Chapter 3 explores this in greater detail.

These studies [62, 63, 72] highlight the importance of domain specificity and emotional phrases in determining how textual data can be analysed in an unstructured manner. This could be applied to the thesis question by utilising a developing corpus and emotions by utilising a lexicon that associates emotions with words. For example, the word “hate” is classified as representing anger. This could help in deriving a model where the usage of

the anger emotion is more likely to lead to a lower perception of the bank. The studies by Jain et al. [64], Reichheld [66], Anselmsson and Bondesson [67], Marsden et al. [68] showcase the value of using alternative sources such as review data and a method in which to examine these through the use of NPS. Meanwhile, Faheem et al. [70], Narayan and Narayan [71] present headline data analysis as another valuable source of information.

2.4.2.2 Topic Modelling Methods applied to Unstructured Data

One of the key challenges in unstructured data analysis is being able to transform large amounts of textual data into an easy-to-interpret and understand format. This transformation is useful for simplifying unstructured data into easily analysable results. However, additionally identifying topics in the text it provides an approach to aggregate the data (by topic). As an example, perhaps news headline could be translated into an overarching topic that could help inform how bank perception changes, which in turn could be used for how pricing dynamics fluctuate. An example of a topic that could be derived from news headlines is RBA cash rate changes.

Liu et al. [1] provide a review of topic modelling approaches. A high level visualisation from their overview is shown in Fig. 2.2. Topic modelling approaches are generally based on a bag of words. This means that the document corpus can be represented as a table, with each document having a specific frequency at which each word appears. It does not take into account the sentence structure.

A topic is a probability distribution over a bag of words. This involves creating a probability that each word belongs to one of the 'K' topics. Within each topic, the probabilities from highest to lowest are sorted, and the resulting top words would represent each topic. The number of topics 'K' is usually user-defined. As used by Nikita [73] in the ldatuning package, there are a number of methods for determining the ideal number of topics, 'K'.

After identifying a set of topics, it is possible to develop a generative process to create user-defined documents. The standard generative processes applied in two fundamental topical models are Probabilistic Latent Semantic Analysis (PLSA) [74] and Latent Dirichlet Allocation (LDA) [75]. The major difference between PLSA and LDA is how the

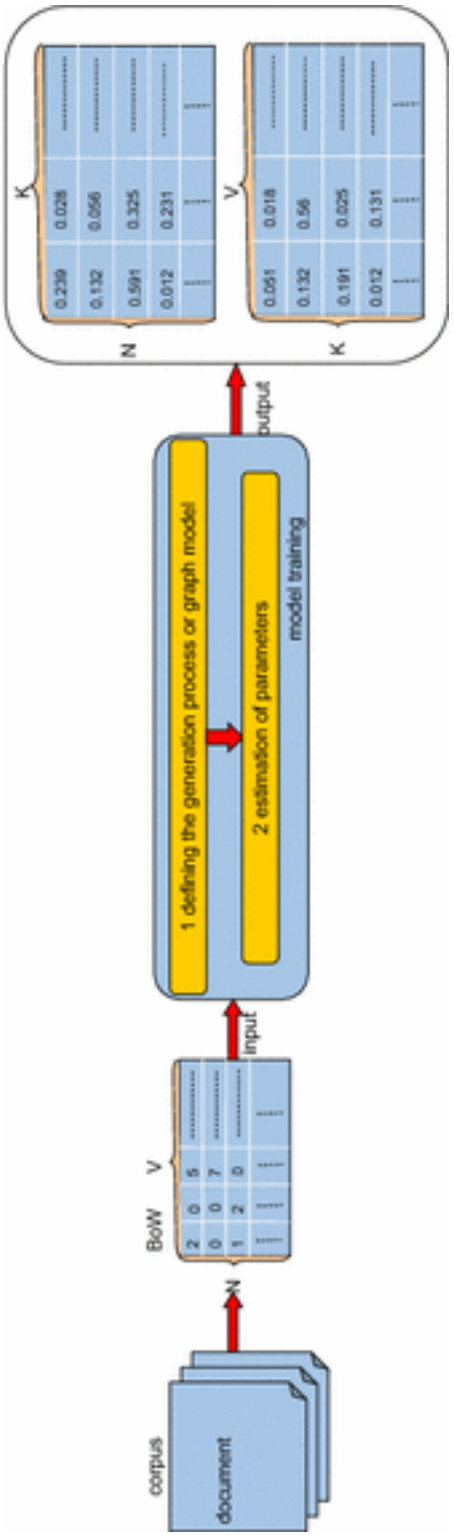

FIGURE 2.2: Diagram on topic modelling (Liu et al. [1] : Page 3)

conditional probability is assigned. Most developments in the topic modelling area focus on this concept. PLSA assumes no prior probability distribution while LDA assumes the prior distribution to be a Dirichlet distribution with given values. The assumption is that conditional probabilities have a multinomial distribution; this is a natural choice given that the Dirichlet distribution is a conjugate prior to the multinomial distribution.

The above methodology helps generate documents; however, the goal is to identify the topics in an existing document. This means reversing the generating process. Topic modelling, therefore, identifies the hidden topic structure and hidden word structure that have the highest likelihood of producing a visible document. Therefore, for both PLSA and LDA the log likelihood that the words and topics seen in a document were generated by the provided parameters is maximised. PLSA typically maximises likelihood using the expectation maximisation algorithm [76]. LDA maximises the joint distribution using techniques such as Gibbs sampling and a variational algorithm for learning. [77] claims that there are advantages and disadvantages for each method, with Gibbs sampling being more accurate while the variational algorithm is arguably faster computationally.

There are many other derivative and alternative models for topic models. This poses the question of how researchers can select the best model. Chang et al. [78] look at PLSA, LDA and the Correlated Topic Model (CTM) [79]. They note that these topic models are typically compared on how well they perform in terms of maximising likelihood in a hold-out sample; however, this does not necessarily mean they are better models in terms of interpretation of the topics. For example, it may lead to topics that don't make sense. Chang et al. [78] identify that likelihood and human ability to interpret the topic can sometimes be negatively correlated through word intrusion and topic intrusion. Note that word intrusion is a measure of whether words in a topic make sense and have an underlying cohesion, and topic intrusion is a measure of whether the mixture of topics makes sense, given the nature of the document. This experiment would need to be done on a larger scale to be conclusive. However, this evidence does suggest that there is an element of qualitative choice in topic modelling. This is not unexpected, given that the definition of a topic is qualitative in itself.

As mentioned above, there are many types of topic modelling, such as supervised LDA [80]

and hierarchical LDA [81]. Supervised LDA is based on knowing the topics in advance, while in hierarchical LDA, there is sometimes a correlation between topics that should be considered. The concepts of hierarchical LDA is more suited for this research, given the desire to see topics arise organically from the data. This provides an exercise to interpret these topics, which provides insights that may not be reached by providing the topics in advance (which would occur in a supervised approach).

Within this research, a hierarchical LDA approach is initially applied to capture general topics for news headlines over time. The topics will be analysed on their own merit to better understand the banking sector and track how it has changed each month to help answer the first research question. Once this is completed, a sample use case is to aggregate the topics at a monthly view to see the frequency of the topics and identify if this helps better understand the perception of banking and if it can feed into a pricing model.

2.4.3 Applying Perception to Hayne Royal Commission

The HRC in Australia investigated the misconduct in the banking, superannuation and financial services industries from 2017 to 2019. The greed and recurring scandals within these industries suggested a need to examine financial institutions in greater detail for elements such as turning a blind eye to financing terrorism, insufficient reporting responsibilities, and money laundering. It was a high-impact event for the banking industry during the horizon of the analysis performed by the thesis and is directly related to the concept of perception. During this time, mass media concerns about trust in banks was reflected in the news and in reviews.

Current research in this area has generally suggested there are shortcomings in the HRC, such that, in practice, the HRC focuses more on market conduct and customer protection matters [13]. This implies that systemic issues around financial stability are construed as being of only secondary concern; obviously this is not ideal because systemic issues can lead to events similar to those of the GFC. Similarly, concerns [14, 15] were raised that the HRC was not properly addressing corporate culture, and if that culture is not improved through government policy, then the issues identified by the HRC could rise again. The way in which banks responded to the HRC was also questioned [16] which

suggested that the banks had tended to be in denial in order to avoid accountability. An angle not examined by past studies was the impact of HRC on the perception of different banks as a result of increased transparency.

Most notably, the literature on the HRC showed that the commission was not considered favourably by existing research. One of the limitations of the approach of past literature is it focused on the banking industry as a whole rather than considering the idiosyncratic impact. Idiosyncrasy in this context means each bank would have been impacted differently. An idiosyncratic view may lead to a different conclusion whereby certain banks were impacted more by the HRC than others, through public perception. Secondly, the past approaches were not quantitative. The focus was more on the legislative angle. A quantitative approach could provide an opportunity to see whether the data could shed further light on the impact of the HRC on the banking industry.

2.5 Conceptual Framework

Before presenting the conceptual framework, a summary of the key gaps in the literature that motivate the framework is discussed. Firstly, there is an advantage to a quantitative measure for perception. As discussed in Section 2.4.1, the concept of how a bank has been perceived has been examined for niche concepts at specific points in time through survey data [17–20, 60]. The concept of perception has a strong focus in these studies on specific elements such as CRM [20] or by asking why someone would choose a particular bank [17]. As such, a gap exists in relation to an index that changes over time. Some key benefits of filling this gap are that it allows perception to be analysed over time and used for modelling purposes. Seeing a movement in perception over time is useful from a behavioural perspective; for example, a bank might look at a decrease in the index and wonder why that happened and if any actions could prevent it going forward.

Another gap highlighted in Section 2.4.3 shows that studies examining HRC from a qualitative perspective [13–16] have tended towards a more legislative angle and on a holistic bank level. By deriving a quantitative index for Banking Perception, it would be possible to examine the impact of the HRC from a different perspective and derive unique insight.

For example, were there repercussions beyond fines on banks such that their ability to attract customers was lost from a lack of trust as represented by a quantitative measure of perception?

Movements in banking perception across individual banks are another element that the HRC has not considered in great detail. Existing research focused on the bank-wide impact of HRC. This study hypothesises that since some banks were affected more than others, this would lead to asymmetric impacts. Utilising the BPI, it would be possible to measure the bank-specific impacts. For example, were the biggest four banks harmed more in terms of reputation than challenger banks due to higher expectations? Or were those with the most notable infringements and resulting media attention hurt twice, firstly with a fine and secondly with a loss in trust and ultimately value proposition of the organisation?

Another element of key interest is Asymmetric Pricing. There is a strong base of existing literature in an Australian context on the asymmetric pricing movements for a period up to early to mid 2010s [5–7]. This study will examine asymmetric pricing in a more recent period, which includes structural change after the GFC and the HRC period. Irrespective of methodological updates performed by this thesis, the result of the changes may lead to a different outcome of the models due to changes in the market.

Front and back-book pricing was shown in Section 2.3, where it was identified prior studies into asymmetric pricing have not explicitly considered the difference between front-book and back-book rates. This might be a result of it being more predominant in Australia as presented by ACCC [8] through the strong variable composition of the book. Regardless, it is an interesting topic due to the social implications of lack of transparency, as indicated in Section 1.1.2.

Finally, the behavioural element of pricing was covered as an area for improvement in banking literature in Section 2.4.1.2, where it highlights how sentiment is used to drive pricing in other areas, such as REIT and oil [22, 23]. However, it has not been examined in great detail in a banking context. In light of the HRC and the increased publicity on banks, it is beneficial to examine how sentiment might influence pricing decisions. It also provides an opportunity to expand the field of pricing and incorporate more machine learning and data science techniques. As evident in Section 2.2.3, a strong Economics

and Finance background drives these models. However, there are advantages to taking a multi disciplinary view on such topics. Where perception might have previously been considered immeasurable, Section 2.4.2 showcases the developments in other areas that can be leveraged to gain a greater understanding. It also has the advantage of using publicly available data and being less reliant on industry to provide data where a conflict of interest may arise or to utilise small sample surveys where confidence in inference will question the number of sample points used.

In Section 2.3, a stylised view of the current state of literature on pricing modelling for banks is represented. Notably, in Figure 2.1, it was shown that the predominant explicit drivers for pricing were asymmetric pricing and cost of funds. The thesis question proposed is focused on the inter-relationship between perception and pricing and gaining a greater understanding of the split between front and back-book pricing. The literature presented in Section 2.4 showcased the potential to measure perception by leveraging literature outside banking on topic modelling and analysing unstructured data. It further presented an advantage in considering the implications of HRC using this data. The literature analysed is sufficient to devise an effective methodology to capture front-book and back-book price differentiation, as discussed in Chapter 5. Overall, the amalgamation of these topics is represented in Figure 2.3, with the objectives referenced within aligning to Section 1.4.

In Figure 2.3, the thesis structure is organised into two main components, encompassed within Chapters 4 and 5. Chapter 5 is central to the development of the pricing model, building upon the foundational research presented in earlier chapters. Prior to this, Chapter 4 lays the groundwork by quantitatively examining the concept of customer perception, a key factor influencing the pricing model. Chapter 3 is instrumental in conducting a systematic review of methodologies applied to sentiment analysis in banking headlines. This analysis is crucial for shaping the methodology in Chapter 4, providing insights into a range of relevant methodologies that support the overall study. By implementing this approach, the thesis aims to address the identified research gaps and contribute substantively to the field, in line with the objectives and contributions outlined in Section 1.5.

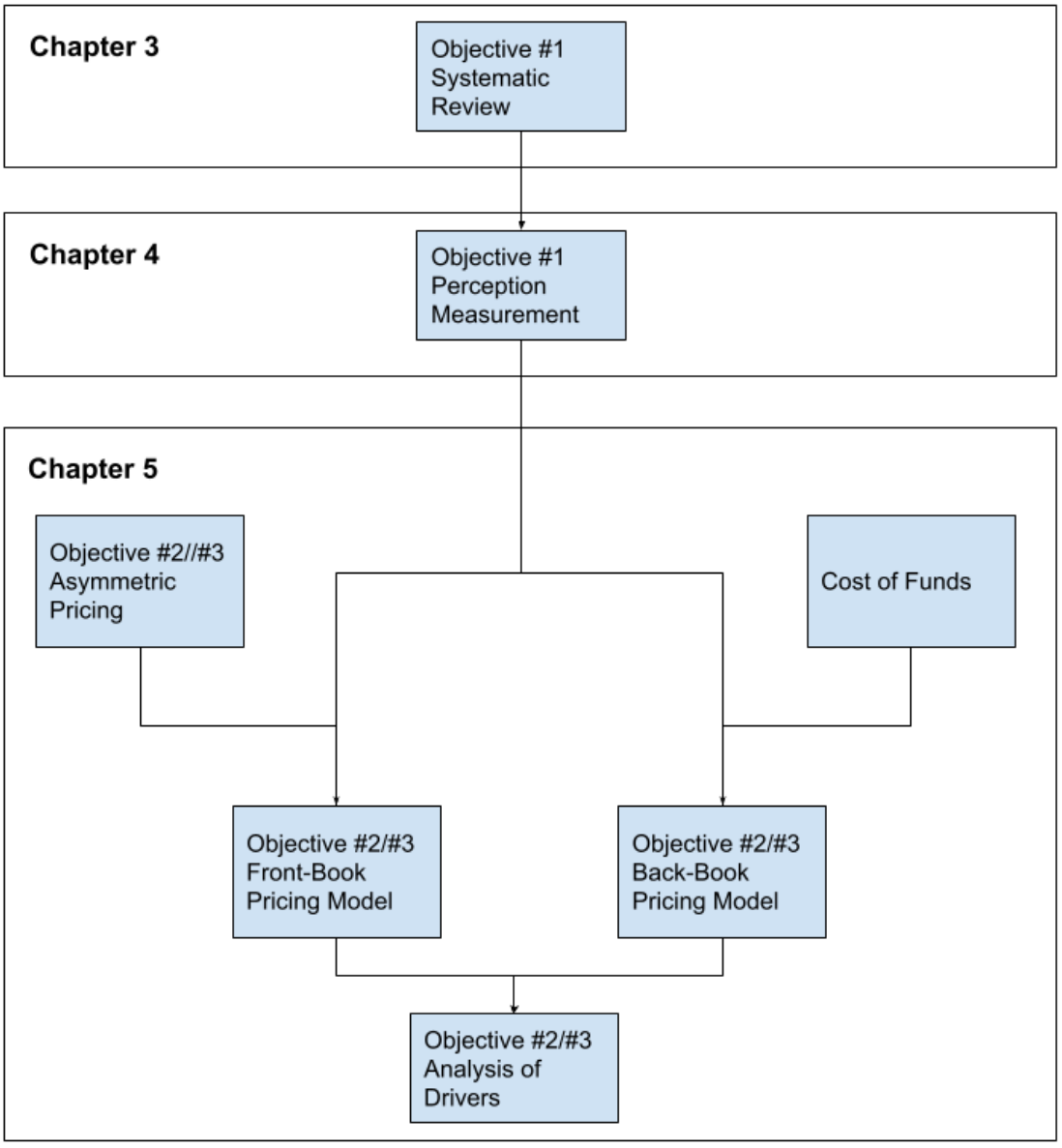

FIGURE 2.3: Proposed approach for pricing modelling based on literature

Chapter 3

Sentiment Analysis of Headlines in Banking: A Systematic Review

3.1 Introduction

Customer perception is a central theme of this thesis, particularly in its role as a behavioural influence on mortgage pricing decisions by Australian banks. To quantify perception in a reproducible way, this thesis explores sentiment analysis as a methodological foundation. Specifically, it investigates the use of sentiment analysis on banking-related headlines as a proxy for public sentiment and reputational standing. The techniques reviewed are also applicable to other short-text formats such as online reviews. This chapter presents a systematic review of relevant literature to guide the selection of suitable methods and highlight key methodological considerations.

Sentiment analysis—the process of identifying and quantifying emotional tone in text—is increasingly used in finance to interpret customer views, market expectations, and broader public discourse. In the banking context, headlines provide a concise and high-frequency source of sentiment signals that may reflect underlying perceptions of financial institutions. These signals, while indirect, offer a scalable way to infer how the public responds to bank actions, announcements, and pricing behaviour.

The review focuses on sentiment analysis in financial and banking domains, with particular attention to short-text applications such as headlines and customer reviews. While many studies originate from international contexts that differ from the Australian setting, they provide methodological insights that are transferable and adaptable. Where appropriate, contextual limitations are acknowledged. By systematically evaluating the literature, this chapter lays the foundation for applying sentiment analysis to quantify perception in subsequent chapters.

3.2 Previous Works

Previous systematic reviews in sentiment analysis have focused primarily on topics not related to news headlines and the banking sector. To ensure that this research is novel, the research process highlighted in Figure 3.1 was applied. In particular, the process leads to three articles deemed relevant to directly. To begin with a comprehensive Scopus search with the query [“News Headlines” AND “Sentiment Analysis” AND “Systematic Review”] yielded no results.

To broaden our scope, we conducted an additional search using the query [“NLP” AND “Sentiment Analysis” AND “Systematic Review”], resulting in the identification of seventeen articles and reviews per Figure 3.1. These works encompassed diverse applications, including sentiment analysis in the context of application of NLP to health fields [82], virtual consumerism [83], and housing safety [84]. Among these, Sharma et al. [85] systematic review was most relevant in that it considered big data in financial institutions. Their study looks generally at the concept of NLP, big data and finance. They suggest that researchers tend to use social media for research purposes as it is more available than confidential financial data. Large Language Models (LLM) is touched as a possibility to improve thematic analysis. However, Sharma et al. [85] did not specifically consider headlines or banking strategy beyond data. Rather, it focused on papers that discuss the usage of NLP techniques within finance with regard to big data.

Furthermore, our searches using the terms [“Sentiment Analysis” AND “Systematic Review” AND “Banking”] and [“NLP” AND “Systematic Review” AND “Banking”] yielded

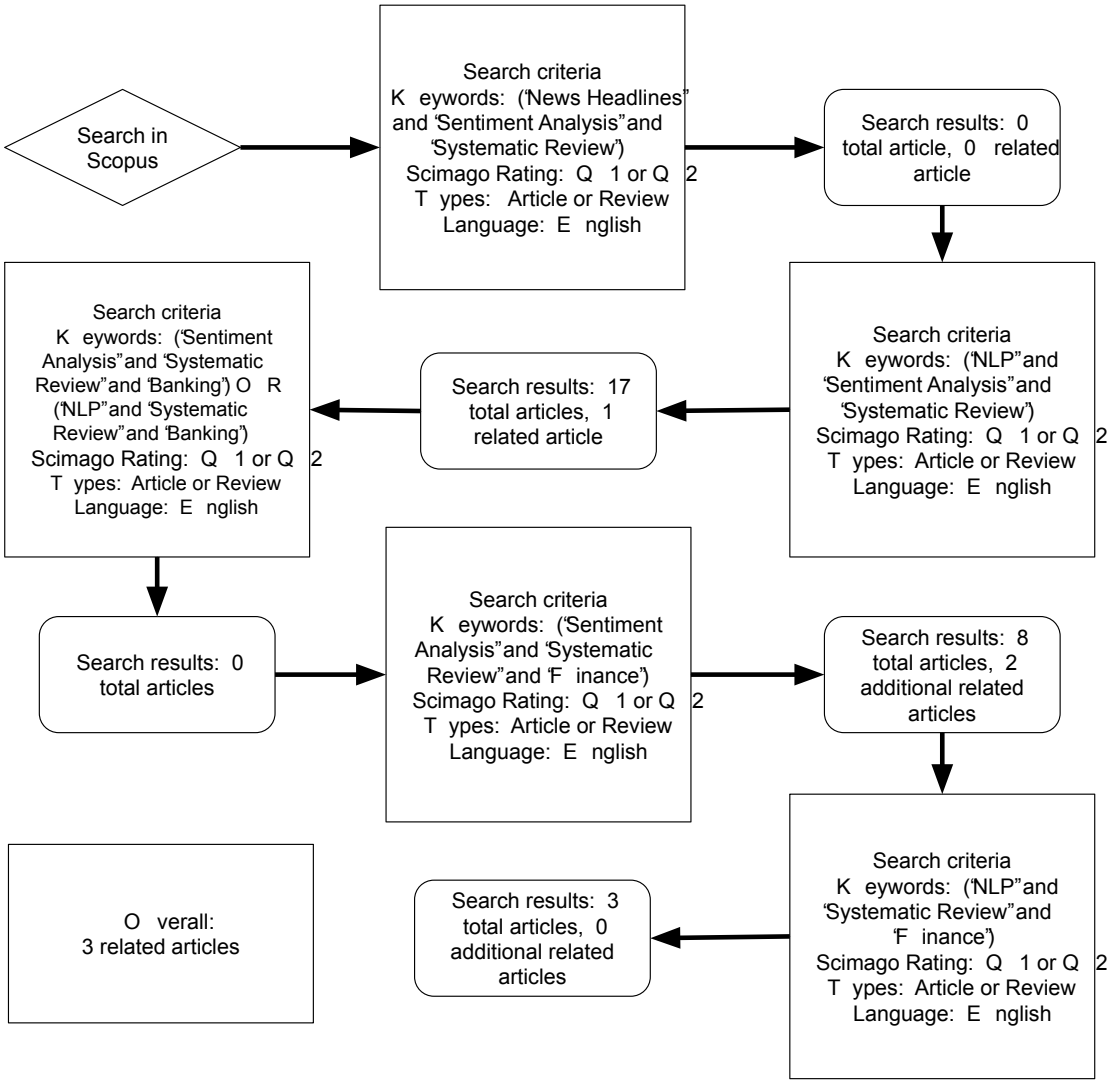

FIGURE 3.1: Flowchart representing related works approach.

zero articles. Expanding the search term to ["Sentiment Analysis" AND "Systematic Review" AND "Finance"] produced eight articles. Among these, Warin and Stojkov [86] examined the application of machine learning in finance, focusing on the technical analysis of financial market trends, indicating the potential value of such techniques for policymakers and the scientific community. However, this paper primarily emphasised metadata analysis rather than article content. The second relevant article, Ferreira et al. [87], explored the application of artificial intelligence to stock market trading and indirectly referenced financial sentiment analysis. The search term ["NLP" AND "Systematic Review" AND "Finance"] yielded three articles; two were within prior searches and the additional article

was not directly related.

Table 3.1 summarises the three articles referenced in Figure 3.1 in the context of why it was considered relevant, what the reviews themselves focused on, and why it does not cover the area of study proposed by this paper.

TABLE 3.1: Overview of relevant previous works

Paper	**Relevance**	**Focus**	**Limitations relative to the area of study**
Sharma et al. [85]	Financial institutions	NLP, Big Data, Finance	Not headline-specific; primarily focused on big data. Limited relevance to banking strategy beyond data analysis.
Warin and Stojkov [86]	Financial markets	Machine Learning, Technical Analysis	Emphasis on metadata analysis rather than article content; not directly related to sentiment analysis or headlines.
Ferreira et al. [87]	Stock market trading	Artificial Intelligence, Sentiment Analysis	Indirectly references financial sentiment analysis; lacks a direct focus on banking headlines or practical applications within banking.

As seen in Table 3.1, these papers highlight the interest in the use of techniques such as NLP, machine learning, and sentiment analysis in the finance field. However, the general exploration of these articles, combined with the limited search results, underscores the scarcity of research dedicated to applying sentiment analysis methodologies to the banking industry and leveraging headline data. Additionally, it becomes evident that recent advancements in this field, such as Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-Trained Transformers (GPT), have not been comprehensively integrated into existing systematic reviews within the scope of papers considered. Hence, a detailed and focused review in this area is essential to provide insight into the methodologies currently employed and their relevance to the banking sector and to address the research gap made evident in Figure 3.1 and Table 3.1.

This chapter aims to bridge this research gap by assessing the applicability of existing sentiment analysis techniques to the banking industry. The significance of this inquiry lies in the role of confidence within the financial sector in macroeconomic performance. Headlines are often considered a reflection of the sentiments prevailing among financial

sector participants, rendering them potential indicators of confidence. For example, the collapse of a bank would likely result in negative headlines, influencing perceptions of both the affected institution and the banking industry as a whole. In contrast, responsible rate management or initiatives promoting Environmental, Social, and Corporate Governance (ESG) may generate more positive sentiments.

In summary, this review intends to evaluate whether the sentiment analysis techniques investigated in previous research are relevant and effective within the context of the banking industry, using the unique characteristics of headline data.

3.3 Review Methodology

To conduct a comprehensive systematic review of sentiment analysis in the banking industry, with a focus on the analysis of headlines, we implemented a structured methodology. This methodology allowed us to identify relevant research articles, categorize them by their subject matter and methodology, and draw meaningful insights from the literature. A summary of the approach can be seen in Figure 3.2. A breakdown of the articles considered is captured in Section 3.4.

3.3.1 Search Strategy and Exclusion Criteria

As seen in Figure 3.2, our search strategy primarily involved accessing the Scopus database, a reliable source of academic publications. We designed a specific search query to capture articles related to sentiment analysis and banking, with an emphasis on headlines. Our search query considered keywords and phrases such as "sentiment analysis," "banking," "headlines," and their synonyms. To ensure a broad foundation, the final search criteria considered ["Large Language Models" and "Headlines"] or ["NLP" and "Headlines"].

In particular, it is not possible to limit the search to banking itself, given the limited research in the area. The applicability to banking is determined on the basis of the nature of the topic. Implicit in the search is the importance of capturing headlines and methods to explain the content of the headlines in a quantitative and automated fashion.

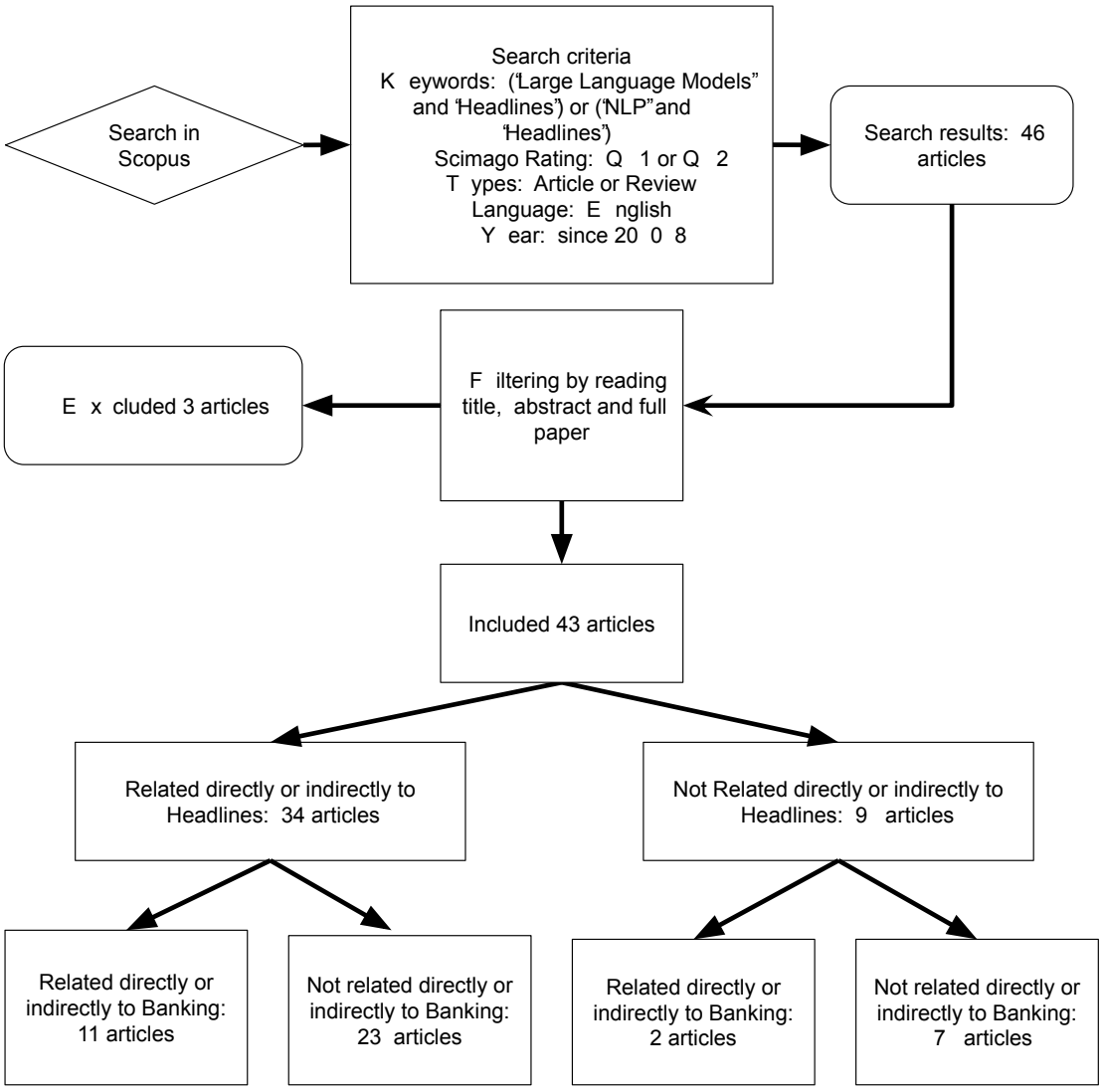

FIGURE 3.2: Flowchart representing systematic review approach.

We limited the publication date to articles published from 2008 onwards to ensure the relevance of the research in contemporary contexts. Furthermore, we focus on articles published in English, as it is a widely accessible language for academic literature.

In the process of our search, there are additional exclusion criteria of articles that are not related to text analysis, sentiment analysis, or banking. In applying our exclusion criteria, we removed articles that were not relevant to text-based sentiment analysis or not meaningfully related to the banking or financial services sector. Screening was primarily conducted at the title and abstract level, followed by full-text review where necessary.

For instance, three papers were excluded despite containing relevant keywords: Roe and Perkins [88], while headline-focused, examined how AI is sensationalised in media without applying sentiment modelling; Dale [89] discussed LLM startups but lacked methodological detail or application; and Ma et al. [90] focused on information extraction from scanned documents, which was considered out of scope relative to the studies retained.

3.3.2 Data Collection and Screening

Following the execution of our search query, we obtained a list of potentially relevant articles from the Scopus database. We then performed a preliminary screening of these articles to assess their relevance based on the criteria and research goals. Articles that met the criteria were retained for further analysis, while those that did not meet the criteria were excluded.

3.3.3 Categorisation of Articles and Analysis and Insights

To provide a comprehensive overview of the literature, we categorised the included articles into several groups based on their topic matter and methodologies. For example, we identified articles related to headline analysis in banking, articles applying sentiment analysis to banking without direct focus on headlines, and articles that focused on NLP techniques in the broader context of finance or economics.

We systematically reviewed the selected articles and extracted relevant insights and findings. These insights were categorised into the following areas:

- Purpose and objectives of the studies.
- Methodologies and techniques employed, including specific NLP models and algorithms.
- Outcomes and results, with a focus on the performance and applicability of the methods.

- Trends in the field of sentiment analysis in banking, including popular models and emerging approaches.

To facilitate a clear understanding of the trends and patterns in the reviewed literature, we used visual representations such as charts and graphs. These visuals helped highlight the frequency of certain methodologies, the evolution of research over time, and the distribution of articles across subject areas.

Our systematic review methodology allowed us to provide a comprehensive overview of sentiment analysis in the banking industry, with a specific emphasis on the analysis of headlines. It allowed us to identify gaps in the literature, emerging trends, and areas with untapped research potential.

3.3.4 Insights from High-Level Overview

In this section, we present high-level insights derived from our analysis of the reviewed articles. These insights cover various aspects, including the distribution of the topics covered, the growth in the number of articles and citations over the years, and the geographical origin of the reviewed literature. These findings provide a comprehensive view of sentiment analysis in the banking and finance sector, setting the stage for a more detailed exploration of methodologies, applications, and outcomes in subsequent sections.

- Figure 3.3 presents a breakdown of the topic areas covered in the reviewed articles. In particular, most papers fall within Computer Science (31.1%) and Engineering (16.5%), suggesting a potential focus on methodological advancements rather than practical applications.
- Figure 3.4 illustrates the number of articles and citations related to those examined. Notably, the articles considered are all post 2021 highlighting the novelty of this area. Dale [91] is the most cited paper in 2021 with a total count of 119. Of the sample considered, it is one of the earliest papers to talk to trust associated with GPT-3.

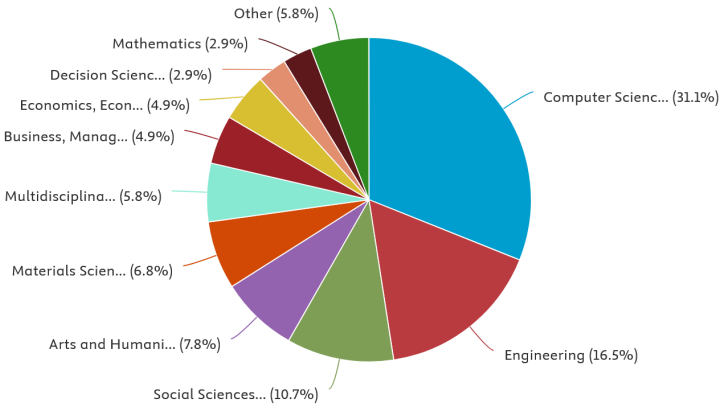

FIGURE 3.3: Frequency of subject area by articles considered.

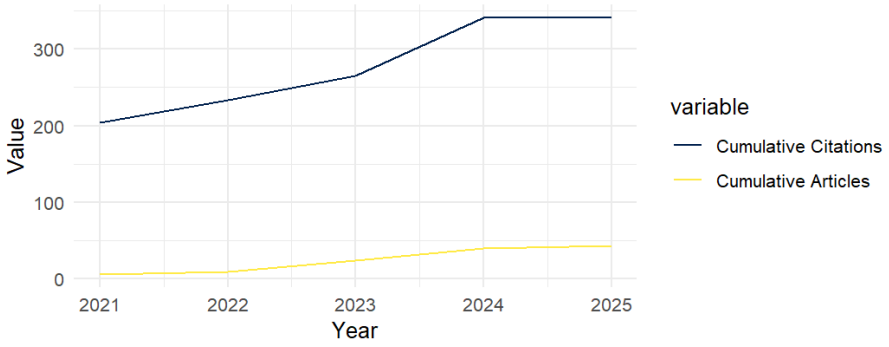

FIGURE 3.4: Citation frequency of articles considered.

- Figure 3.5 displays the geographical distribution of the origin of the reviewed articles. Most of the papers originate from India, the United States, and China, which may reflect the population sizes of these countries. This study focuses on Australia, despite this, these articles are of interest from a methodological standpoint as the goal is to identify industry practice to measure the sentiment analysis, and by extension perception. However, there is potential to foster global interest in this research area, especially given its universal relevance in the banking sector.

- Figure 3.6 uses the author keywords from Scopus to segment the articles reviewed into clusters. In particular, there are four clusters. The yellow cluster directly relates to headlines and financial sentiment analysis linking to this article's purpose directly. In blue, it implies a use of machine learning and deep learning for the purpose of clickbait analysis. Purple indicates the link between LLM and AI. For Green, the techniques involving the techniques of BERT, word2Vec and Glove to

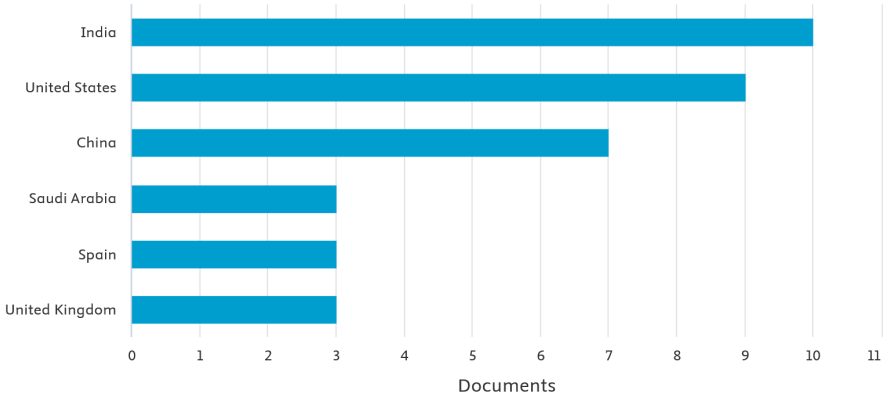

FIGURE 3.5: Country of origin of articles with at least 3 documents.

sarcasm detection. Generative AI and ChatGPT are directly linked as expected for red, but interestingly it connects to the concept of bias, suggesting either a measure for bias through this or an inherent bias based on calibration.

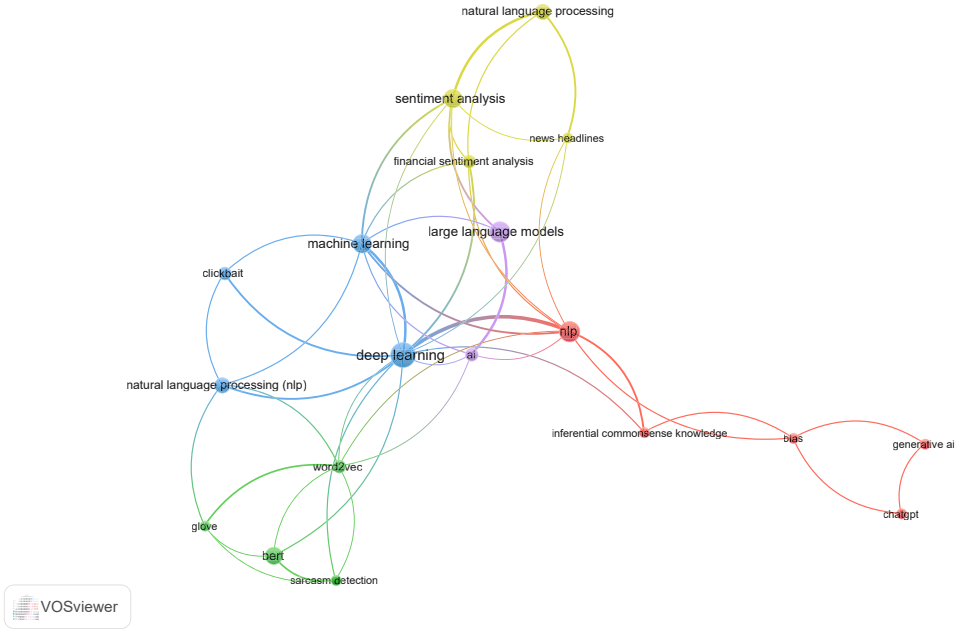

FIGURE 3.6: Map of index keywords.

Our systematic review methodology enables us to offer a comprehensive overview of sentiment analysis in the banking industry, with a specific focus on headline analysis. It also facilitates the identification of research gaps, emerging trends, and areas ripe for further investigation.

3.4 Analysis of Trends in Reviewed Articles

This section presents a comprehensive analysis of the trends observed in the literature pertaining to sentiment analysis in the banking sector, with a specific focus on news headlines. The objective of this review is to systematically examine the evolution of research methodologies, thematic concentrations, and the application of various techniques within this domain. By analysing trends in the accumulated literature, we aim to identify the prevailing research directions, highlight the methods and tools most frequently used, and uncover potential gaps in the current body of research. This analysis provides valuable information on the state of sentiment analysis in banking, particularly in how it has adapted and responded to the challenges and opportunities presented by advances in methodologies. In addition, we explore the extent to which these developments have been incorporated into practical applications within the banking industry. Through this evaluation, we seek to understand the implications of these trends for future research and the potential impact on banking practice.

We classify the articles reviewed in our systematic analysis into four distinct categories based on their relevance to headlines and the banking sector. A high-level reasoning is provided for why it is allocated to headlines or banking, or if it is not. This is covered in Figure 3.7. The details of links to headlines and banking, such as what is meant to be headline generation, are discussed in greater detail in Section 3.4.2.

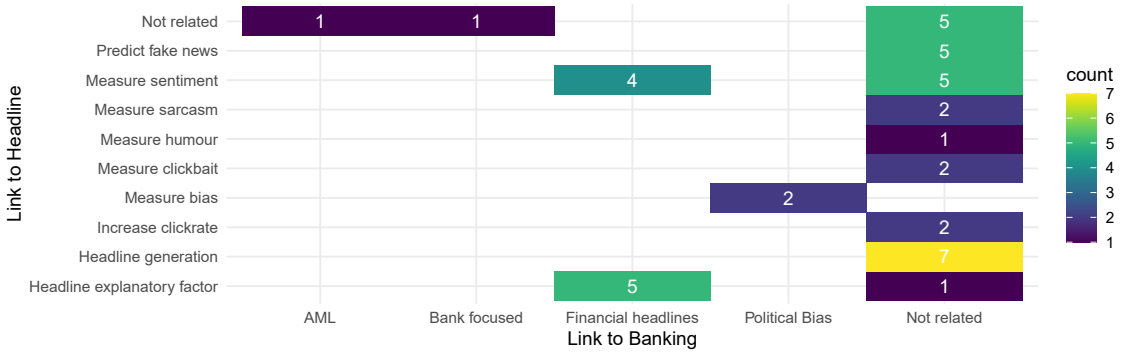

FIGURE 3.7: Article relevance to headlines and banking split by categorisation.

Per Figure 3.7 each category is defined into four groups based on whether the link to the headlines or the link to banking is "Not related" or not:

1. **Headline but not banking related:** Articles in this category are related to headlines but not specifically focused on the banking domain. They may provide valuable information on the sentiment analysis methods used in short-form data. Szczepański et al. [92] for example looked at how to measure fake news detection using BERT-based models. Although banking was not specifically referenced, the techniques used for fake news detection referenced are usable in a banking context. Similarly, Awais and Muhammad Adeel Nawab [93] considered how text summarisation could be used in the Urdu language. This form of summarisation involves looking at headlines and articles, which allows for applicability of the techniques to a wider context. Shao et al. [94] considered how energy vehicle sales could be forecasted using news headlines as an explanatory variable. This link allows for a better understanding of market demand through headlines, which is a concept of interest from a strategic perspective for business management. In particular, the three examples provided highlight valuable insights into headline data modelling, while not being specifically applied to the banking industry.

2. **Headline and banking related:** Articles in this category directly relate to both headlines and the banking sector. They are highly pertinent to the objective of the systematic review. Anamika and Subramaniam [95] examined determining the investor sentiment for cryptocurrency-specific news headlines using NLP techniques, and then applying this to determine the influence it has on cryptocurrency returns. Zhang et al. [96] considered how to improve financial sentiment analysis to better understand the sentimental orientation of financial texts (ie bullish or bearish), highlighting the value of mining financial industry stock-related opinions. Ma et al. [97] observe that the use of ChatGPT provides better performance to predict Chinese equity premiums compared to more traditional Bag-of-Words (BoW) methods. Overall these are directly related to headlines and indirectly related to banking. The indirect nature is demonstrated through the relationship with financial markets, and it is required to apply an indirect lens given limited research on specifically banking behaviour.

3. **Not headline or banking related:** Articles that were not related to headlines, banking, or sentiment analysis. These did not satisfy the exclusion criteria and

were included in the analysis due to the methodologies applied considered relevant. Scola and Segura-Bedmar [98] consider how BERT can be used to detect sarcasm for social media-type data. While social media data does not directly relate to headlines, for example, it can be considered a short-form text data and therefore techniques can be broadly applicable. Wahlster [99] is a systematic review that considers the development of Large Language Model literature, concluding that there are benefits in human trainers combining with interactive machine learning. In general, these topics do not have any relation to banking or headlines, but there are techniques and considerations that are applicable to text data analysis and could be seen as useful in approaching headline studies.

Cobb [100] suggest how LLM might be beneficial in an alternative area of archaeological work, concluding on the potential value it could have in the process highlighting the development of the space. Similarly, Rathje et al. [101] showcased the value of BERT in multilingual psychological text analysis, detecting psychological constructs such as sentiment, discrete emotions, offensiveness and moral foundation. This broad applicability suggests that it could be used for banking purposes

4. **Banking but not related to headlines:** Articles that focus on banking but do not address headlines or sentiment analysis were included due to the subject matter. There are two articles within this category. One is a critical review by Kute et al. [102] that examines the implementation of techniques such as Machine Learning and Deep Learning in the realm of Anti-Money Laundering (AML). Although AML is indirectly linked to banking, since banks must address money laundering issues, the article centres on the application to AML detection rather than focussing on headline data. The second article, authored by Mathebula et al. [103], investigates sentiment classification using real-time reviews, drawing on feedback about South African banks as a data source. This article addresses banking directly by analysing review data instead of using headlines.

3.4.1 Purpose

The analysis of headlines in the literature reveals several predominant themes and applications. These themes provide valuable insight into the multifaceted nature of headline analysis within the field of sentiment analysis and natural language processing.

Figure 3.7 provides a visual breakdown of articles related to headlines and the banking sector. The links to the headlines are discussed in more detail in the following.

1. **Headline Generation:** This theme includes articles focused on the conversion of full articles into concise headlines. These studies aim to effectively summarise the core content in a summarised form. Gorenz and Schwarz [104] tested the humour production abilities of ChatGPT compared to professional comedy writers in producing satirical headlines similar to *The Onion*, and based on a survey findings suggested the jokes were at least equally funny for ChatGPT regardless of comedic task and expertise of human comedy writer. Fatima et al. [105] utilised part-of-speech tagging to support headline text generation approach using GPT suggested the generated headlines had a significant improvement in performance. Singh et al. [106] suggest an approach to summarisation and headline generation. Using deep learning they suggest this approach leads to effective headlines.

   Although the overarching theme is headline generation, this includes general summarisation techniques. For example, Benedetto et al. [107] uses a variety of language models, including LLM, to summarise Italian legal news documents. They concluded that the latest LLM type models outperform models like Bayesian Additive Regression Trees (BART) in terms of informativeness. They do note, however, that nuances of legal reasoning were not captured, potentially driven by not having models specialised to the legal domain. In addition, they raise concerns about privacy concerns, high computational demands, and potential bias in output. This concept of bias in AI-generated output in relation to summarisation was also captured by Fang et al. [108]. They used seven representative LLM, such as ChatGPT and Large Language Model Meta AI (Llama), to generate headlines using news articles and conclude the

potential for racial and gender bias in the output. A recurring theme in the literature review, this was also discussed by Breazu and Katsos [109] who questioned the perspective that ChatGPT is reproducing. They used the context of the UK referendum of 2016 and compared the generated headlines with actual headlines on eastern European Roma migrants, and identified that ChatGPT was less biased and less sensationalised compared to the right-wing media. Most of these articles highlight methods in which headlines could be generated with higher quality.

2. **Explanatory Headlines:** Under this theme, headlines are used as explanatory factors in various models. These studies explore the use of headline sentiment to predict market movements or other outcomes. Chandola et al. [110] look at the prediction of the directional movement of stock prices using deep learning, leveraging headline data as an explanatory factor, and finding its inclusion beneficial. Liu and Huang [111] consider the prediction of crude oil price forecasting, noting that prior studies tend to focus on it as a time series or econometric variable prediction problem. Although some do consider raw news headlines or topic models, they do not consider event information in detail. They suggest a framework for extracting underlying related events and a text sentiment analysis algorithm to extract sentiment, leading to better performance compared to benchmark methods.

   An alternative perspective is suggested by Glasserman and Lin [112] who reference the look-ahead bias in stock price predictions where it is informed specifically by GPT sentiment analysis. There are look-ahead bias bias limits backtesting capabilities, as the LLM is trained on many years of data. In addition, there is distraction bias, since it has general knowledge on the companies that could influence the results. To overcome this, they anonymised the headlines, noting that surprisingly, this improved in-sample performance suggests that distraction bias might be larger than look-ahead bias. Overall, this showcases an application of headline data as input into other analysis and highlights that it has the potential to be a significant contributor, particularly to prices in existing literature.

3. **Sentiment Measurement:** This category comprises studies that focus on measuring the sentiment expressed in headlines. The goal is to gauge public perception or the emotional tone conveyed. Zhou et al. [113] suggests a model based on BERT

targeted at short text classification. They experiment with a number of datasets, including a headline news corpus, and determine that this proposed approach offers a better performance than standard BERT models by looking at accuracy and F1 value performance metrics. Jannani et al. [114] analyse perception and discourse by categorising headlines into themes such as politics, business, and education and obtaining the sentiment. They use techniques such as LDA and BERT to derive an index representing well-being. Dangi et al. [115] proposes the value of using the artificial rabbits optimised robust random vector functional link network to improve sentiment analysis accuracy, suggesting a limitation of existing sentiment analysis work being a lack of consideration of randomisation-based neural networks.

There are papers in this area focused on broader language applicability of sentiment measurement. Pan et al. [116] evaluated transformer models for financial-targeted sentiment analysis in Spanish. They compiled a corpus of financial tweets and news headlines in Spanish and identified which Spanish-specific LLM. Benítez et al. [117] considered if data augmentation techniques using machine learning and deep learning can improve classification for Spanish data, noting that Spanish large label data are scarce. They do cite concerns with augmentation techniques impacting semantic integrity, however, despite this, the augmentation techniques were suggested to have the capability to enhance sentiment and emotion analysis. Overall this showcases application of sentiment analysis for predictions and the potential to help further refine analysis in this area.

4. **Fake News, Clickbait Detection and Click Rate:** This area of research deals with the detection of fake news through analysis of headlines, leveraging technology to discern the authenticity of news content. This category also considers clickbait headlines, which while might not necessarily be entirely false, are sensationalist. Supriya et al. [118] use the dissimilarity between headlines and articles to determine if clickbait. They measure this through a Sentence-BERT (SBERT) method suggesting this provides better performance than current state-of-the-art models. Farokhian et al. [119] uses two parallel BERT networks, one based on headline data and the other checking for important text in an article's newsbody to detect fake news, noting that this approach leads to a higher performance. Devarajan et al. [120] proposes

a framework for fake news detection using deep NLP model based on four layers: publisher layer, social media network layer, edge layer embedded and cloud layer. They suggest a better performance as a result of this. García-Ferrero and Altuna [121] propose a dataset called NoticIA which consists of Spanish news articles with clickbait headlines, each paired with a single-sentence summary written by humans. They suggest its value in task-specific models for clickbait summarisation.

As a different view, DeVerna et al. [122] suggests that ChatGPT can be used for fact checking to determine false headlines. However, using ChatGPT specifically, while accurate 90%, has the potential harm of decreasing belief in true headlines and increasing belief in false headlines. In a similar vein, another perspective was provided by Bajaj and Vishwakarma [123] which suggested that it is possible to bypass deep learning clickbait detection mechanisms by adversarial modifications of headline data. By highlighting this weakness, they suggest that improvements would be beneficial to overcome this weakness. Notably the majority of papers were focused on how to better distinguish fake news or clickbait using more complex methodologies.

An alternative angle are studies focused on how to increase click rate. This is something that is useful for a business trying to sell a product, for example, in this scenario, the headline could be the title of an email. Nguyen et al. [124] propose an approach to build an email open rate predictor for marketing purposes. The improvement in approach is based on using headline characteristics as predictors, similar to a computer science view, but also appending this with additional marketing based variables. This was identified to provide better performance. Qiu and Golman [125] use NLP to identify headlines with a salient question, convey importance, and appear surprising, with negative valence, have higher click rates, but not necessarily long-term reader engagement.

5. **Measuring Specific Elements:** These studies investigate specific elements of headlines, such as political bias, humour, or sarcasm, in order to quantify and identify unique headline attributes. Shatnawi et al. [126] examine headlines, but in the context of detecting humour. They propose a variation of the BERT model which is

an ensemble of different state-of-the-art pretrained models suggesting good performance as a result.

Goel et al. [127] apply a number of different neural techniques, such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and Convolutional Neural Network (CNN) in an ensemble model to detect sarcasm for a news headline and a Reddit dataset. They identified that using an ensemble model with word embedding outperformed other state-of-the-art models. Sharma et al. [128] consider sarcasm detection for headlines, Reddit and Twitter. They suggested the use of an ensemble approach that considers text embedding and also includes fuzzy evolutionary logic before making the final classification. This approach was suggested to be more accurate than earlier state-of-the-art models.

Swati et al. [129] create a framework for predicting political bias in headlines, suggesting that existing methodologies do not recognise the potential of common sense reasoning. They overcome this, they introduce a neural network framework which leverages inferential commonsense knowledge. They concluded that this leads to better performance. Swati et al. [130] also look at political bias in headlines, but in how to determine it for low-resource languages. The framework leverages commonsense knowledge as well and notes that the proposed framework is the best performing. These articles focused on how extending existing techniques could lead to a better fit of performance for purpose.

Despite the diverse and valuable contributions of these various approaches, their direct application to the field of banking has been notably limited. Although none of the reviewed literature directly addresses banking-related sentiments, indirect connections are observed in the examination of stock prices, energy markets, and financial headlines. In particular, researchers commonly employ financial headlines to gain insight into potential price movements within financial markets. Furthermore, some studies consider the degree of political bias in headlines related to the banking sector and explore topics like antimoney laundering, which is associated with financial services.

However, there remains a significant research gap in comprehensive understanding how headline analysis can be leveraged to gain insight into banking behaviour and decision-making processes. This gap presents an intriguing research opportunity for future research in the field.

3.4.2 Methodologies Employed in Literature

Figure 3.8 provides a summary of the prevalence of different methodologies utilised in articles considered within the systematic review. In instances where GPT and BERT are mentioned, they have been distinctly categorized apart from LLM, due to their respective widespread adoption.

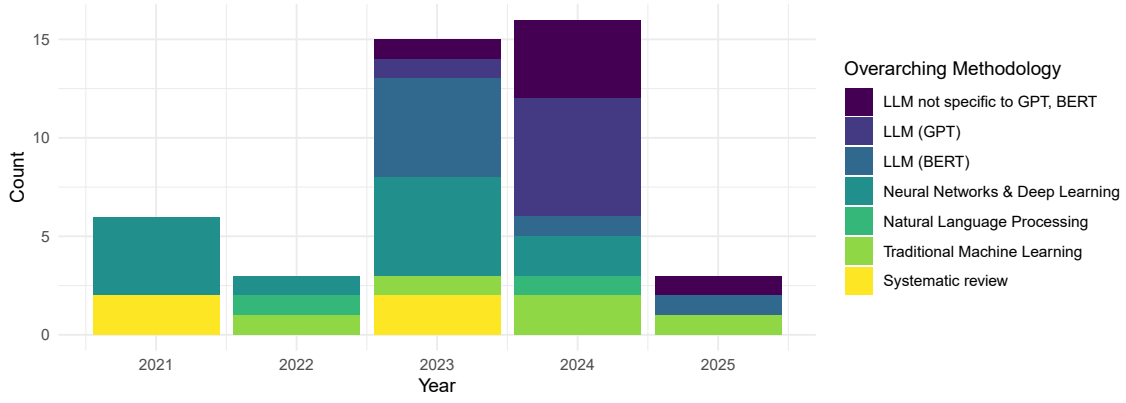

FIGURE 3.8: Methodologies observed in articles reviewed by year.

A summary of the methodologies represented in our review is discussed in this section (see Figure 3.8). Firstly, the **Neural Networks & Deep Learning** category encompasses approaches based on artificial neural networks designed to identify complex patterns through deep hierarchical structures. These methods excel in learning from large volumes of data and capture subtle relationships that are not easily identified by traditional methods. Specific methodologies include *Neural Networks*, computational models inspired by biological neurons effective in pattern recognition and predictive analytics; *Deep Learning*, involving advanced multi-layered neural networks designed to learn intricate data representations used in domains such as image and speech recognition; *GRU, LSTM, and Recurrent Neural Network (RNN)*, types of recurrent neural networks specialising in sequential data analysis ideal for language processing and time-series forecasting; *CNN*, neural networks

tailored specifically for spatial data like images and videos; *Artificial Rabbits Optimization*, a biologically inspired algorithm used to solve complex optimisation tasks efficiently; and *Ensemble* methods that combine predictions from multiple neural networks to enhance accuracy and reliability.

The **Large Language Models** group comprises extensive neural architectures trained on vast textual datasets to produce coherent, contextually relevant language, uniquely addressing tasks related to language generation and comprehension. Key methodologies include *GPT*, known for generating human-like text useful in automated content creation, summarisation, and conversational AI; *BERT*, notable for its deep contextual understanding essential for search optimisation and text classification; *Llama*, Meta's large language model optimised for efficient training and fine-tuning; and general *LLM* architectures instrumental in complex comprehension and generative tasks.

Traditional Machine Learning methods involve conventional statistical and algorithmic approaches for predictive modelling and classification, valued for their interpretability and computational efficiency compared to deep learning models. Included in this category are *Machine Learning* algorithms that learn patterns to predict outcomes effectively, *SVM* noted for powerful classification capabilities, especially in high-dimensional spaces, and *Regression* methods useful in forecasting continuous outcomes and exploring relationships within datasets.

Natural Language Processing (NLP) techniques focus specifically on analysing, interpreting, and generating human language, facilitating automated textual analysis and sentiment identification. Specific methodologies include general *NLP* approaches foundational for language-based tasks; *Lexicon*-based methods employing curated word lists for basic language processing; *Sentiment Analysis*, designed to systematically evaluate emotions and opinions prevalent in social networks and market research; and *Event Ontology*, which provides structured semantic frameworks to categorise textual descriptions of events.

Systematic Reviews represent a distinct category that does not focus on developing or applying machine learning models directly. Instead, these studies take a meta-analytical approach to synthesise findings in a body of literature, comparing methodologies, summarising results, and identifying overarching patterns and gaps in the field. Their inclusion

provides a valuable foundation for understanding the methodological landscape and guiding future research directions.

Noting the above definitions, Figure 3.8 highlights the consistency of more traditional techniques such as NLP, machine learning and neural networks, and deep learning in general. Interestingly, LLM have gained prominence from 2023, and dominated the research articles considered for 2024 and for the beginning of 2025. Most notably BERT made a large portion of these articles in 2023, and this was then succeeded by GPT in 2024. Figure 3.9 compliments this analysis by presenting the headline categories discussed in Section 3.4.2 to the different methodologies represented in Figure 3.8

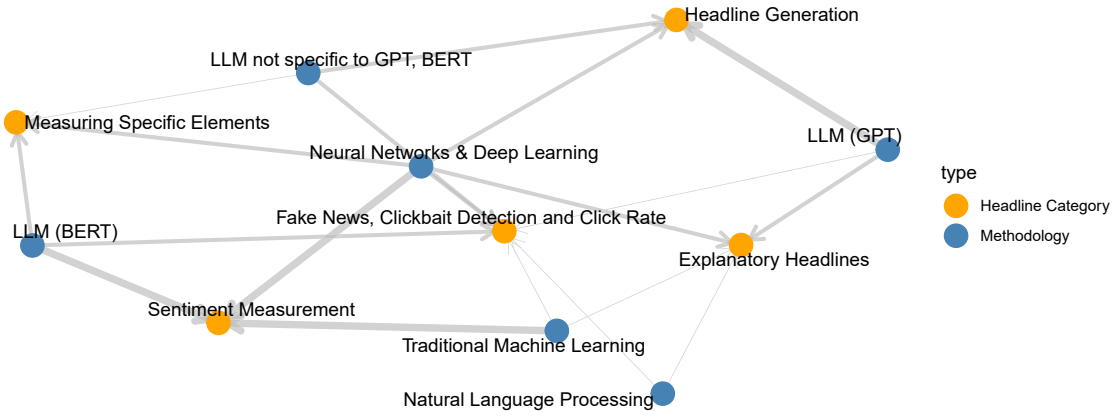

FIGURE 3.9: Network diagram between headline category and methodology

The network diagram in Figure 3.9 shows the most popular technique for given purposes. For example, sentiment measurement broadly benefits from machine learning, neural networks, and BERT. BERT is more often used for sentiment measurement and measuring specific elements such as bias. Meanwhile, GPT is more popular in relation to creating explanatory factors using headline and headline generation. This suggests that the reduced frequency of BERT from 2023 to 2024, could be driven by a different outcome of research being prioritised for headlines in addition to GPT becoming more popular. Fake news, clickbait detection, and click rate appear to benefit from a broad range of techniques. Instead, headline generation is most benefited by the neural network class, with the exception of BERT.

Figure 3.10 illustrates the popularity of methodologies in the reviewed articles, distinguishing between those within the banking sector and those from other fields.

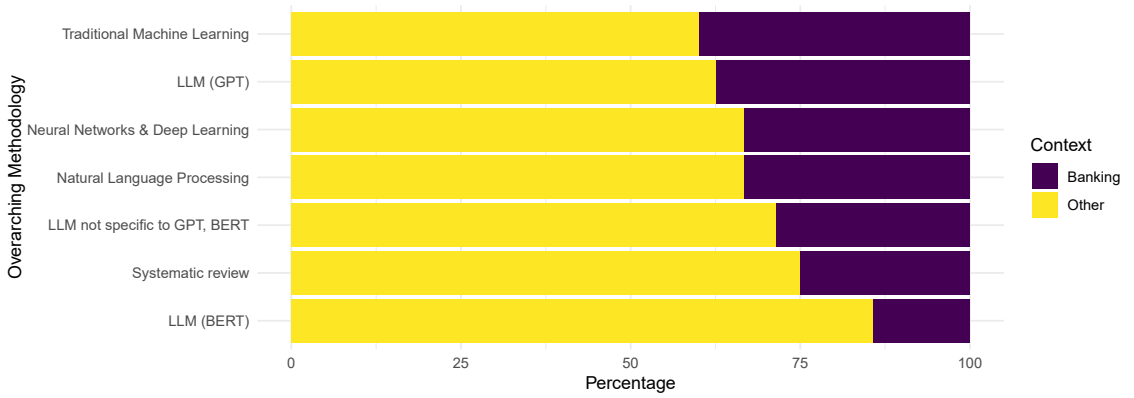

FIGURE 3.10: Methodology popularity over time.

As shown in Figure 3.10, there are more articles from outside the banking sector than within it, but the important observation lies in their relative proportions. Specifically, banking articles more frequently employ traditional methods such as NLP and machine learning. Where GPT has been applied in banking, it typically serves to generate explanatory variables from prompts based on financial headlines, while neural networks have been utilised to analyse financial domain-specific vocabulary and political biases. This suggests considerable potential for broader applications of advanced techniques such as GPT, and particularly BERT, within the banking context.

Table 3.2 covers a more broader scope. It includes the papers based on the exclusion criteria, but also incorporates papers with Scimago rating less than Q2 and conference papers. This means all other search criteria outlined in Section 3.3.1 and ensuring it followed the grouped methodologies listed. This is done to highlight the general direction of analytical research. The shift in distribution from Neural Network, Deep Learning and Machine Learning to specifically LLM is notable when comparing the percentage of articles from 2024 and 2025 to all articles. This mirrors the observations in Figure 3.8, highlighting that even with the broader scope of articles considered, the general trend remains.

In conclusion, the systematic review reveals a dynamic landscape of methodologies, with certain approaches gaining prominence in recent years, reflecting the evolving trends in the field.

Grouped methodology	References	% of all articles	% from 2024/25
Machine Learning	[94, 123, 131–151]	19.5%	16.7%
Neural Network & Deep Learning	[117, 152–193]	35%	5.6%
NLP based	[90, 125, 194–209]	14.6%	5.6%
LLM	[88, 89, 97, 101, 103–105, 108, 109, 112–114, 116, 118, 121, 122, 124, 210–230]	30.9%	72.2%

TABLE 3.2: List of methodologies

3.4.3 Outcomes

The results of the articles reviewed reveal the various objectives pursued by the researchers, as depicted in Figure 3.11. This links the outcome to how it relates to banking or headlines. There are three outcomes, better performance, analysis, and systematic review. Better performance relates to the researcher aiming for a higher goodness-of-fit or better out-of-sample performance. Analysis is where the researcher predominantly concludes on how the use of methods helped to better understand a particular problem. The systematic review refers to a synthesis of research with the intention of informing the public about a particular topic. Note that the allocation of the outcome was simplified, so while for example the outcome could technically be defined as applicability to a different language, if the goal is to improve the performance of the model, then the allocated outcome would be better performance.

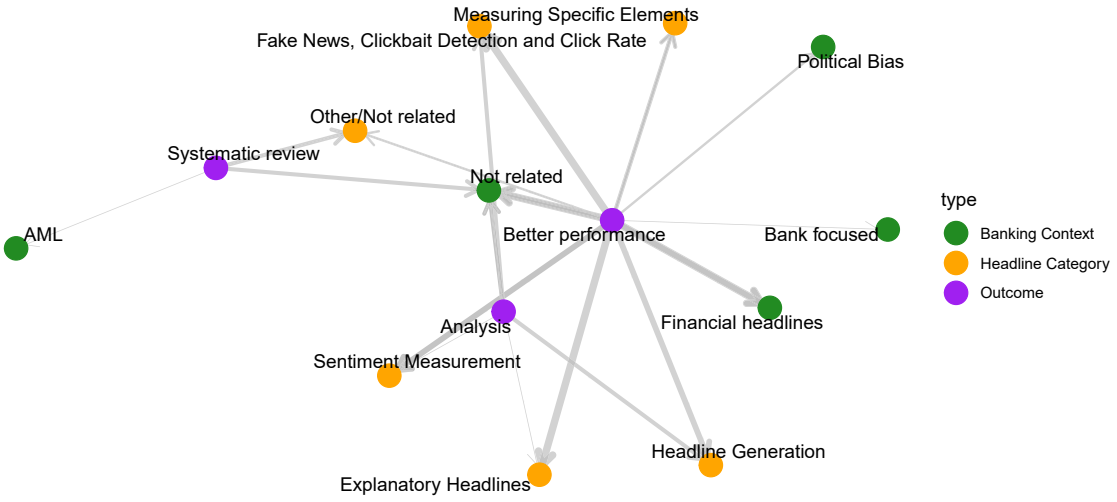

FIGURE 3.11: Network diagram between banking, headline and outcome.

Figure 3.11 showcases the predominance of papers that focus on better performance, specifically to be able to measure elements of the text such as sentiment or bias, as well as the potential to create explanatory variables through headlines and headline generation. In contrast, the analysis focused on fake news, clickbait detection, and click rate and headline generation categories. Most systematic reviews focused on exploring broad techniques with potential applications. However, in the context of banking, only one such article focused specifically on anti-money laundering (AML). The research potential is in firstly more articles in the analysis and systematic review style in the area to take advantage of the better performance available to the underlying models such as GPT and BERT. Secondly, more research papers are required in the banking area; currently the focus is relatively limited, the most popular use case being financial headlines to improve the performance of prediction.

3.5 Discussion

In this section, we examine the essential aspects and findings derived from our comprehensive review of sentiment analysis. From the standpoint of identified research gaps, we observe that: (i) banking-specific analyses remain limited in their engagement with recent advancements in textual or NLP analysis; (ii) there exists significant potential for methodologies incorporating recent advancements in LLM such as those in GPT and BERT; and (iii) existing research in text analysis has predominantly prioritised performance improvements (e.g. accuracy) over considerations of practical applicability and decision-making utility as shown in Section 3.4.3, which discussed research outcomes. These gaps are examined in this section and point to the need for more research in the banking domain that applies these tools in a practical, decision-focused context. This application is explored in more detail in the following section.

3.5.1 Limited Banking Analysis

Our review revealed a notable lack of existing literature on the use of sentiment analysis within the banking industry, specifically related to headlines. Although sentiment

analysis has been thoroughly investigated in multiple fields, including social networks and healthcare, its implementation in the banking sector remains limited. This shortcoming highlights the opportunity for additional research in this domain, as understanding public sentiment towards the banking industry is vital for informed decision making and ensuring financial stability.

This is evident in thirteen articles related either directly or indirectly to banking for the search terms considered. Of these articles, five focused on the use of textual data to create an explanatory variable to improve model performance, and four of these articles considered sentiment measurement. A wordcloud is presented in Figure 3.12 to highlight the areas of interest based on the summary of purpose of the articles performed during the systematic review, it excludes headlines, analysis and reviews, among others, to ensure

FIGURE 3.12: Word cloud for themes relating banking related papers.

The stock prediction, politics, money laundering and cryptocurrency as key words showcases the relation to banking and financial services. There is not as much focus on concepts such as strategy, marketing, or pricing which papers outside banking have considered. Furthermore, analysis has focused on the sentiment most prominently. With the advent of textual data analysis, it would be expected that more decision support software would be developed with the intention of leveraging this information. Despite the current limitations in academic research in this regard, there are notable areas of opportunity that can benefit from headline analysis.

3.5.2 GPT, New and Emerging

Our review, particularly as reflected in the methodologies described in Figure 3.8, demonstrates the increasing relevance of GPT in 2024 compared to 2023. This trend showcases that either GPT will continue to be more popular in 2025, or it could also suggest that it could be surpassed by an alternative LLM method such as Llama. This suggests that this is an evolving area and that it is important to note the available techniques.

Furthermore, some of these papers on GPT instead focused on some of the shortcomings. For example using GPT to derive explanatory variables from headlines has a risk of the GPT being based on the data after the event itself occurred. Therefore, providing it with a future view is not valuable for back-testing. Additionally, GPT might use information it knows in general to fill in the gaps, and not consider the information at face value, encouraging the researcher to ignore known organisations for example. Others talk about the potential copyright issues of GPT in how the model itself is trained.

Despite this, the shortcomings of the method will have increasingly better solutions, as is evident from the results of the researchers focused on better performance in Figure 3.11. It is important that a researcher for this space uses these methodologies while recognising weaknesses. The refined GPT language modelling capabilities could be instrumental in deciphering often ambiguous and jargon-laden financial news, which is crucial for banks in assessing market sentiments and consumer confidence.

3.5.3 BERT is a Complementary Versatile Approach

BERT and GPT are both transformer-based language models, but they differ fundamentally in architecture and usage. BERT is a bidirectional encoder model, trained to understand the context of both directions in a sentence simultaneously, making it well suited for classification, extraction, and sentence-level understanding tasks. In contrast, GPT is a unidirectional decoder model, trained in a left-to-right manner to predict the next word in a sequence, enabling it to excel in text generation, completion, and creative language tasks.

Figure 3.9 showcased this, as BERT has not been used as much to create explanatory headlines or to generate headlines for the sample considered as the main technique. A future research area of interest might be an ensemble that leverages the advantages of BERT and GPT, for example a system that uses BERT for the classification of review or headline data and GPT to provide decision support through proposed actions to improve sentiment.

The prevalence and versatility of BERT, especially in the analysis of small text formats such as headlines, is evident from the findings in Section 3.4.2. In the banking context, this means leveraging BERT's robust contextual understanding of BERT to analyse headlines that often carry significant weight in influencing market movements and shaping public opinion. However, as shown in Figure 3.10, the application in banking is limited compared to other techniques.

The ability of BERT to discern nuanced sentiments in financial news can be a crucial tool for banks to predict market trends and understand public perception towards financial products and policies. This is particularly relevant in today's fast-paced information age, where headlines can dramatically sway investor behaviour and customer trust.

3.5.4 Research Less Focused on Application

The results of the reviewed articles indicate a predominant focus on showcasing the superiority of proposed methods over previous approaches through metrics such as accuracy and F1 value performance metrics. This is highlighted in Figure 3.11. The purpose of the researchers has been to demonstrate that their chosen methods perform better in varied textual tasks, thereby contributing to the development of more accurate models. However, there is room for further research that goes beyond performance improvement and explores the broader application of sentiment analysis, such as in the banking industry.

3.6 Future Perspective

This section builds on the identified research gaps by examining how recent advancements in LLM and NLP can be applied to banking-specific sentiment analysis. Our findings indicate that headlines, as concise encapsulations of critical information, hold untapped potential for banking analysis. Without limiting the view to banking, the general area of text analysis is growing as captured in Figure 3.4 and discussed in Section 3.3.4. The succinct nature of headlines makes them ideal for rapid sentiment analysis, providing immediate insight into market trends and public opinion. Using sentiment analysis for headlines can aid banks in real-time decision making, risk assessment, and trend forecasting. Future research should explore how banks can integrate headline analysis into their data analytics frameworks to enhance responsiveness and strategic planning.

Through a synthesis of current literature, this chapter highlights the evolving methodological landscape of sentiment analysis and its relevance to the specific needs of the banking sector. It emphasises the importance of adapting recent innovations, particularly large language models, to suit domain-specific applications. The analysis provides a foundation for future academic inquiry, especially in the addressing of persistent challenges such as sentiment detection. It also identifies a notable gap in the use of headline data within financial services and highlights the limited focus on explainable artificial intelligence (Explainable Artificial Intelligence (XAI)) in existing research, suggesting a clear area for further exploration. From a managerial perspective, the findings offer practical information by illustrating how headline data have been used in related fields and how similar approaches could support more informed data-driven decision making in dynamic financial environments. To achieve this, this section is divided into (i) the underutilisation of LLM within banking; (ii) the opportunities presented by headline-based sentiment analysis; and (iii) the growing relevance of these tools for real-time decision-making and strategic forecasting.

3.6.1 LLM has Large Potential

The systematic review, particularly in Sections 3.3 and 3.4.2, underscores the potential of LLM in sentiment analysis, despite their current underutilisation in banking. This is further established in Section 3.5.3 which highlights the popularity of BERT in recent years. The advanced capabilities of LLM, especially in capturing and generating nuanced language, open new frontiers for the analysis of the banking sector. Future research could focus on harnessing models like GPT for more in-depth understanding of market sentiments, customer opinions, and economic trends. In particular, GPT is currently underused in the literature as discussed in Section 3.5.2, suggesting further potential even outside of banking.

The research establishes different LLM used for different purposes in the context of headlines. To help visualise which LLM has been used for different areas, Figure 3.13 is provided.

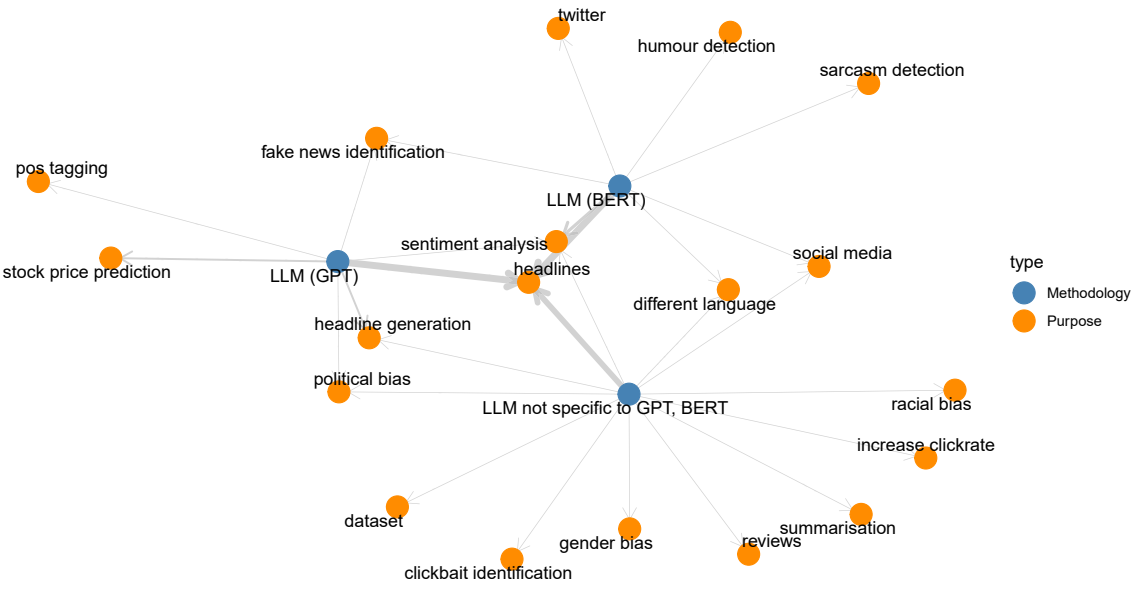

FIGURE 3.13: Network diagram between LLM methodology and paper purpose.

Within Figure 3.13, it is possible to note that sentiment analysis, humour detection, and sarcasm detection leverage BERT, while fake news identification could utilise either BERT or GPT. In the case of bias, broader methods are used, as is evident from the links to LLM not specific to GPT or BERT. This breakdown can help guide to know what has

been considered so it might be used for business purposes, or alternatively, what has not been considered so that it might define a potential research opportunity.

The adaptation of LLM to banking-specific needs could revolutionise the way financial institutions interact with and understand their market environment. This potential, coupled with the increasing availability of sophisticated NLP tools, sets the stage for significant advances in this field over the next decade.

3.6.2 Headlines Complement Banking Analysis

The headlines offer a unique advantage for sentiment analysis in the banking industry. As shown in Section 3.5.2, there are several papers that have used headline data for financial headlines, where these papers tended to focus on cryptocurrency or stock markets predominantly. However, where headlines were used for explanatory purpose per Section 3.4.2, six articles directly leveraged this, with five considered directly related to banking.

This is a research opportunity, as headlines provide a concise summary of news and events, making them a valuable source of information for financial institutions. Banks can leverage headline sentiment analysis to gain insight into public perception, predict market trends, and inform strategic decision-making. This advantage highlights the potential for further research and practical applications in utilising headlines for banking analysis. To provide a parallel scenario, consider Khalil et al. [231] who look at optimising the hybrid process of the AI-assisted Letter of Credit exam to improve trade finance. They are able to leverage artificial intelligence to, among other purposes, reduce operational risks. If headline data could be used similarly, this could benefit other areas and could be practically integrated into business as usual in banking decision making.

Despite this, one of the challenges in sentiment analysis is one, especially when applied to headlines, is the limited amount of text available for analysis as headlines are inherently concise. Therefore, extracting meaningful sentiment from such a brevity can be challenging Researchers need to develop innovative techniques to overcome this limitation and ensure the precision of sentiment analysis in short text formats. Noting this, with the advancement of techniques such as BERT discussed in Section 3.5.3 and the potential

driven by GPT as discussed in Section 3.5.2, the tools for doing so are becoming more advanced, and therefore this limitation is becoming less prevalent.

3.6.3 Dynamic Research Area

The dynamic and ever-changing nature of NLP and sentiment analysis in banking, highlighted throughout this review, underscores the need for continuous adaptation and innovation in this field. Rapid advancements after 2018 have revolutionised sentiment analysis, making it more accessible and relevant for banking applications. As the field continues to evolve, it will be crucial for both academia and industry to stay abreast of the latest developments, ensuring that methodologies and applications remain cutting-edge and relevant to the changing landscape of banking and finance. Figure 3.10 showcases this change as some methods fade out of use or see limited use while new methods such as BERT and GPT gain popularity.

Given the context of financial services, it is expected that in the future as LLM are adopted for decision making, there will also be a desire for greater XAI which will allow a greater understanding of the rationale behind the output behind LLM. A paper that highlights the trends in XAI is Saranya and Subhashini [232], which highlights examples of how this could be used in social media that have similarities to headline data. Although the systematic review did not explicitly identify articles focused on this topic, the concept of XAI is, from our perspective, closely aligned with the rising studies on LLM and the ability to trust its results.

3.7 Summary

In summary, this systematic review has examined the application of sentiment analysis in the context of news headlines, with a particular focus on its relevance to the banking and finance sector. The analysis has traced the evolution of sentiment methodologies, from traditional machine learning approaches to advanced deep learning models such as BERT and GPT, and assessed their suitability for short-text formats.

The review highlights diverse applications within the banking context, including sentiment measurement, fake news detection, political bias analysis, and classification tasks. These use cases demonstrate the methodological adaptability of sentiment analysis and its potential value in financial decision-making. Despite these developments, there remains a notable gap in directly integrating sentiment analysis into banking practices, especially for modelling constructs such as public perception.

This gap provides a key opportunity—one that this thesis aims to address. By systematically assessing sentiment analysis techniques, this chapter lays the groundwork for their application in modelling banking perception. In particular, sentiment derived from headlines and other short texts is positioned as a scalable proxy for perception, which is otherwise difficult to quantify. This perspective underpins the development of the Banking Perception Index (BPI) in the next chapter.

Chapter 4 builds directly on these findings, introducing a framework for quantifying banking perception using sentiment signals from headline data. The BPI aims to bridge the conceptual and empirical gap by capturing how public discourse, as reflected in headlines, responds to bank behaviour and events. This approach supports the broader thesis objective: to incorporate perception as a measurable behavioural input into models of mortgage pricing and strategic bank behaviour.

Chapter 4

Modelling and Application of Banking Perception

4.1 Introduction

Banking perception refers to the public's view or regard for a bank. This can fluctuate based on the actions and strategies undertaken by the organisation. If properly modelled, this can help establish a cause-and-effect relationship between organisational actions and their impact on perception, aiding future strategies. An example of this is the HRC which inquired into and reported on misconduct in the banking, superannuation, and financial services industry. Elements reported from the HRC would negatively affect the perception of the implicated financial institutions. Quantifying this impact, including both positive and negative dimensions, is an area of interest. In order to quantify the impact of perception, this chapter draws on the insights from Chapter 3 relating sentiment analysis of short-form text data such as headlines and reviews.

Section 4.3 will introduce theoretical foundations and justify the direction of the analysis. This is followed by Section 4.4, which represents the methodology and articulates the characteristics of the BPI. Section 4.4.2 will highlight the data used for the analysis. This is followed by breaking down the BPI into microeconomics, macroeconomics and combined

in Sections 4.4.3, 4.4.4, 4.4.5 respectively. This is combined into a single index of BPI in Section 4.4.6. Section 4.5 represents the results.

Section 4.5 highlights the outcomes of BPI in Section 4.5.1. Section 4.5.2 provides outcomes for each component that aggregate to the BPI. This is finished by a section demonstrating the topic modelling and derivation of the Monthly Headline Score (MHS) in Section 4.5.3. Following this section is a discussion in Section 4.6 with consideration placed on how it connects to the HRC. A summary of key findings concludes the chapter in Section 4.8.

4.2 Determinants Influencing Perception

This chapter addresses research questions one to three as outlined in the research questions section, Section 1.3. These questions are: (1) How can banking perception be measured quantitatively? (2) Does banking perception vary due to the HRC? (3) Do individual banks experience different movements in perception over time, and if so, what drives them?

These questions are addressed by deriving the BPI, a time-variant quantitative measure of perception. This index supports the broader research aim of assessing how perception influences pricing behaviour in the banking industry.

As outlined in Chapter 2, the literature reveals that "perception" in banking lacks a consistent definition. Existing studies typically rely on point-in-time survey data that focuses on customer preferences [17–20, 60]. However, in practice, banks are more concerned with how perception shifts over time and how these shifts affect strategic positioning.

In Chapter 3, sentiment analysis of short-form text (e.g., news headlines) emerged as a promising method for measuring perception over time. The majority of studies reviewed show that headlines can be analysed for various signals including emotional tone, fake news detection, click-through prediction, and sentiment classification [113–115]. These techniques allow for scalable and continuous tracking of how institutions are perceived. The limited research of these techniques in banking, as discussed in Section 3.5, emphasises the need for a domain-specific approach to sentiment modelling in this study.

Three primary sources are selected for deriving perception:

- Headlines: capturing macroeconomic, regulatory, and reputational signals.
- Reviews: capturing direct consumer sentiment and lived experience.
- Growth: capturing behavioural outcomes that indicate brand effectiveness.

These were selected to balance subjectivity (from sentiment) and objectivity (from observable outcomes). Each captures a distinct dimension of perception: social discourse, customer experience, and behavioural response. Their strengths and limitations are summarised in Table 4.1.

TABLE 4.1: Summary of perception sources and associated literature

Source	**Pros**	**Cons**	**Literature**
Headlines	Provides a macro-level view of the organisation. Typically less biased than reviews as they are curated or edited. Captures broader economic and reputational shifts such as rate changes or financial events.	Short-form headlines may miss nuance or organisational context. Sensationalism or editorial framing may skew sentiment.	Sentiment from financial news is a strong economic indicator and reflects broad market perception [233, 234].
Reviews	Direct customer voice, includes both praise and complaints. Rich in emotional tone and customer experiences. Star ratings can be used as inputs into perception indices.	Subjective and susceptible to bias, particularly a negativity bias. Authenticity of reviews can be questionable.	Reviews influence consumer choice and reflect brand sentiment; however, negative reviews tend to be overrepresented [235–237].
Growth	Provides an objective signal of consumer preference via acquisition or usage behaviour. Used in strategic scorecards to track brand effectiveness.	Growth can result from multiple factors not necessarily related to brand perception (e.g., pricing strategy, advertising, mergers).	Market performance and brand-based intangible assets are linked, but confounded by external factors [238, 239].

By combining these three sources—headlines, reviews, and growth—the model captures both perception and response, triangulating sentiment against behaviour. Notably, reviews and headlines allow subjective insight into customer and media perspectives, while growth offers an objective cross-check.

This multi-source design ensures that the BPI reflects a well-rounded, longitudinal view of perception. It also allows for comparison across banks and through time, enabling empirical testing of perception shocks like the HRC and their effect on funding costs and strategic behaviour. The following chapter describes the quantitative considerations when developing an index.

Evaluating the optimality of such an index is not straightforward. Typically, with these type of indexes you would want to compare this to another indicator to showcase a link. For example, Reichheld [66] uses relative growth of a business to propose that NPS is a good measure and worth adapting. For reference, NPS is a measure of customer satisfaction by looking at number of promoters and detractors for a product. However there is not a way to statistically prove NPS is very predictive in the same manner as a model with actual value and predicted values. As a result, the BPI suitability can be based on whether or not the outcome is reasonable. Therefore, this study leverages the HRC as a reference point. For example, if the HRC had adversely impacted a particular organisation, then the BPI should decrease for that organisation relative to past performance.

4.3 State-of-the-art vs Proposed Approach

Figure 4.1 highlights the quantitative approach undertaken by this study to develop a relationship between the cost of funds and the price point. This is represented to highlight the value of incorporating perception data for the overall thesis. Note that this chapter is dedicated to the section labeled objective 1 in the figure, while the next chapter will provide further details on the sections labeled objective 2 and 3.

The figure compares state-of-the-art approach and a proposed approach. The state-of-the-art approach is as defined in the current state section of the literature review, found at Section 2.2. The proposed approach is based on a combination of existing literature

suggesting value in perception and front-book and back-book differentiation as highlighted in the section on proposed state in section 2.4, the state of sentiment analysis and by extension perception as defined in the systematic review in Chapter 3, and by the available sources of information covered in the prior section. Both the state-of-the-art and proposed approach is broken down into taking input data, applying a transformation to this data to ensure it can be modelled effectively, incorporating into the model and producing output which can then be analysed.

The state-of-the-art approach highlights the marginal cost based pricing approach identified in the literature. It is a common approach to modelling pricing that has developed over time to incorporate concepts such as asymmetry of pricing. The research performed by Apergis and Cooray [5], De Bondt [25], Fuertes et al. [47], Valadkhani and Worthington [48], Belke et al. [49] utilise models in line with the state-of-the-art approach including marginal cost and/or asymmetric pricing. This refers to how the price change varies based on if cost of funds go up relative to if they go down. The proposed approach extends this through the derivation of BPI (Objective 1) and incorporation into the state-of-the-art model approach (Objective 2). The BPI intended to cover a common concept in marketing and pricing strategy, as seen by the highly cited paper by [9] which speaks to perceived value, and in other areas [22, 23], into the concept of banking pricing. Objective 2 also accounts for front-book and back-book asymmetry which prior papers have not covered explicitly. The closest in concept being in the Canadian market, where Allen and McVanel [53] divide their analysis into posted rates and discounted rates. Objective 3 provides insights on the outcomes of these models and their implications to a wide range of stakeholders and is a predominant contribution of this study.

Objective 1 involves deriving the BPI by utilising three new data sources of reviews, headlines and growth data consistent with the prior section. These three sources drive the values for Monthly Review Score (MRS), MHS and Monthly Growth Score (MGS) respectively. MRS, MHS and MGS are conceptually associated with the concepts of microeconomic, macroeconomic and combined respectively. The terms for microeconomic, macroeconomic and combined have been defined for this study as relating to different layers of perception and to simplify explanation. The rationale behind the term microeconomic relates to the type of perception from an individual level, so for example if a customer had a

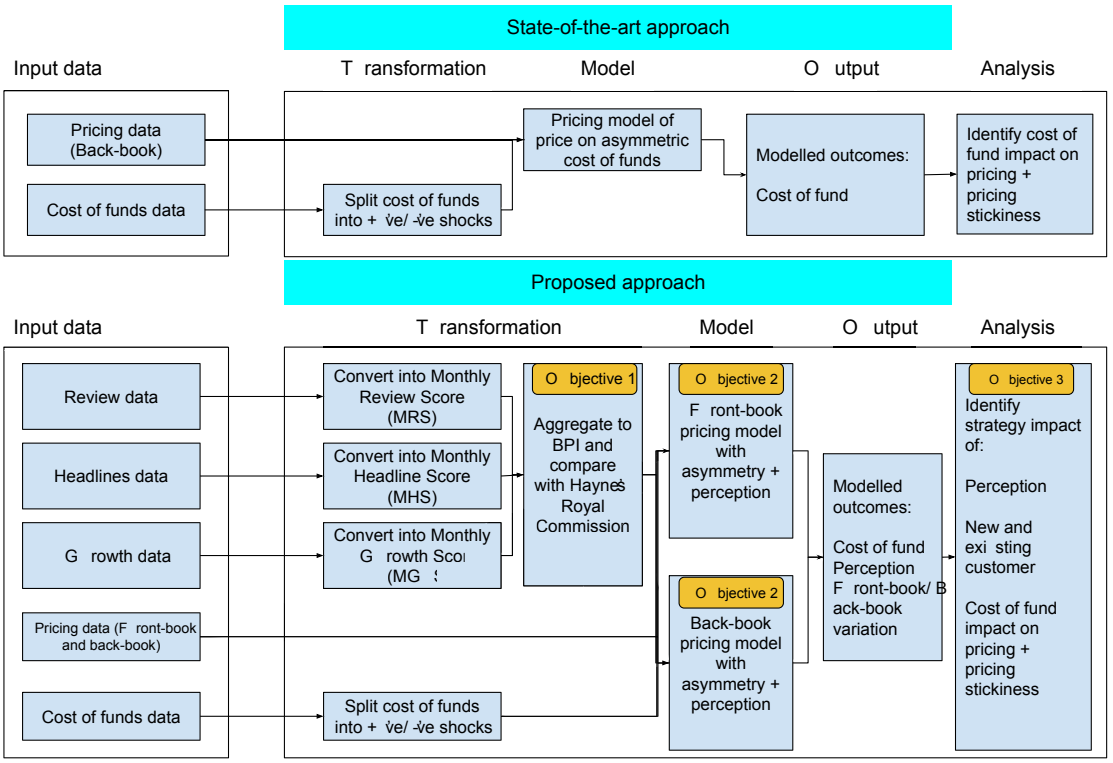

FIGURE 4.1: Comparison between state-of-the-art and proposed approach.

poor experience with the teller at a bank that would be considered a micro-level concern. This is because it does not change how other customers view the bank, as they may not have encountered the same issue. The concept of macroeconomic is something that impacts everyone and it could be a bank that increases their rates more aggressively than other banks. This would impact all the customers to that particular bank, and indirectly changes non-customers views of that same bank. A combined view would be something like the growth of the business, it is reflective of the impacts of both microeconomic and macroeconomic concerns.

There are a number of equations within this study; Table 4.2 highlights the commonly used notations.

MRS relates to the concept of reviews. At a high level it represents if customer reviews have been positive or negative. As the methodology will highlight, this relates to the scores provided by customers as well as the wording choice of the review. Review scores are seen to be a representation of perception as it shows a quantitative view on how the customer

TABLE 4.2: Commonly used notations

$BPI_{i,k}$	$\triangleq$	Retail Bank Perception Index (BPI) for bank i at month k;
$MRS_{i,k}$	$\triangleq$	Monthly Review Score (MRS) for bank i at month k;
$MGS_{i,k}$	$\triangleq$	Monthly Growth Score (MGS) for bank i at month k;
$MHS_{i,k}$	$\triangleq$	Monthly Headline Score (MHS) for bank i at month k;
i	$\triangleq$	index value for bank over a sample of 8 banks;
k	$\triangleq$	index value for month ranges from Jan 2013 to Dec 2019;

ranks the bank. The nature of reviews tends to be personal, such as a bad interaction with staff at the bank, and is considered to align to the concept of a microeconomic view of perception.

MHS is a representation of the macroeconomic view as it relates to news headlines. News headlines are interpreted as how the public perceives a bank. For example, a headline that suggests a bank has been affected by a cyber-attack would naturally lead to poorer perception of the safety of the bank, and the bank as a whole.

MGS is the combined view, that captures the bottom line impact to a bank of a change in perception. It is quantified using the bank's growth data, measured by volume. Growth is a function of new customers joining the bank in the form of new settlements and existing customers leaving the bank due to either repaying their loan or refinancing to another bank. Therefore, it captures the concept of "voting with your wallet".

As indicated in Section 4.2, when reviews (MRS), headlines (MHS) and growth (MGS) are combined we have a broader perspective on the perception of the bank as the negatives associated with each individual indicator are supported by the positives of the alternative indicators (Table 4.1). This is why it is aggregated into a BPI. However these indexes can also be considered in isolation for a more strategic angle as presented in Table 4.3. The strategies highlighted in Table 4.3 identify the weakest index, and consider if it is possible to leverage the more powerful index to help stimulate the weaker indexes. If all indexes show a poor performance then this suggests a strategic overhaul is required.

TABLE 4.3: Potential strategies on the back of indexes in isolation

	Good MRS	Good MHS	Good MGS
Poor MRS	-	Market headline success to individual customers to create greater sense of trust.	Be wary of reviews being a leading indicator to lower volume growth going forward.
Poor MHS	Monitor if headlines impact reviews going forward and front-foot reassure customers of vision.	-	Consider how to improve publicity with strong growth and poor headlines.
Poor MGS	Reviews not translating to growth. Need to market being well reviewed.	Headlines not translating to growth. Perhaps including the success on the website could create awareness.	-

4.4 Data and Methodology

4.4.1 Approach

To detail the approach applied, this section begins by first presenting Objective 1 of the thesis (also highlighted in Figure 4.1), which is the output and aggregation of MRS, MHS and MGS into the BPI, and developing the components necessary to achieve this. The aggregation of BPI is obtained by summing the MRS, MHS, and MGS values that are equal to either 1 or 0. This was assigned to each bank in the sample at each monthly time point.

A value of 1 in MRS, MHS or MGS shows that bank has outperformed for the respective index at that point of time. The definition of what outperformed means is highlighted in each respective section. Taking this perspective however of outperforming relative to under-performing further drives the angle that this can benefit with deriving strategy as shown in Table 4.3. In contrast, a value of 0 in any of the respective indexes would imply an under-performance. After obtaining each indicator (MRS, MHS, MGS) the BPI is derived using Equation 4.1.

$$BPI_{i,k} = MRS_{i,k} + MHS_{i,k} + MGS_{i,k} \tag{4.1}$$

Given it is a sum of the three indexes, the BPI value ranges from 0 to 3, with higher values indicating more positive perception. Each index represents over (1) or under (0) performing, and therefore the interpretation of BPI is seen as how many metrics are over-performing. This positive perception would therefore be a function of having performed well across all three indexes. Note that these indexes are naturally correlated as for example, negative reviews at a given time point will likely lead to less growth for the organisation. This does not deter the value of the index as the combination of these is being interpreted. It makes sense when they move in tandem and showcases that perception of that organisation is indeed strong when the value is 3. If the value were instead 0, then everything needs to improve. When they do not align and the BPI is either 1 or 2, it means there is something that the organisation needs to look into to find out what the driver of the misalignment is and consider it an opportunity for growth if overcome. Perhaps for example the largest banks tend to perform better on growth (MGS) and reviews (MRS), but poorly on headlines (MHS) due to controversies and higher expectations. Challenger banks in contrast tend to do better on reviews (MRS) and headlines (MHS), but are not able to translate this into growth (MGS). Fundamental to Equation 4.1 are the concepts of MRS, MHS and MGS, each of which has a dedicated subsection of Section 4.4.3, Section 4.4.4 and Section 4.4.5 respectively. The BPI Equation is then revisited in Section 4.4.6.

4.4.2 Data

In order to derive the necessary components underlying Equation 4.1, requires data on reviews (MRS), headlines (MHS) and growth (MGS). The data sources were analysed from the beginning of 2013 to end of 2019. This is the period following the GFC and preceding the COVID-19 period (beginning 2020). It also covers the HRC (2017 - 2019). This section provides additional details on the input data used per Figure 4.1 including rationale for the choice of this period and the sample size examined.

4.4.2.1 Rationale for Study Period

The study focuses on the period from January 2013 to December 2019. This timeframe was chosen for three key reasons.

The selection of the 2013–2019 period reflects a relatively stable phase in the Australian banking sector, positioned between two major systemic disruptions: the GFC and the COVID-19 pandemic. Following the GFC, regulatory reforms such as Basel III were progressively implemented, strengthening capital positions and restoring market confidence [240]. Meanwhile, the onset of the pandemic in 2020 introduced unprecedented shifts in consumer behaviour, credit risk, and monetary policy settings [241, 242]. Focusing on the intervening period mitigates crisis-related distortions and offers a clearer view of perception and pricing dynamics under relatively typical competitive conditions.

Second, the period includes the HRC, conducted from late 2017 to early 2019. This was a highly salient event that impacted both customer sentiment and media scrutiny [13–16]. The inclusion of this period enables an empirical test of how negative perception—driven by public hearings, media coverage, and regulatory focus—translates into pricing behaviour and customer growth. Figure 4.2 illustrates the increase in banking-related headlines during this time.

Third, this period aligns with the availability of high-frequency, web-based data. Prior to 2013, reliable and consistent online reviews and headline archives are less accessible or complete, and many review platforms only reached critical mass around that time. Data post-2019 is confounded by the onset of COVID-19 and associated government interventions, such as mortgage deferrals and record-low cash rates, which distort pricing decisions and customer reactions.

The 2013 to 2019 window therefore offers a theoretically sound and empirically tractable timeframe for analysing how perception indices—based on review, headline, and growth data—can be used to understand pricing asymmetries and competitive strategy for banking.

4.4.2.2 Details on data sources

The sample comprises 8 banks, each of which was anonymised to maintain the intent of the study to research what drives each bank to individually vary from each other. The sample includes the Big-4 banks (the four largest banks) and 4 high-impact challenger banks (smaller, but still large competitors). The reason for this choice of 8 banks is to ensure that each has a sufficient amount of review data, headline data and growth data to have meaningful index values. A smaller bank trying to replicate this study could utilise internal bank data to supplement results, for example instead of web-based reviews, using data collected from their call centres which tends to be in a free-form text or audio format.

The source for review data required to derive MRS is from the Product Review website at `https://www.productreview.com.au/`. This data was in a free form text and was web-scraped for each bank. All the available reviews were pulled for each bank. From the website, the review text and customer provided a review score; the score on the website ranged from 1 to 5 with 5 representing customer satisfaction with the respective bank and 1 representing dissatisfaction. The dataset consisted of 3716 records across 8 banks.

Headline data was sourced from the Australian Broadcasting Corporation (ABC) (`https://www.abc.net.au/`). The data is in a free form text format and was web-scraped. Each headline was assigned a bank based on whether or not a bank had been referenced. The final dataset had date month end, bank and corresponding headlines. Only headlines relating to banks were kept and this provided a sample of 1015 rows. As expected bigger banks tended to get more headlines.

The headlines data for the MHS was cleaned by removing punctuation and removing stop words. The magnitude of monthly data for headlines by bank is shown in Figure 4.2. The biggest banks (anonymised) have a higher frequency of headlines because they have a larger customer base and more media focus. The height of the HRC in 2018 experienced the most headlines. It was also identified that there is a increase in the banking related news around rate cut announcements by the RBA.

The data for growth came from Australian Prudential Regulatory Authority (APRA) at `https://www.apra.gov.au/`. This was used for obtaining the MGS. This data contains

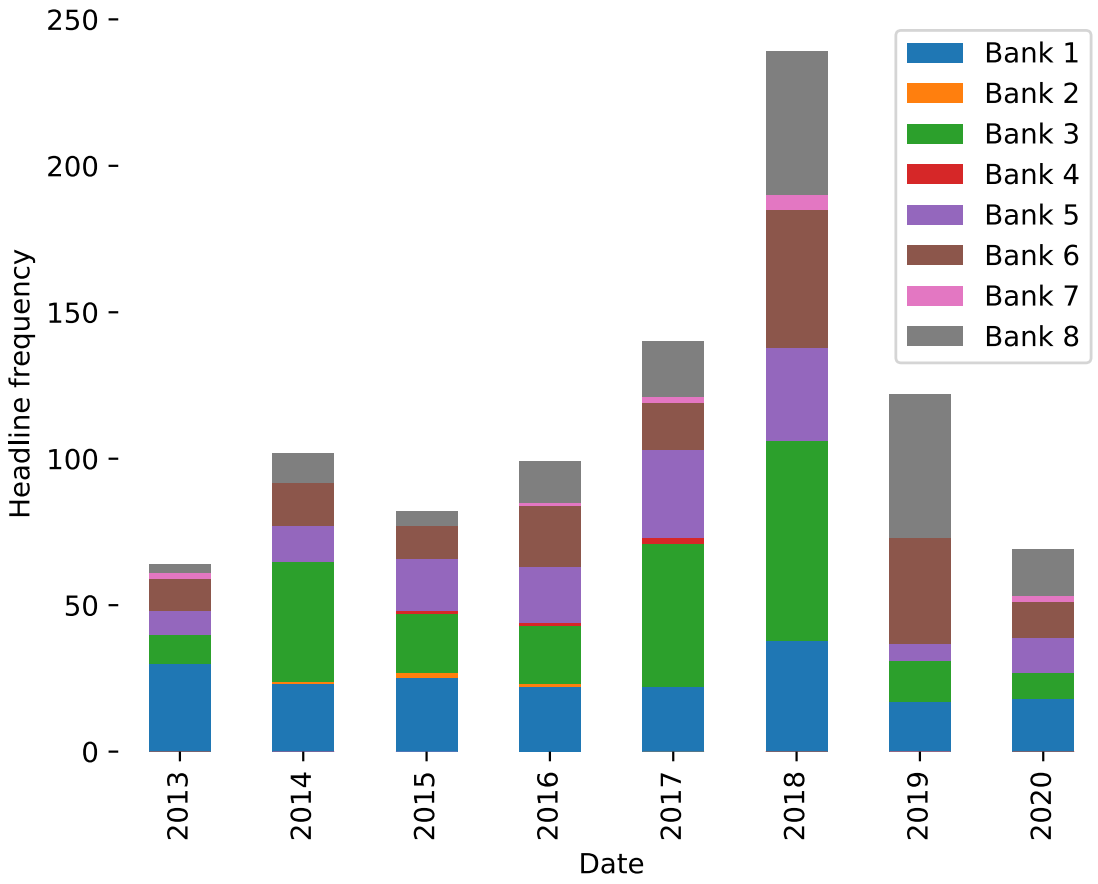

FIGURE 4.2: Headline mix by bank.

mortgage growth data across each bank. The final dataset had date month end, bank and corresponding mortgages growth as $ volume. This data includes monthly data for each of the 8 banks over the period of 2013 to 2019 (inclusive).

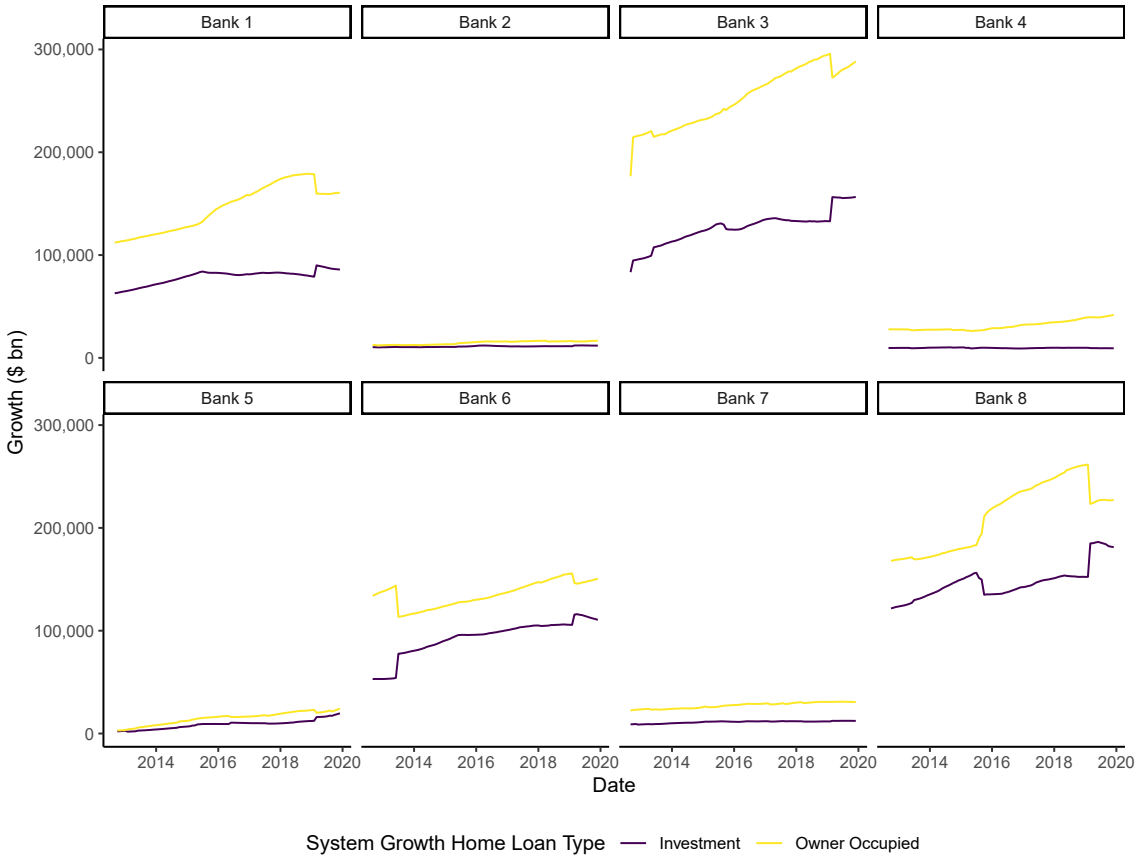

FIGURE 4.3: System data without modification from APRA website.

The unmodified data is visualised in Figure 4.3. Notably, this data has the occasional spike driven by the data collection method; for example, if the definition of a loan changes, the distribution of loans also changes. To address this, two methods were applied to assess changes in value between periods. The first method checks whether the change in value was greater than the 95th percentile or lower than the 5th percentile; if this condition is satisfied then the median change is used. The second method checks the rolling median, so if the change was higher or lower than the rolling median (over 5 periods) then the change value is replaced with the median value.

The approach chosen is percentage change using percentiles because these values better align with the raw data and are therefore more representative of the trend. This is shown in Figure 4.4. Note that the data captures the key deviations in terms of movement while being less volatile to a single time point shift relative to Figure 4.3.

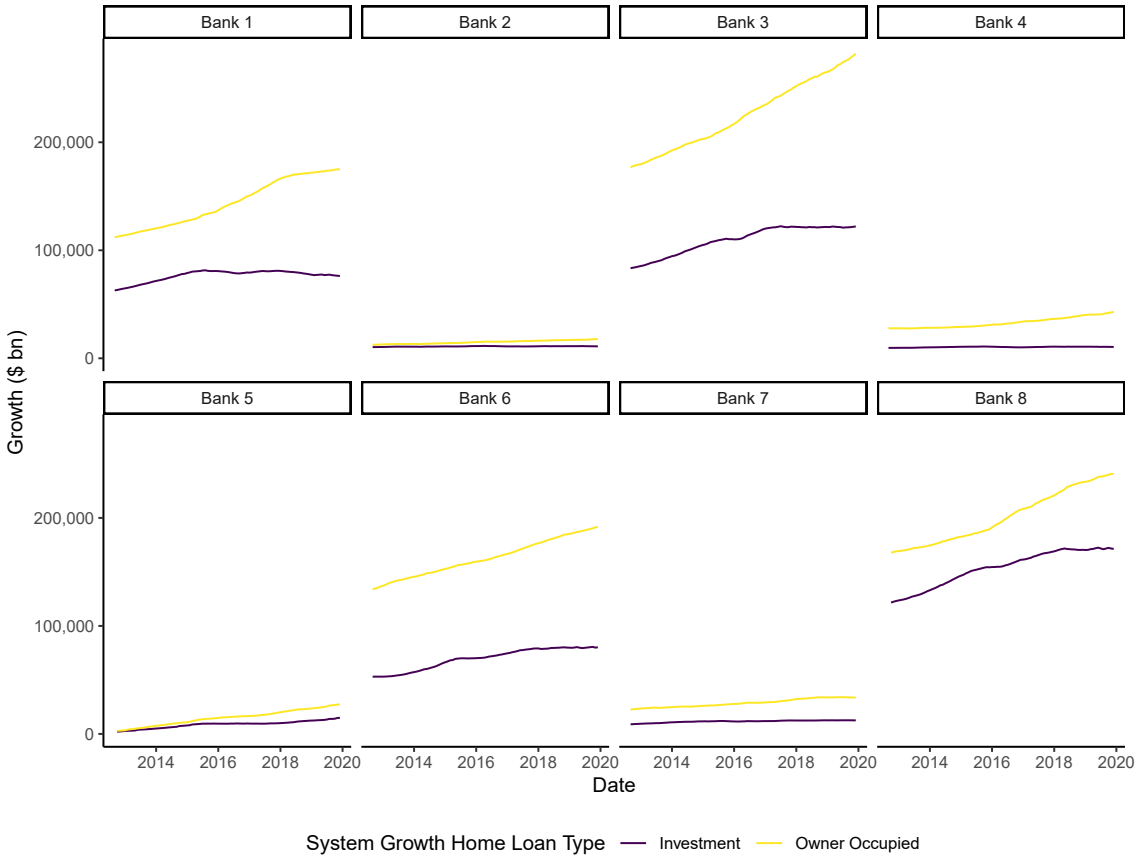

FIGURE 4.4: System data with modification from APRA website.

4.4.3 Microeconomics

The first element of the BPI equation (Equation 4.1) is the MRS. The product review data represents microeconomics conceptually because it relates to an individual's perception of a corresponding bank. Contrast this with the data utilised in Section 4.4.4 and Section 4.4.5.

Data from the Product Review website `https://www.productreview.com.au/` was transformed into a score by utilising the NPS equation. The NPS is a popular metric to measure customer loyalty and has been suggested as the only metric that matters [66]. However another study has suggested NPS is not sufficient for measuring customer loyalty and instead encouraged a multidimensional approach in its place [69]. This study overcame this weakness by using multiple metrics such as the MGS and the MHS.

The NPS equation works by assigning promoters and detractors. It tends to be used to transform a scale of numbers. For example determining the NPS from a scale from 1 to 10 would consider a promoter someone who gave a score of 9 or 10, a detractor as someone who gave a score of 0 to 6 and anyone with a score of 7 or 8 as a passive. Once this is determined this would be substituted in Equation 4.2.

$$NPS = \frac{Total\ promoters - Total\ detractors}{Total\ respondents_{i,k}} \tag{4.2}$$

A notable dynamic of Equation 4.2 is the denominator includes passives, but the numerator does not. So having more passives would imply a lower impact of promoters and detractors on the overall percentage differential. The range of promoter and detractor percentage is 0% to 100%. So NPS can range from a value of -1 to 1, with a value of -1 representing significant dissatisfaction, and a value of 1 implying significant satisfaction.

This equation is applied to obtaining the MRS. It can be applied to the review score. The underlying (raw) MRS equation was obtained by Equation 4.3. Within this equation, promoters are defined as reviews receiving a score of 5. Detractors are defined as reviews receiving a score from 1 to 3 (inclusive). Passives have a value of 4.

$$Raw\ MRS_{i,k} = \frac{Total\ promoters_{i,k} - Total\ detractors_{i,k}}{Total\ respondents_{i,k}} \tag{4.3}$$

Similar to NPS, the value of MRS will take a value between -1 and 1 since the percentage of promoters and detractors range from 0% to 100%. As described in the beginning of Section 4.4.1 the final MRS score is either 1 or 0. The transformation from raw MRS from Equation 4.3 is presented in Equation 4.4.

$$\begin{aligned} MRS_{i,k} = 1 &\iff Raw\ MRS_{i,k} >= 0 \\ MRS_{i,k} = 0 &\iff Raw\ MRS_{i,k} < 0 \end{aligned} \tag{4.4}$$

Converting the review score index to 0 or 1 positions allows the MRS to represent under-performance or over-performance. Over-performance is defined as having a greater promoter percentage than detractor percentage, while the inverse is true for under-performance.

This allows for a clearer interpretation of what the BPI represents at the cost of losing some of the granular value in promoters relative to detractors. This interpretation is that BPI sums each element of over-performance. If MRS is an under-performing element for a bank, there is no reason why the organisation could not explore the Raw MRS from Equation 4.3 directly as part of a deep-dive.

4.4.4 Macroeconomics

The second element of the BPI equation (Equation 4.1) is the MGS. Headline data is considered representative of macroeconomics conceptually because it relates to the perception of the bank by the nation. This would focus more on issues relating to the HRC and scandals, but would also cover positive events such as strong profit or charity efforts. It might also encompass events such as rate changes and therefore is the big-picture view of the bank. It would have an influence on individual customers perceptions of the bank, but at a large scale. The expectation is many customers could read these headlines and be persuaded to think in line of the headlines. Alternatively the headlines themselves could be the function of the thoughts of a number of customers in the case of a scandal. Overall, it is a representation of perception to the public as a whole.

Note that headline data (`https://www.abc.net.au/`) is not scored and therefore lacks a view on positivity or negativity. To overcome this, topic modelling and prediction modelling were applied to the review data to identify whether a headline was positive or negative. To provide a high-level view, we know that with review data we had free-text and it had a corresponding score to show whether it was aligned with a positive or negative perception. Using this free-text and review score as a reference point, we could apply the same line of thinking that derived a score for those reviews to headlines and therefore capture how a customer might interpret the headline. A summary of the approach applied is presented in Figure 4.5.

To explain this approach we begin at the end of Figure 4.5. The ultimate goal is to create an NPS type of metric for headlines data. This is an NPS type metric because it would similarly consider the concept of promoters and detractors as highlighted in Equation

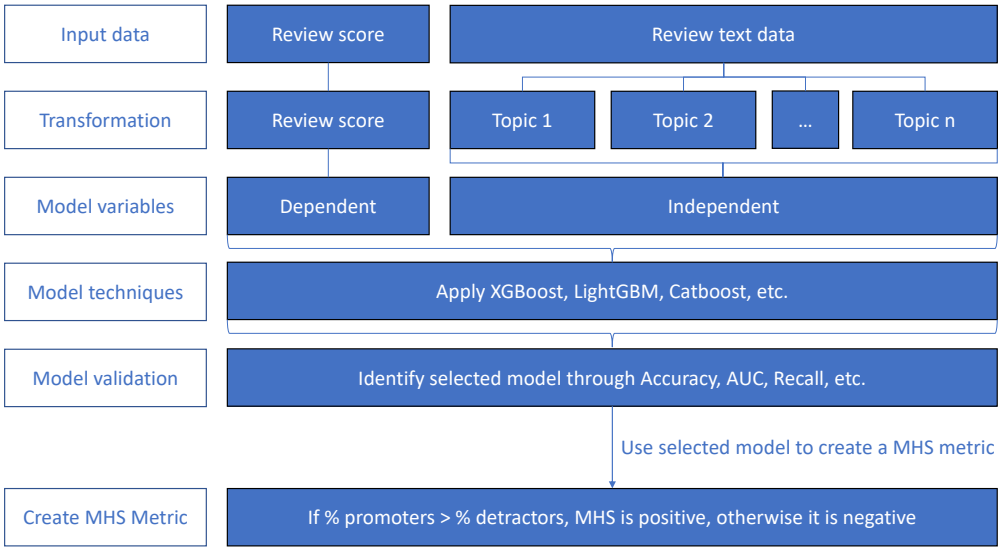

FIGURE 4.5: Model development steps.

4.2. For a direct application to the context of headlines please refer to Equation 4.5 and Equation 4.6.

$$Raw\ MHS_{i,k} = \frac{Total\ promoters_{i,k} - Total\ detractors_{i,k}}{Total\ respondents_{i,k}} \tag{4.5}$$

$$\begin{aligned} MHS_{i,k} = 1 &\iff Raw\ MHS_{i,k} >= 0 \\ MHS_{i,k} = 0 &\iff Raw\ MHS_{i,k} < 0 \end{aligned} \tag{4.6}$$

Note that promoters, detractors, and respondents are as described in Section 4.4.3 with the exception that instead of review data, headline data is used. In other words, the number of respondents is equivalent to the number of headlines for a given point of time. A promoter is someone with a modelled output review score from the headline of 5. A detractor in contrast would have had a modelled output review score from the headline data of 1 to 3. A passive would have modelled an outcome of 4. Similar to how it was done for MRS, the Raw MHS is converted into MHS by testing whether or not the Raw MHS has more promoters than detractors with a value larger than 0 or vice versa with a value less than 0.

Notably headlines do not have a score and therefore a model is trained on review scores and text and applied to headlines to obtain a headline score. This can be used to determine whether a headline is a promoter or a detractor. In this scenario we are applying the same definition or view of perception for both review and headlines, by applying the idea of review score and NPS. This applies machine learning techniques presented in Chapter 3 through the use of review data, and then applies it to headlines. It deviates from those studies by focusing on the concept of 'scoring' headlines.

In this thesis, machine learning techniques are applied to model review data, as illustrated in Figure 4.5. The approach involves generating a score from the review data, where the review score serves as the dependent variable, and the topics extracted from the free-form text of the reviews act as independent variables. The Latent Dirichlet Allocation (LDA) method, as proposed by Blei et al. [243], was employed to identify these topics. LDA facilitates the assignment of topics by determining the conditional probability of words within a review belonging to specific topics.

The incorporation of topics serves a dual purpose: enhancing the predictive model's performance and providing interpretive value to the independent variables. It is important to note that topics, such as 'customer service', are not inherently positive or negative. Rather, they provide a foundation for deeper analysis, offering insights into potential factors influencing the review score given by a customer.

Chapter 3 of this thesis reviewed several studies that employed sentiment analysis and related methods, including topic modelling, to establish explanatory variables. Drawing on these methodologies, this study applies them to review data as an alternative data source. The aim is not to directly determine the sentiment of the review but to ascertain whether the topics can predict the review score. This approach is then aligned with headline data to provide a broader understanding of customer perception in banking.

With topics being identified, the next step was to develop a model to predict customer views on the bank within a review of the probability of belonging to different topics. A simplified view of this is presented in Equation 4.7. There are two key reasons for doing this; first, it allows for a supervised prediction of customer perception since we are able to apply topic modelling to new review data, and second, it provides an interpretative value

to each topic. This allows for questions such as does customer service (for example Topic 3) negatively or positively impact the overall score to be answered.

$$Review\ Score = f(Topic1, Topic2, ...) \tag{4.7}$$

Machine learning models fit for the purpose of estimating Equation 4.7 include CatBoost [244], Light Generalised Boosting Model (GBM) [245], Random Forest [246], eXtreme Gradient Boosting (XGBoost) [247] and Decision Tree [248]. Note a broad range of machine learning techniques are commonly used for text based analysis as highlighted in Chapter 3. Models utilised were selected based on their compatibility with SHapley Additive exPlanations (SHAP) [249], a method used to interpret the models. An example of insight from the SHAP approach would be if topics related to customer service tended to have a negative connotation associated with them towards the review score, this would imply that banks could improve their approach to customer service. This is in line with understanding how variation in commentary of individual banks impact on that banks perception. The reason for using SHAP is machine learning methods tend to lack some of the interpretability typically aligned with statistical models such as linear and logistic regression. SHAP is able to give this interpretation power by assigning a contribution value to each feature. This is done through the use of Shapley values which were originally developed for cooperative game theory as a method to fairly distribute payouts when multiple players contribute to the same goal. Analogously this aligns with the idea of features each contributing to the outcome variable.

Choosing the most appropriate machine learning technique is based on a number of factors. For example, the main difference between XGBoost and other gradient boosting is that it uses a different regularisation technique for over-fitting such as L1 (Lasso) and L2 (Ridge). Light GBM was built to decrease the implementation time of XGBoost. It has advantages to XGBoost in better accuracy, faster training speeds, and is capable of handling large-scale data. CatBoost uses permutation techniques on categorical columns and target-based statistics; it also uses an ordered boosting methodology which allows for a lower chance of over-fitting. All of these methods are applied to ensure that the model chosen is the

one that works most effectively for the data at hand. In order to choose the most effective model an evaluation criteria needs to be applied.

The method chosen to represent reviews was based on considerations of Accuracy, Area Under the Curve (AUC), Recall, Precision, F1-Score and Matthew's Correlation Coefficient (MCC). Accuracy represents the proportion of correct predictions. Precision is how accurately the model predicts the positive classes, and recall is the ratio of predicted positive classes. The F1-Score is the weighted average score of recall and precision. MCC is considered to perform well for binary classification estimation [250] because it takes into account true and false positives and negatives, thus allowing it to be a balanced measure.

To reiterate, the aim was to follow the steps of Figure 4.5. By using a range of techniques we were able to obtain a predictive model for text data through Equation 4.7. This was subsequently applied to headline data, and the MHS was derived using Equation 4.5 and Equation 4.6. These equations are motivated by NPS, consistent with its application for MRS. The end result is a value for MHS of either 1 or 0 representing over-performance relative to under-performance on headlines. This is used as an input to the BPI (see Equation 4.1) as a representation of a macroeconomic view.

4.4.5 Combined

The final component of the BPI equation (Equation 4.1) is the MGS. Mortgages growth data is considered representative of a combined microeconomic and macroeconomic view because it is a function of individual customer perception as well as the state of the economy. For example, rate changes by the RBA may influence the demand for lending from a customer behaviour level and it would affect this at a macroeconomic level by impacting all customers at the same time. The customer level impact would vary based on fixed relative to variable position and potentially the pricing strategy of the customers respective bank. The end outcome is seen through overall growth, which is made up of new customers coming to the organisation and existing customers leaving the organisation.

The equation applied to the data (from `https://www.apra.gov.au/`) to obtain Raw MGS is shown in Equation 4.8.

$$Raw\ MGS_{i,k} = \frac{Mortgages\ growth_{i,k}}{\sum_{j=1}^{N} \frac{Mortgages\ growth_{j,k}}{N}} \tag{4.8}$$

The Raw MGS numerator represents the growth of that respective bank (k) in a particular period (i). N refers to the number of banks in the dataset. The denominator is the average growth of all the organisations in the sample, otherwise referred to as system growth. Ultimately the ratio represents if the growth of the individual organisation surpasses average system growth. The fraction represents the system multiplier. If the system multiplier is greater than 1 this means the organisation performed better than the market in terms of growth while if it is less than 1 it means it performed worse than the market in growth. This is calculated for each bank for each month and then converted into a value of 1 or 0 consistent with what was described at the beginning of Section 4.4.1 through the Equation 4.9.

$$\begin{aligned} MGS_{i,k} = 1 &\iff Raw\ MGS_{i,k} >= 1 \\ MGS_{i,k} = 0 &\iff Raw\ MGS_{i,k} < 1 \end{aligned} \tag{4.9}$$

The intuition behind the Equation 4.9 is a value greater than 1 for Raw MGS because it represents growth that is greater than the market, which makes it a natural cut-off point for the determination of out-performance relative to under-performance against the market. Despite only 8 banks being included in the sample, it is referred to as the market. This is because, these 8 banks make up for more than 85% of the market throughout the sample period.

4.4.6 Banking Performance Index

The first form of BPI is Raw BPI which looks at the count of metrics that are true for an organisation each month. This was presented in Equation 4.1 as an aggregation of Section 4.4.3, Section 4.4.4 and Section 4.4.5. A higher BPI indicates a stronger performance. A bias in the Raw BPI was where banks with less headlines or reviews might appear to be more favourable than other banks. For example, the biggest banks would have a lot more headlines while relatively smaller (challenger) banks would have fewer headlines. The way

this is evaluated is based on if the Raw MHS is greater than or equal to 0 then it is provided a value of 1. This makes banks without headlines to be considered a positive rather than a negative. The intuition is headlines are more likely related to the negatives than positives, this means no news is seen as good news. The bias with the Raw BPI therefore is challenger banks will appear to be better perceived than the largest banks. This might be the index working as intended, but it is possible to improve the index further. To overcome and improve the index more so, the second form of the BPI (Scaled BPI) is based on how well the BPI compares to the organisation itself, as presented in Equation 4.10.

$$\begin{aligned} Scaled\, BPI_{i,k} = 1 &\iff BPI_{i,k} >= Median\, BPI_k \\ Scaled\, BPI_{i,k} = 0 &\iff BPI_{i,k} < Median\, BPI_k \end{aligned} \tag{4.10}$$

This is done for each organisation i for each month k. The median is used to represent the center point of Raw BPI for that organisation over time. As a result this shifts the view of Scaled BPI to being the half of the time the bank outperformed relative to the half of the time it under-performed. This provides a balanced view of organisational performance, highlighting factors contributing to success or underperformance during specific periods. This metric was created and then used as a quantitative customer behaviour index to help understand the impact of the HRC by observing how the value changes over time. With Scaled BPI, the question is wheter, relative to prior years, the organisation performed its best or worst during the HRC, or whether or not it was potentially unaffected.

4.5 Results

4.5.1 Banking Perception Index and Scaled Banking Perception Index

Using the methodology outlined in Section 4.4 resulted in the BPI and the Scaled BPI. The underlying inputs into these BPI metrics are the MRS, MHS and MGS. In order to derive the MHS, a variety of machine learning models were applied.

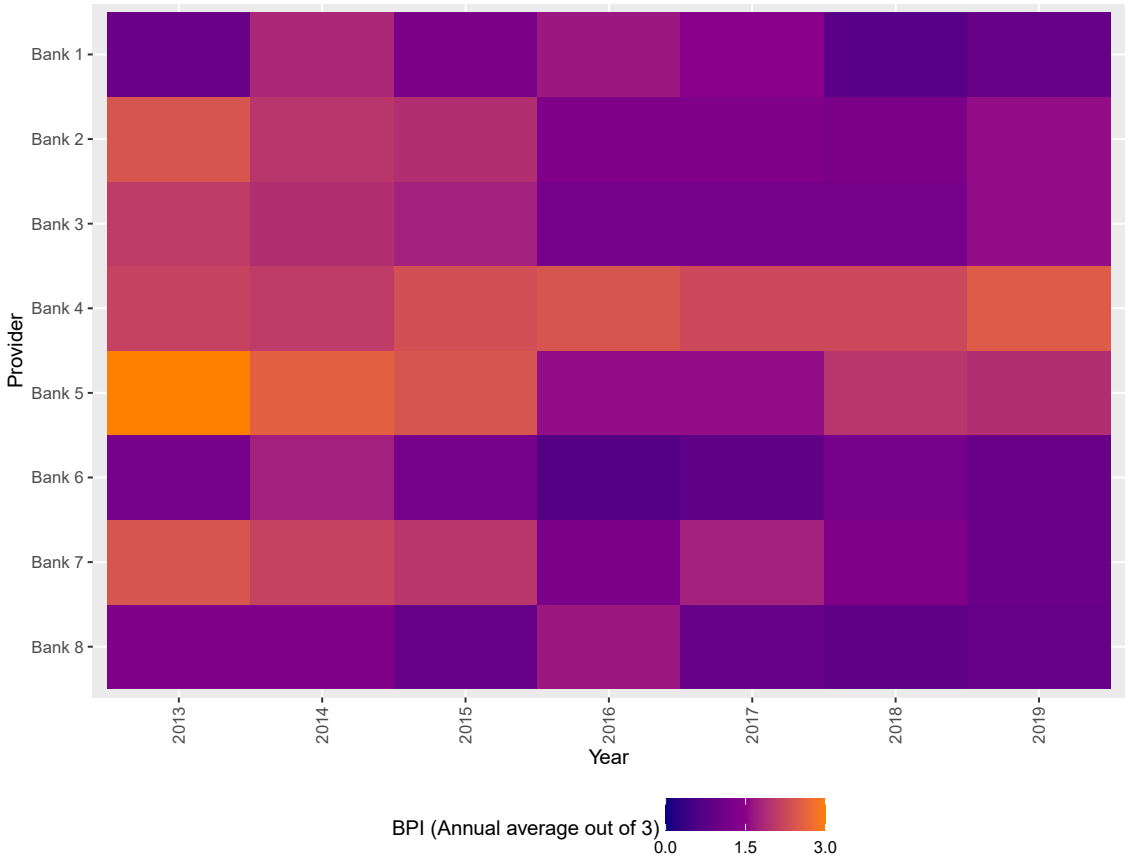

FIGURE 4.6: Raw Banking Perception Index.

The BPI values are shown in Figure 4.6. A higher BPI indicates a stronger perception. Banks 1 and 8 experienced the most significant perception declines during the HRC. This decline was maintained into 2019. Bank 6 faced worse perception in 2016 relative to other periods.

The Scaled BPI, as indicated in Equation 4.10, adjusts the BPI to determine whether an individual bank outperformed other banks for a given month. The end result can be seen in Figure 4.7. During the HRC (2017 to 2019), Banks 4 and 5 outperformed the median BPI, while Banks 1 and 8 underperformed.

To observe the BPI of different banks and rank them by levels of perception over the period of 2013 to 2019, it is possible to take the mean BPI, as shown in Table 4.4. Looking at the mean score for Raw BPI highlights that Bank 2, Bank 4, Bank 5 and Bank 7 average greater than or equal to 2. This is equivalent to doing on average well on two indicators,

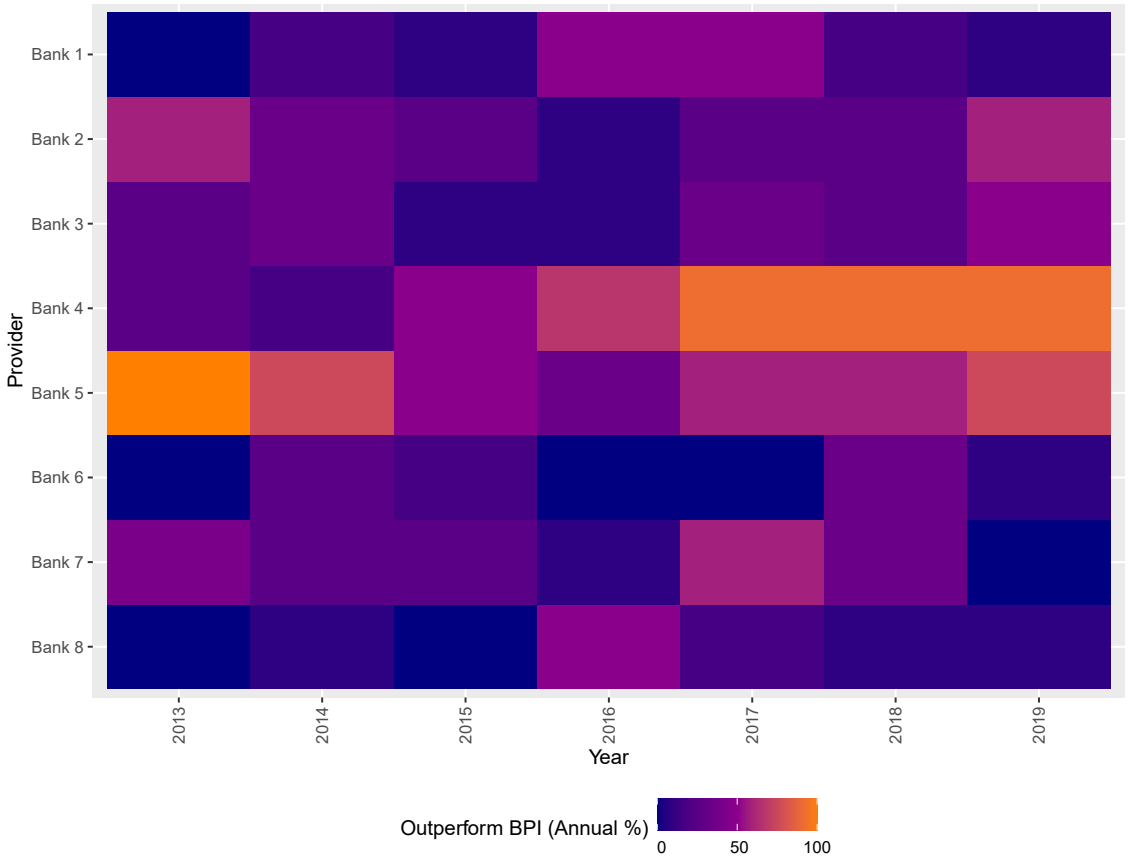

FIGURE 4.7: Scaled Banking Perception Index outperform by organisation.

whether it is MRS, MHS or MGS. In contrast, the other banks have less indicators on which they perform well on.

Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7	Bank 8
1.6	2.1	1.7	2.3	2.3	1.4	2.0	1.6

TABLE 4.4: Mean raw Banking Perception Index by industry.

Table 4.5 summarises the results of a t-test distribution for each of the derived metrics (MGS, MHS, MRS and BPI) and then comparing them before and after the HRC. The hypothesis is summarised in Equation 4.11 and was performed separately for each bank. The purpose of the hypothesis is to test how the mean BPI varies at two different time points. Using standard deviations as per t-test methodology enables the creation of a

statistical test.

$$\begin{aligned} H0 &: Mean(Index_{After\,Commission}) >= Mean(Index_{Before\,Commission}) \\ H1 &: Mean(Index_{After\,Commission}) < Mean(Index_{Before\,Commission}) \end{aligned} \tag{4.11}$$

Note that the equation *Index* in Equation 4.11 refers to MGS, MHS, MRS and BPI. Rejecting the null hypothesis is considered to be that bank under performing post the HRC. If the p-values in Table 4.5 are less than or equal to 0.05 then the null hypothesis is considered to be rejected. Overall, using the t-test Bank 1, Bank 2, Bank 5, Bank 7 and Bank 8 under performed following the HRC. This means only Bank 3, Bank 4 and Bank 6 performed well during that period. The reasons for this under performance varies, for example, Bank 1 and Bank 7 demonstrate poor performance due to MGS and MRS, as evidenced by their lack of statistical significance. It is worth noting that the t-test was performed for all indicators allowing these to be considered in isolation and to help identify the root cause of BPI performance.

Provider	MGS	MHS	MRS	BPI
Bank 1	0.00	0.55	0.00	0.00
Bank 2	0.26	0.84	0.00	0.00
Bank 3	0.74	0.41	0.00	0.08
Bank 4	0.95	0.84	0.16	0.84
Bank 5	0.77	0.22	0.01	0.04
Bank 6	0.92	0.50	0.00	0.39
Bank 7	0.00	0.14	0.00	0.00
Bank 8	0.92	0.00	0.00	0.01

TABLE 4.5: t-test for performance before and after banking commission (p-values).

4.5.2 Banking Perception Index Components

Below are the key outputs of the analysis comprising the BPI:

- MRS in Figure 4.8: The trend towards negative reviews became more prominent after 2015. This coincides with the timing of a number of high profile scandals in the Australian banking industry which arguably helped to motivate the HRC. By the time of the HRC, banking sentiment through reviews was already negative. Over

the 7 years, Bank 2 got progressively worse reviews over the sample period, Bank 4 maintained a positive image throughout, and Bank 8 faced negative sentiments earlier than most banks. This highlights how banks do vary in terms of perception at an organisational level and therefore analysis focused on the industry might not capture these variations.

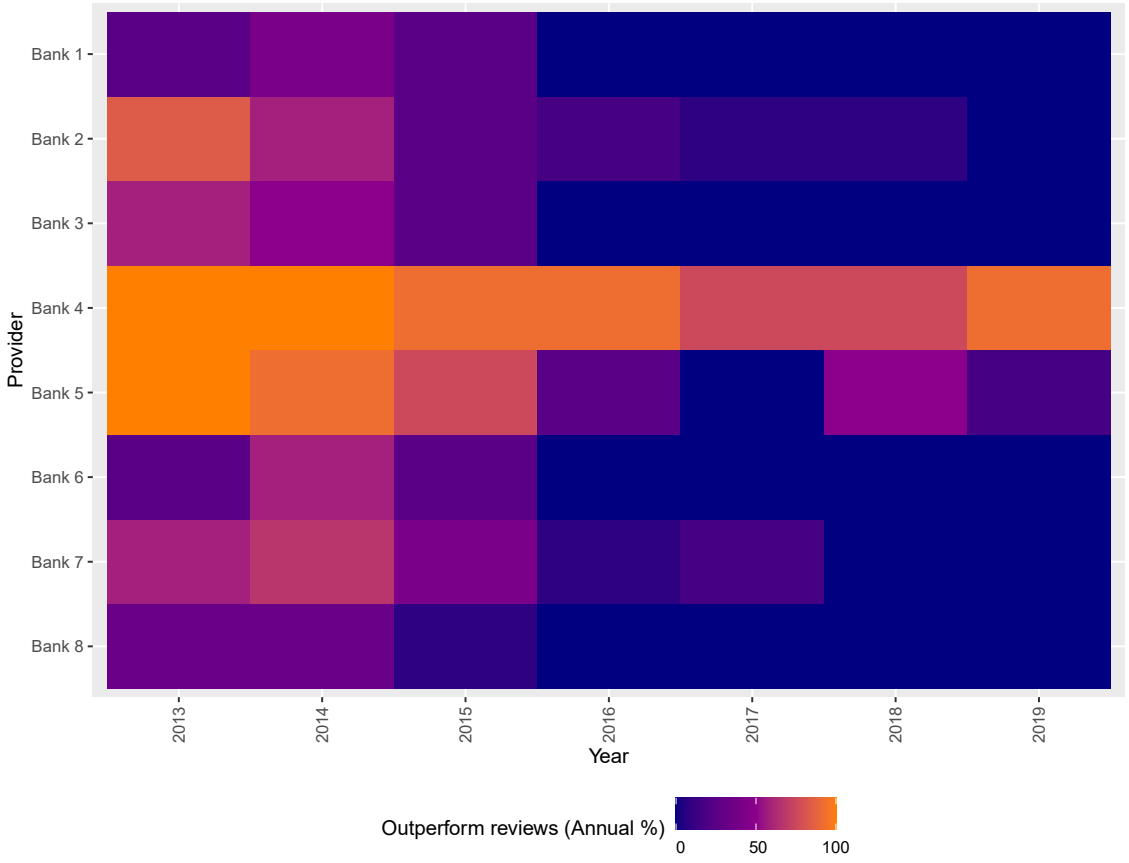

FIGURE 4.8: Monthly Review Score (MRS).

- MHS in Figure 4.9: Unlike reviews, headlines do not demonstrate a clear trend. The HRC period had worse headlines for Bank 5 and Bank 8 compared to previous performance. Certain banks tended to have more positive headlines. Bank 1 retained a similar level of scrutiny from prior to the HRC. There are enough variations to suggest that banks do receive varying levels of positive and negative press.

- MGS in Figure 4.10: Bank 5 consistently outperformed the market while Bank 6 and Bank 8 experienced long periods of under performing in the market. Bank 1

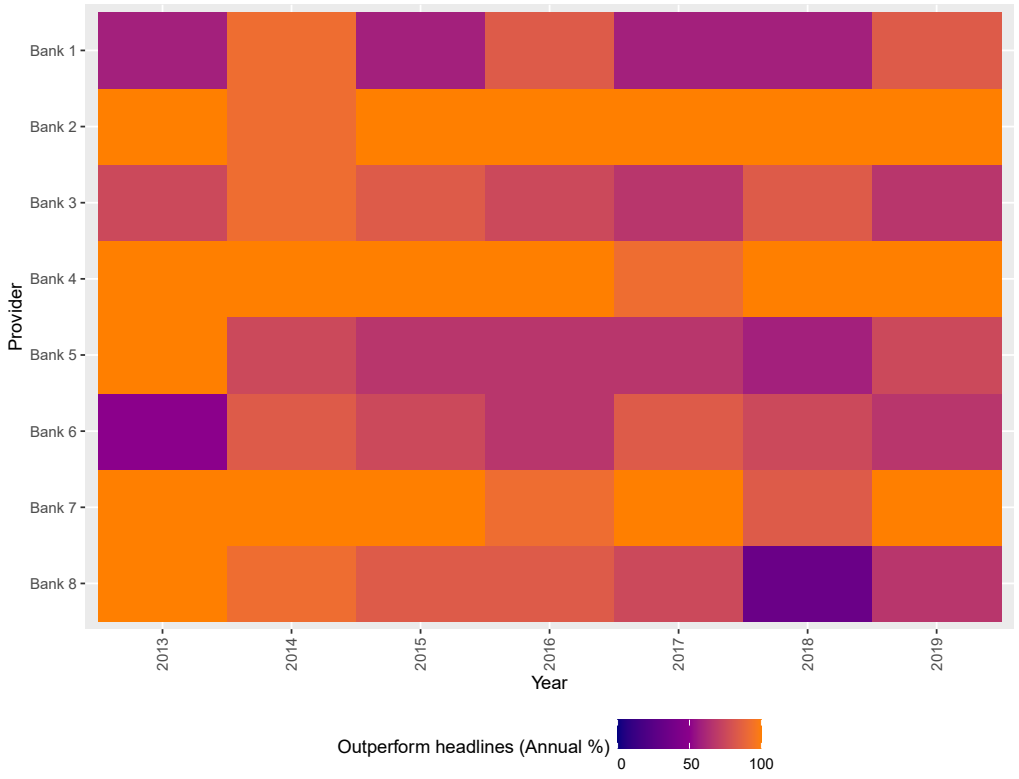

FIGURE 4.9: Monthly Headline Score (MHS).

appears to be the most impacted by the HRC based on the timing of their negative growth coinciding with 2018.

4.5.3 Deriving Monthly Headline Score

From the methodology highlighted in Figure 4.5, once data on reviews is gathered it is transformed into topics in order to be modelled for application to headlines data. The top 10 highest weighting words of each topic are summarised in Table 4.6. Using these top 10 words as an indication of the topic, each topic is described in further detail as follows:

- Topic 0 is considered to be related to account fees charged and the views associated with this.
- Topic 1 refers to experience with credit cards whether positive or negative.
- Topic 2 mainly about customer service.

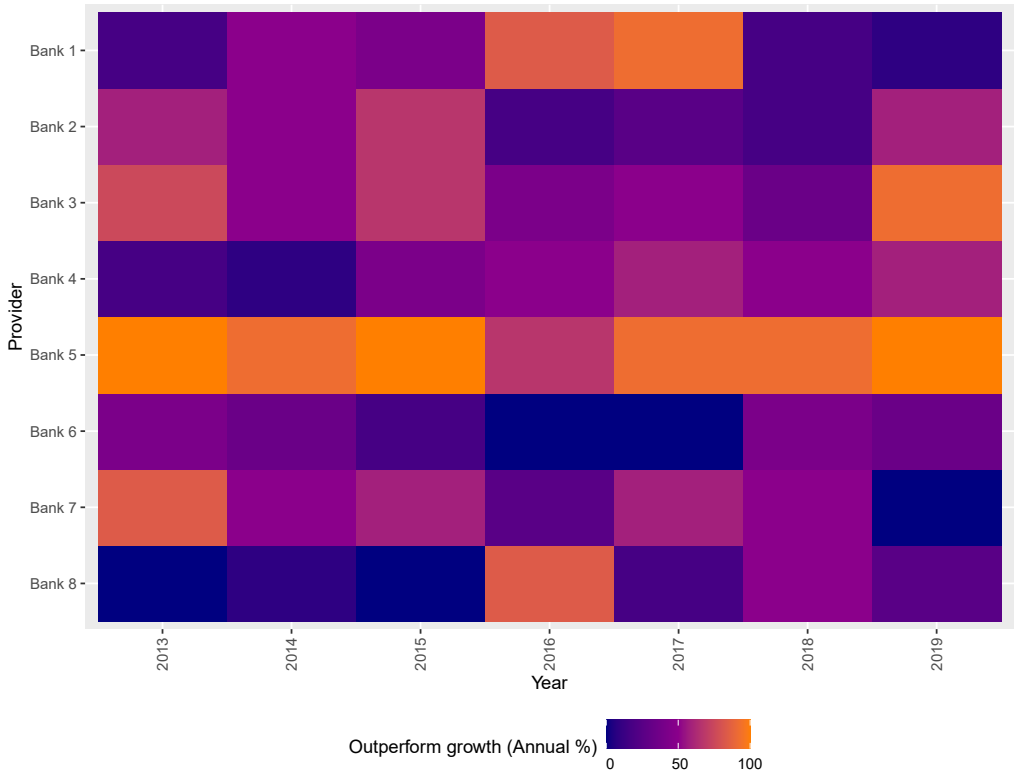

FIGURE 4.10: Monthly Growth Score(MGS).

- Topic 3 focuses on interactions with the bank in the form of calls.

Topic 0	Topic 1	Topic 2	Topic 3
fee	card	service	call
account	loan	customer	bank
bank	bank	bank	customer
money	credit	branch	go
charge	account	good	time
use	get	banking	branch
transfer	tell	staff	wait
pay	go	account	service
transaction	call	bad	phone
day	would	year	get

TABLE 4.6: Top 10 words in product reviews by topic.

Following topic generation, a model is fit to predict topics for any given text with trained data from reviews. The best performing one is selected by metrics highlighted in Section

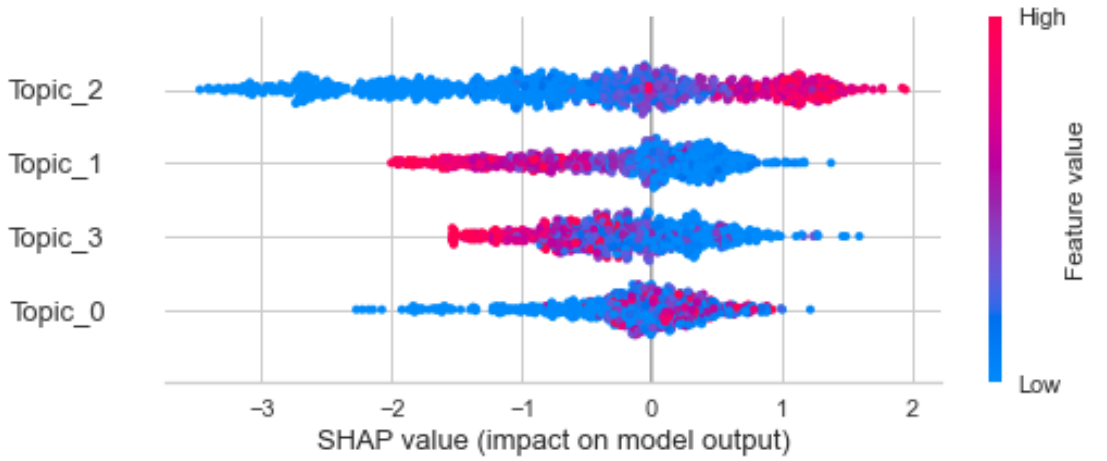

FIGURE 4.11: SHAP values for different topic models.

4.4.4. The validation outcomes are presented in Table 4.7. The CatBoost Classifier performed the best out of the options in all metrics, except for accuracy. This determination is made as the higher the metric the better it performs for those presented.

Model	Accuracy	AUC	Recall	Precision	F1	MCC
CatBoost	0.76	0.78	0.63	0.35	0.45	0.34
Light GBM	0.76	0.77	0.62	0.34	0.43	0.32
Random Forest	0.77	0.75	0.53	0.34	0.41	0.29
Extreme GBM	0.75	0.75	0.55	0.31	0.40	0.27
Decision Tree	0.74	0.63	0.47	0.29	0.36	0.22

TABLE 4.7: Review topic model performance metrics.

Supporting model interpretation, the SHAP values have been plotted in Figure 4.11. A red colour corresponds to a high likelihood of belonging to the topic, while blue represents a lower likelihood of belonging to the same topic. A positive SHAP value (as indicated by the x axis) corresponds to a higher chance of being a positive review and a negative SHAP value corresponds to a higher chance of being a negative review. Topic 1 and Topic 3 tended towards positive reviews while topics 2 and 0 tended towards negative reviews that highlight concerns with customer service and account fees.

Table 4.8 is the out of sample test set of data. Notably, the metrics performed well, except for precision which measures where the chance of false positive is higher, possibly driven

by the few positive reviews in the dataset. Overall, the value of testing out of sample suggests that the model is less likely to over-fit.

Accuracy	Sensitivity	Specificity	Precision
0.84	0.82	0.84	0.44

TABLE 4.8: OOS topic model metrics.

The predictive model created for reviews was also applied to headlines and presented to showcase the insights gained and the driving variables that helped derive the perception. The resulting topics of headlines are captured in Figure 4.12. Notably, all the topics were represented in the period between 2017 and 2019. Topic 0 gained less prominence from 2016 to 2017, because it related to fees. Considerations on customer service and credit cards, however, maintained and increased in prominence in headlines.

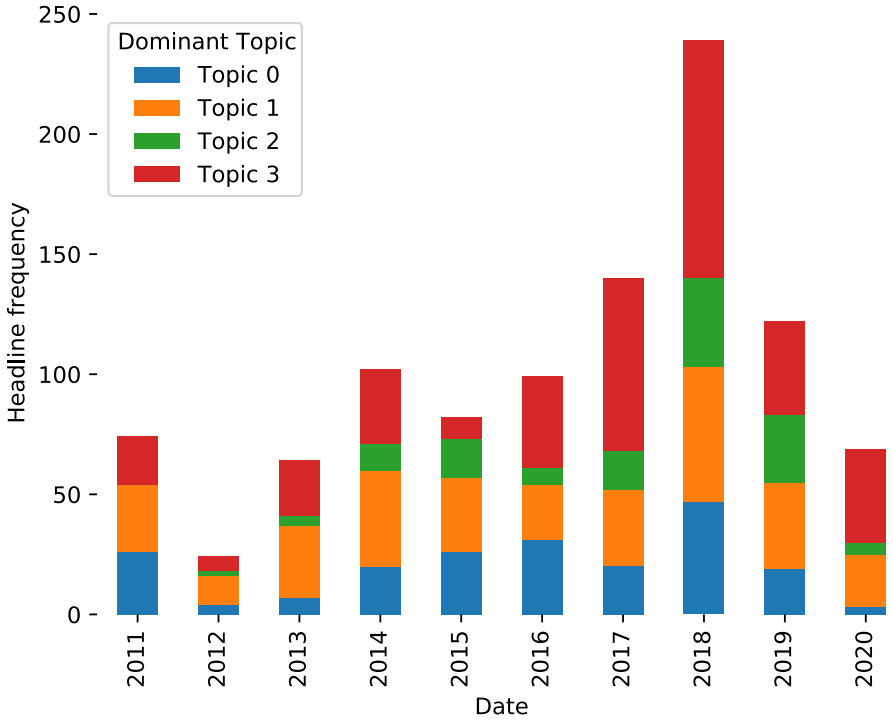

FIGURE 4.12: Topic modelling on headlines.

4.6 Discussion

Chapter 2 highlighted that perception plays a significant role in pricing strategy Ruscheinsky et al. [22], Qadan and Nama [23]. However, no prior studies to our knowledge have examined how perception influences pricing in banking using a marginal cost-based framework. Marketing papers in particular have a concept of perceived value Zeithaml [9] which draws a link between perception and pricing. Chapter 3 identified a growing use of sentiment analysis in finance, but found limited studies applying these techniques to institutional reputation in banking, particularly using short-form text like headlines. From this it was identified the growing nature of techniques applied, and the limited number of papers focused on the relationship between headlines and banking domain specifically with some examples being from Anamika and Subramaniam [95], Zhang et al. [96], Ma et al. [97].

This chapter aimed to develop a quantitative metric for perception to address the research gap and has achieved this through the use of BPI. It did this by leveraging multiple data sources adding to the novelty of the study. In part to test the intuitiveness of the BPI, this was subsequently applied to analyse the HRC as a use case and this application is considered a key contribution of this study given the less quantitative nature of prior analysis of the HRC [13–16] as discussed in Chapter 2.4.3. The metric BPI therefore should captures the bank-level variation of impacts of perceptions during the period of the HRC given the aforementioned prior literature and impact of the commission.

The initial hypothesis is that banks were impacted differently by the HRC, as witnessed through customer behaviour and perceptions. It is suggested that this mechanism has the potential to drive better behaviour by banks because a poor customer perception leads to lower overall performance and growth. In order for this mechanism to take effect, banks would need to have noticed an impact on their reputation and ability to grow. The MRS, MHS, MGS, and BPI derived by this chapter highlight how publicly available data firstly strengthens the view that banks have been impacted by HRC, and secondly, that these banks have been impacted to varying extents, with Banks 4 and 5 experiencing relatively less negative impact in terms of Raw BPI, while Banks 4 and 6 performed better relative to their own performance prior to the HRC, as seen through Scaled BPI.

This finding aligns with the view that banks experienced varied impacts, with some performing better on indexes due to customer satisfaction from positive reviews, some aimed to improve their public image through headlines, while others achieved strong growth. All of these contributed to a common goal of presence and profitability. The BPI index introduced in this chapter can be used for comparison before and after an event, similar to what is observed in Table 4.5.

While the intent behind this chapter was originally philosophical in the sense that banks are perceived a particular way, the metrics derived are practical. This overcomes a weakness of prior perception based analysis which tended to focus on survey based and/or point-in-time data [17, 60]. The goal was to make each measure easy to understand and useful as standalone metrics, namely MRS, MHS, MGS, and BPI. These indices are useful as a source of secondary data to complement future research in this area in the banking sector as well as in relation to strategic questions such as how a bank can improve their presence. Similar methodologies to those applied in this chapter could be extended to other industries in the services sector due to readily accessible reviews, headlines, and growth metrics.

4.7 Limitations

The limitations with this chapter include focusing on elements based on literature and intuition. This means the BPI is not a robust statistical measure. Instead, it is an index used to understand how well an organisation is performing in terms of reviews, headlines, and growth. It therefore does not explicitly control for the natural correlation between these three factors where headlines might influence reviews and growth for example. Additionally, it does not account for banks' strategic direction, such as products offered, broker attitudes, economic conditions, and interest rates. The underlying assumption is that these elements are captured at the bank level where, financial institutions retain consistent strategies. For example, if Bank A focused their pricing strategy on retail banking customers while Bank B focused on commercial customers, the HRC would not change this. This means the fluctuations in BPI are a function of the variable factors driven by

the HRC rather than a change in individual bank strategy. This is an assumption that could be rectified in a further study.

An oversight of this assumption might be if Bank A was called out for poor treatment of retail customers as part of the HRC, this might then lead to a change in strategic direction. To overcome this, the analysis was limited to 2019 to capture short term impact. An additional reason for this limitation was to stop the results from being impacted by the COVID-19 period. Since a larger sample of data becomes available over time, a worthwhile further study would be to extend the period and control for the impacts of COVID-19 in order to gain a better understanding of the larger scale strategic changes that would allow for a long-term impact study.

In relation to the time period applied, the data started from 2013 due to the availability of review data. This was due to the nature of online reviews which were becoming more prominent. This means the study did not account for the impact of increased transparency on illegal activities by banks before 2013 or the implications of these events. A further study could avoid using review data and focus on headlines and growth, but this would lose the value of individual customer concerns with banks.

Another limitation is the reliance a single website for reviews and headlines, which might introduce bias due to the nature of the website's audience. Product review and ABC headlines were chosen as being websites with a high sample of available reviews and headlines. A further study could consider expanding the scope of the websites considered to include a wider range of opinions. A tangential but interesting topic could be how different news reporting sites presented similar headlines during the HRC.

4.8 Summary

During the period of 2017 to 2019 the HRC in Australia was examining misconduct in the industry. Existing research has suggested that this has been ineffective in fixing corporate culture within banking [13–16] when looking at the industry as a whole. This chapter hypothesises that while the HRC imposed limited punitive actions, banks were tested by customer adversity stemming from increased transparency regarding illegal activities. To

represent this, a perception index would be required over a long period. However, existing literature that focused on perceptions within banking was limited to point-in-time survey data [17–20, 60, 67, 251].

In order to derive the perception index as required for the hypothesis posited by this section and the thesis overall, in order to use to inform pricing decisioning, a quantitative metric for BPI was created by amalgamating three concomitant metrics in MRS, MHS, and MGS. This involved utilising novel datasets not previously examined in a similar manner; this included reviews, headlines, and growth information across banks from 2013 to 2019. Given the distinctive nature of the data-sets, unique techniques in the form of machine learning and statistical analysis were applied to generate meaningful indexes. By covering the aforementioned research gaps, this metric concluded that there was a bank-variant impact by the HRC and provided a metric to compare banking performance with making informed strategic decisions.

Two banks were shown to be least affected due to the limited impact the HRC had on them. This conclusion, based on a t-test on BPI before and after the HRC, suggests that while other banks experienced significant shifts, these two banks remained largely unaffected. Assuming that all else is equal in terms of strategy for elements such as pricing at a bank level, this suggests the HRC has impacted banks differently. This also suggests that customers remained satisfied with the two banks despite the negative media attention.

In terms of policy and strategic implications, from a bank perspective, they were able to target their weakest area by examining where the shortfall was in the form of MRS, MHS and/or MGS. By making this determination, a bank can examine why reviews (MRS) were negative and implement corresponding changes. From a government perspective it highlights the additional potential impact of HRC. Bringing appropriate transparency and knowledge, to the public regarding illegal behaviour by these organisations, is likely to generate an ideal outcome for all stakeholders involved. The metric derived in this chapter highlights that varying impacts across banks did occur, as represented through the HRC via the BPI.

Chapter 5

Modelling Asymmetric Price on Front and Back-Book with Perception

5.1 Introduction

Pricing behaviour in the banking sector has predominantly focused on the impact of changes in marginal cost, the asymmetry associated with upward and downward movements in cost, and how these changes are passed on to the customer. This chapter emphasizes the importance of incorporating additional dimensions, such as differentiating between front and back-book pricing and considering perception.

Front-book pricing refers to the prices visible to customers on the website for new products, while back-book pricing refers to the prices charged to existing customers who already hold the product. In Australia, the pricing structure for variable loans allows prices for existing customers to diverge from front-book prices over time.

Pricing behaviour in the banking sector has traditionally centred on the effects of changes in marginal cost, the asymmetry associated with upward and downward cost movements, and the extent to which these changes are passed on to customers. This chapter underscores

the need to incorporate additional dimensions into the analysis, such as the distinction between front-book and back-book pricing, as well as the role of customer perception. Front-book pricing refers to the publicly advertised prices for new products, typically displayed on a bank's website, whereas back-book pricing pertains to the prices applied to existing customers who already hold the product. In Australia, the pricing structure for variable loans enables prices for existing customers to fluctuate over time, potentially diverging from front-book prices.

To incorporate perception, a measurable approach was employed, captured through the BPI, as detailed in Section 4. Section 5.2 presents the motivation for the proposed model. Section 5.3 outlines the modelling approach, including the required data and the incorporation of asymmetry, front- and back-book pricing, and behavioural pricing. Results are presented in Section 5.4, with statistical tests linking them to the thesis hypothesis. Conclusions and a summary follow in Sections 5.5 and 5.6.

5.2 Theory

This section addresses research questions four to six, as introduced in Section 1.3. Question four focuses on whether pricing is asymmetric for the sample period and banks considered. Question five examines whether there is a differentiation between front and back-book pricing in terms of the influence of drivers such as asymmetry. Question six investigates whether there is a behavioural element that drives pricing beyond considerations of marginal cost. These questions aim to address the key research objective of identifying the influence of perception on the pricing behaviour of banks.

A robust pricing model requires an understanding of both short- and long-term dynamics. Short-term shocks applied to long-term scenarios could lead to unsustainable pricing strategies. For example, if a bank's model assumes a 10% price increase in response to shocks but another bank's prices remain aligned with the shocks, the former's prices could become unsustainably high over time.

The asymmetry of cost-of-funds shocks (research question four) will be incorporated by examining how positive and negative shocks impact price points differently. It is commonly

observed that banks tend to raise rates quickly when cash rates increase but are slower and less aggressive in lowering rates when cash rates decrease. It will be of particular interest to determine if this asymmetry is reflected in the model results and ensure that these dynamics are fully captured.

The model must also account for the differential between front and back-book pricing (research question five). As discussed in Section 1.1.2 on front and back-book pricing, these concepts help determine whether pricing strategies differ between new and existing customers. From a modelling perspective, this could be achieved by adjusting the dependent or output variable. However, identifying appropriate data to represent back-book pricing is challenging, as these prices are inherently non-transparent. For example, it may not be possible to accurately determine the current rate a customer who obtained a variable-rate home loan three years ago is paying. While this might be possible for fixed-rate products, as identified in Section 1.1.4 which highlighted Australia-specific considerations, Australia predominantly relies on variable-rate products. The findings could provide data-driven evidence supporting the concerns raised by ACCC [8] about the lack of transparency in the market.

Perception is another key element to be included in the model (research question six). It will influence the model's overall structure by serving as an additional driver or feature. The measurement of this driver was detailed in Chapter 4 through the BPI. For instance, if we assume that banks are more likely to raise rates in response to increases in the cost-of-funds, this dynamic might differ when considering whether banks would raise rates in response to positive sentiment. This presents an unusual dynamic: should firms capitalize on a positive sentiment shock by increasing prices and, consequently, profits, potentially risking their reputation with customers? Or should they maintain their positive image by not exploiting the gains in sentiment, thereby sacrificing margin but potentially being rewarded with volume growth?

The asymmetry of perception will also be considered, examining how pricing changes might vary based on positive versus negative movements in sentiment. This could provide valuable insights into the strategies driving banks and might reflect the morality and nature of a free-market system. In essence, the equilibrium for banks that exploit customer

satisfaction could result in a scenario where customers are, at best, net neutral, as any excess satisfaction would be priced out.

5.3 Data and Methodology

5.3.1 Approach

The base for the pricing model begins by considering De Bondt [25] in Equation 5.1. This representation captures the concept of marginal cost as being a key driver of price, in this case marginal cost is represented by the cost-of-funds or market rate (mr) and the rate charged by the bank is represented as bank rate (br). The constant (λ_0) can be seen as the mark-up a bank places based on the risk it takes on the loan. This overall view can be seen as a representation of IRPT theory.

$$br = \lambda_0 + \lambda_1 mr \tag{5.1}$$

An alternative approach using a more granular set-up is highlighted in the literature review and is referred to as the industrial organisation approach [6, 26]. The industrial organisation approach would over-engineer the problem and require more granular and less accessible bank-level data which would limit the scope of the analysis to banks willing to provide such information. As a result, the IRPT approach is considered as a basis in order to improve the replicability of the research. This study suggests that the marginal cost-based pricing approach, having a constant to capture behavioural dynamics would lead to a biased view on the process undergone when pricing and proposes extensions to overcome this. This hypothesis to be tested is that the banks are expected to be willing to deviate from the cost-of-funds if it means they can improve their reputation. This dynamic is time-dependent and would not be captured by a constant.

The literature expands this concept under IRPT with the inclusion of asymmetric pricing as represented in Equation 5.2.

$$br_{i,t} = \lambda_i + \beta_i^+ mr_{i,t}^+ + \beta_i^- mr_{i,t}^- + \epsilon_{it} \tag{5.2}$$

The positive and negative movements in market rate (mr) and respective coefficients (β) are represented by + and − respectively. Therefore, a positive shock to the market rate would have a different effect to a negative shock. The shock variables have a value of zero unless a directional shock occurs during that period, in which case the magnitude of the shock is considered. At a conceptual level, the inclusion of perception is introduced as per Equation 5.3.

$$br_{i,t} = \lambda_i + \beta_i^+ mr_{i,t}^+ + \beta_i^- mr_{i,t}^- + \theta_i^+ bpi_{i,t}^+ + \theta_i^- bpi_{i,t}^- + \epsilon_{it} \tag{5.3}$$

Positive and negative movements in BPI (bpi) and the respective coefficients (θ) are represented by + and − respectively. Note that BPI, as derived in Chapter 4 incorporates asymmetry, similar to the market rate. Based on whether or not θ has explanatory power through statistical significance, it is possible to determine the influence of perception on pricing. The sign of the coefficient would explain the directional impact.

To capture the concept of front and back-book pricing the outcome variable (br) can be adjusted. It can be represented as shown in 5.4 for the front-book and 5.5 for the back-book.

$$br_{i,t}^B = \lambda_i^B + \beta_i^{B,+} mr_{i,t}^{B,+} + \beta_i^{B,-} mr_{i,t}^{B,-} + \theta_i^{B,+} bpi_{i,t}^{B,+} + \theta_i^- bpi_{i,t}^{B,-} + \epsilon_{it}^B \tag{5.4}$$

$$br_{i,t}^S = \lambda_i^S + \beta_i^{S,+} mr_{i,t}^{B,+} + \beta_i^{S,-} mr_{i,t}^{S,-} + \theta_i^{S,+} bpi_{i,t}^{S,+} + \theta_i^- bpi_{i,t}^{S,-} + \epsilon_{it}^S \tag{5.5}$$

The choice of superscript (B or S) is based on the data applied, as discussed in Section 5.3.2, where superscript B denotes front-book pricing and superscript S is representative of back-book pricing. By comparing the two equations, the coefficient differential is of key interest. For example, if the coefficient of mr varies with a degree of significance between

Equation 5.4 and Equation 5.5, this would suggest that the way in which banks price their front and back-book is distinct.

5.3.2 Data

The sample period examined is of monthly frequency from December 2012 to December 2019 and covered the period between GFC and COVID-19. There are eight large banks, four of which were major banks and four large challenger banks for an overall sample size of 680. During this period, the cash rate was reduced with underlying uncertainty of future increases. Banks therefore undertook out-of-cycle rate [1] increases during this period. In addition, it includes the period of the HRC, and the sample set matches that used for deriving the BPI in Chapter 4. This means the perception index is represented throughout the data period being modelled.

Included in the data are variable or adjustable-rate mortgage rates for the Basic product and Standard Variable Rate (SVR) product for Owner Occupied Principal and Interest (OOPI) repayment loans with a balance of A$250,000 and a 25-30 year maturity. This data was obtained through publicly available listed rates on bank websites. OOPI loans are considered the 'average' loan taken by a customer and represent purchasing a house to live in and paying both principal and interest. Banks tend to encourage principal and interest repayments through lower rates than for interest-only loans. This is partly due to the reduced risk of default when customers repay their loans.

Other loan types for mortgages offered by banks in Australia include Owner Occupied Interest Only (OOIO), Investment Principal and Interest (INVPL), and Investment Interest Only (INVIO). The investment loans (INVPL and INVIO) relate to mortgages where the customer does not live in the property and typically leases it. Due to different risk profiles, there is price differentiation between OOPI, OOIO, INVPL, and INVIO. Typically, the rates for INVIO are the largest, followed by a mix of INVPL and OOIO, with the lowest rates for OOPI.

[1] Out-of-cycle rate increase: When banks increase rates on the back book despite the RBA not making any changes to the cash rate.

The reason for collecting both Basic product rates and SVR rates is to represent front-book and back-book pricing. In the Australian market, a Basic product is a mortgage that typically has minimal fees and represents a rate without any further discount. It is a transparent price point, thus making it principally representative of the concept of a "front-book" rate. In contrast, the SVR product tends to be more representative of a "baseline rate." A discount is applied to this product, and the magnitude of this discount is not always transparent. For instance, a customer could call the bank and negotiate a discount based on their circumstances.

As a result, the SVR tends to more closely replicate movements in the RBA cash rate than the Basic product in practice. A movement in the Basic product rate on the website does not necessarily translate into a movement in the rate charged to existing customers on that product. In contrast, a shift in the SVR product rate tends to align with media announcements of changes, such as banks reducing rates by 25 basis points. Therefore, the SVR could be seen as a back-book rate.

Cost-of-funds is represented by the 1-month BBSW, sourced directly from the Reserve Bank of Australia. In their study, Holland et al. [6] compared the BBSW and the cash rate in the context of asymmetric pricing of mortgages in Australia and found both to be viable measures. For this study, the terms are used interchangeably for cost-of-funds, market rate (mr), and BBSW.

As discussed in Chapter 4, the concept of perception took values between 0 and 3 and is represented by a raw BPI. A greater positive sentiment is indicated by an increased BPI value. This perception index is comprised of three components: MRS, MHS, and MGS. The MRS represents time points when individual banks scored well on online reviews from the Product Review website (`https://www.productreview.com.au/`). The MHS reflects periods when banks received positive headlines from ABC News (`https://www.abc.net.au/news/`), and the MGS captures instances where banks outperformed in mortgage growth based on APRA data (`https://www.apra.gov.au/monthly-authorised-deposit-taking-institution-statistics`).

5.3.3 Asymmetric Pricing

The Autoregressive Distributed Lag (ARDL) approach captures short- and long-term dynamics, while the NARDL approach extends this to incorporate asymmetry. The NARDL prism of Shin et al. [59] is embedded into a panel ARDL structure, where the panel data approach allows for organisational (i) and temporal (t) variations. The model is estimated through the Pooled Mean Group Estimator, consistent with Holland et al. [6]. The Panel NARDL(p,q) approach is represented in Equation 5.6. Equation 5.7 and Equation 5.8 provide further detail on the underlying components of Equation 5.6. This provides a statistical approach to measure Equation 5.2, aligning with established literature.

$$\begin{aligned}\Delta br_{i,t} = \mu_i + \rho_i br_{i,t-1} + \delta_i^+ mr_{i,t}^+ + \delta_i^- mr_{i,t}^- + \sum_{j=1}^{p-1} \lambda_i j \Delta br_{i,t-j} \\ + \sum_{j=0}^{q-1} (\pi_{ij}^+ \Delta mr_{i,t-j}^+ + \pi_{ij}^- \Delta mr_{i,t-j}^-) + \epsilon_{it}\end{aligned} \tag{5.6}$$

$$\Delta mr_{i,t}^+ = \sum_{j=1}^{t} \Delta mr_{ij}^+; \Delta mr_{i,t}^- = \sum_{j=1}^{t} \Delta mr_{ij}^- \tag{5.7}$$

$$\Delta mr_{ij}^+ = max(\Delta mr_{ij}, 0); mr_{ij}^- = min(\Delta mr_{ij}, 0) \tag{5.8}$$

The market rate or cost-of-funds in Equation 5.8 is represented by mr and is equivalent to the 1-month BBSW. Banks are represented by i and the time point is represented by t. A cumulative sum of these asymmetric shocks is applied to obtain Equation 5.7. This is then substituted into Equation 5.6, where the bank rate is represented by br.

The long-run parameter representing the impact of changes in cost-of-funds is expressed as $\beta_i^+ = -\delta^+ i/\rho_i$ and $\beta_i^- = -\delta^- i/\rho_i$. The short-run parameters representing the impact of cost-of-funds are denoted by $\pi^+ ij$ and $\pi^- ij$. An intuitive interpretation is that the short-run relates to shocks, while the long-run reflects where rates will stabilise.

The NARDL model estimates unbiased long-term coefficients, which are expected to be positive, as prices should move in line with past movements ($br_{i,t-j}$) and in the same

direction as cost-of-funds ($mr_{i,t}$). The short-term coefficients are more complex to interpret, as they depend on the interaction between long-run parameters, the error correction coefficient (ρ_i), and model dynamics [59].

Noting research question 4 from Section 1.3, which highlighted the research questions, Hypothesis 1 is developed from the statistical model. Through testing this hypothesis, it is possible to determine the asymmetric impact of cost-of-fund movements on pricing:

- **Hypothesis 1: Long run symmetrical cost-of-fund shocks:** $H_0^{1b} : \beta_i^+ = \beta_i^-$ vs $H_A^{1b} : \beta_i^+ \neq \beta_i^-$

Hypothesis 1 tests whether it is necessary to split cost-of-funds shocks into positive and negative components. If the null hypothesis is rejected, this implies the presence of an asymmetric shock, making the NARDL approach preferable to the ARDL approach, as it accounts for asymmetry.

Conversely, failing to reject the null hypothesis suggests insufficient evidence for asymmetry. The NARDL approach can still be used but offers no distinct advantage over the ARDL approach in terms of measuring asymmetry. When testing this hypothesis, the coefficients will also be analysed to identify the extent and nature of asymmetry.

5.3.4 Front and Back-Book Pricing

Section 5.3.2 discussed Basic product and SVR product data. A discretionary pricing approach is utilised by some Australian banks, where discounts are offered beyond the marketed rate. The SVR product is used as a proxy to represent movements in back-book pricing.[2] The Basic product tends towards a more transparent pricing point and is therefore proxied as the headline rate minus the average discount rate. It is anticipated that the Basic product will fluctuate based on banks' growth ambitions to market this transparent price point, while the SVR product is expected to more closely align with back-book rates.

[2]For example, the rate on the website might suggest the price of a mortgage is 5%, but a call to the bank could result in an actual rate of 4%, including a 1% discount targeted towards the customer.

To observe the pricing behaviour across the back-book and front-book segments, Figure 5.1 presents the spread in rates across all organisations over time. The boxplot represents the cross-sectional distribution at each point in time.

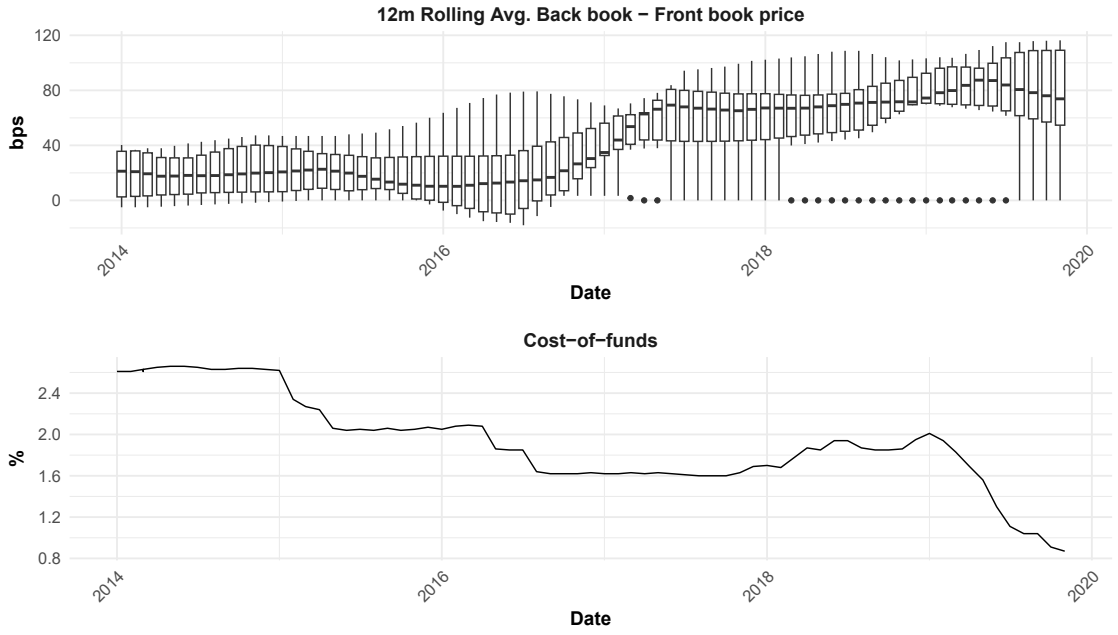

FIGURE 5.1: Back-book relative front-book pricing compared to cost-of-funds based on publicly available data (Chapter 5.3.2).

A 12-month moving average is used to highlight the trend in price differentials, which appears to widen over the observed period. This trend is shown alongside cost-of-funds to suggest a strategic decoupling: as funding costs decrease, the spread between back-book and front-book pricing tends to increase. This aligns with the hypothesis that banks use front-book pricing tactically to attract new customers, while allowing back-book rates to remain more rigid.

To test this hypothesis, Equation 5.6, which focuses on asymmetry, is extended into two equations where $\Delta br_{i,t}$ is replaced by $\Delta br^B_{i,t}$ and $\Delta br^S_{i,t}$ to represent Basic product and SVR product, respectively. The coefficients of $br_{i,t-1}$ are denoted as ρ^B_i and ρ^S_i.

$$\begin{aligned}\Delta br^B_{i,t} = \mu^B_i + \rho^B_i br^B_{i,t-1} + \delta^{B,+}_i mr^+_{i,t} + \delta^{B,-}_i mr^-_{i,t} + \sum_{j=1}^{p-1} \lambda^B_i j \Delta br^B_{i,t-j} \\ + \sum_{j=0}^{q-1} (\pi^{B,+}_{ij} \Delta mr^+_{i,t-j} + \pi^{B,-}_{ij} \Delta mr^-_{i,t-j}) + \epsilon^B_{it}\end{aligned} \tag{5.9}$$

Equation 5.9 is an adaptation of Equation 5.6, focused on asymmetry, with coefficients and variables representing the Basic product. Note that mr remains the same in both scenarios, as the cost-of-funds as a driver is independent of the type of rate charged. However, the rate charged would still be influenced by cost-of-funds. Equation 5.10 adapts Equation 5.9 for the Standard product instead of the Basic product.

$$\begin{aligned}\Delta br^S_{i,t} = \mu^S_i + \rho^S_i br^S_{i,t-1} + \delta^{S,+}_i mr^{S,+}_{i,t} + \delta^{S,-}_i mr^-_{i,t} + \sum_{j=1}^{p-1} \lambda^S_i j \Delta br^S_{i,t-j} \\ + \sum_{j=0}^{q-1} (\pi^{S,+}_{ij} \Delta mr^+_{i,t-j} + \pi^{S,-}_{ij} \Delta mr^-_{i,t-j}) + \epsilon^S_{it}\end{aligned} \tag{5.10}$$

The long-run parameter on impact of change in cost-of-funds for the Basic product is represented as $\beta^{B+}_i = -\delta^{B,+}_i/\rho^B_i$ and $\beta^{B,-}_i = -\delta^{B,-}_i/\rho^B_i$. The short-run parameters for impact of cost-of-funds are represented by the symbols $\pi^{B,+}_{ij}$ and $\pi^{B,-}_{ij}$. For the SVR product the long-run parameter on impact of change in cost-of-funds is represented as $\beta^{S+}_i = -\delta^{S,+}_i/\rho^S_i$ and $\beta^{S,-}_i = -\delta^{S,-}_i/\rho^S_i$. The short-run parameters for impact of cost-of-funds are represented by the symbols $\pi^{S,+}_{ij}$ and $\pi^{S,-}_{ij}$.

To test the hypothesis of differentiation between front- and back-book pricing dynamics, a series of sub-hypotheses were developed. Hypotheses 2a and 2b are directly related to Hypothesis 1, which addresses the asymmetry of individual equations, while Hypotheses 2c and 2d focus on variations between front- and back-book pricing. These relate to Research Question 5 from Section 1.3, which investigates the extent of differentiation in front- and back-book pricing. The hypotheses align with the notation in Equations 5.9 and 5.10.

- **Hypothesis 2a: Hypothesis 1 viability of price model to Basic rates.** H^{2a}_0 : $\beta^{B,+}_i = \beta^{B,-}_i$ vs $H^{2a}_A : \beta^{B,+}_i \neq \beta^{B,-}_i$

- **Hypothesis 2b: Hypothesis 1 viability of price model to Standard Variable.** $H_0^{2b} : \beta_i^{S,+} = \beta_i^{S,-}$ vs $H_A^{2b} : \beta_i^{S,+} \neq \beta_i^{S,-}$
- **Hypothesis 2c: Long run positive cost-of-funds shock same between both products:** $H_0^{2c} : \beta_i^{B,+} = \beta_i^{S,+}$ vs $H_A^{2c} : \beta_i^{B,+} \neq \beta_i^{S,+}$
- **Hypothesis 2d: Long run negative cost-of-funds shock same between both products:** $H_0^{2d} : \beta_i^{B,-} = \beta_i^{S,-}$ vs $H_A^{2d} : \beta_i^{B,-} \neq \beta_i^{S,-}$

Hypotheses 2a and 2b extend Hypothesis 1 to examine asymmetry in front- and back-book pricing individually. These supersede Hypothesis 1 since they reflect the specific dependent variables used. Hypotheses 2c and 2d compare the effects of cost-of-funds on pricing for Basic and SVR products. If the null hypothesis is rejected, this indicates that pricing strategies differ between front-book (Basic) and back-book (SVR) products.

The practical implications are significant: a rejection suggests that pricing approaches vary despite the similarity of the product offerings and the consistency of marginal cost dynamics. Coefficients will also be analysed to gain deeper insights into the dynamics of price movements.

5.3.5 Behavioural Element of Pricing

The BPI is used to represent the behavioural element of pricing. It is incorporated as an asymmetric impact into the model, similar to cost-of-funds. This tests the hypothesis of whether positive and negative shocks to sentiment have a varied impact on prices. The model is run for both Basic and SVR products to identify if banks are more influenced by customer perception for front-book customers (proxied with Basic product rates) than for back-book customers (proxied with SVR). The NARDL model is extended and represented by Equation 5.11 and supported by Equation 5.12 and Equation 5.13.

$$\begin{aligned}\Delta br_{i,t} = \mu_i + \rho_i br_{i,t-1} + \delta_i^+ mr_{i,t}^+ + \delta_i^- mr_{i,t}^- + \tau_i^+ bpi_{i,t}^+ + \tau_i^- bpi_{i,t}^- \\ + \sum_{j=1}^{p-1} \lambda_i j \Delta br_{i,t-j} + \sum_{j=0}^{q-1} (\pi_{ij}^+ \Delta mr_{i,t-j}^+ + \pi_{ij}^- \Delta mr_{i,t-j}^-) \\ + \sum_{j=0}^{q-1} (\theta_{ij}^+ \Delta bpi_{i,t-j}^+ + \theta_{ij}^- \Delta bpi_{i,t-j}^-) + \epsilon_{it}\end{aligned} \tag{5.11}$$

$$\Delta bpi_{i,t}^+ = \sum_{j=1}^{t} \Delta bpi_{ij}^+; \Delta bpi_{i,t}^- = \sum_{j=1}^{t} \Delta bpi_{ij}^- \tag{5.12}$$

$$\Delta bpi_{ij}^+ = max(\Delta bpi_{ij}, 0); bpi_{ij}^- = min(\Delta bpi_{ij}, 0) \tag{5.13}$$

The parameters $\upsilon_i^+ = -\tau_i^+/\rho_i$ and $\upsilon^- = -\delta_i^-/\rho_i$ are representative of the long run impact of *bpi* on mortgages rate while the parameters θ_{ij}^+ and θ_{ij}^- correspond to short run impacts. Hypothesis 3 introduces additional sub-hypotheses, while Hypotheses 1 and 2 are also tested.

To capture the split between Basic and SVR product behavioural pricing, Equation 5.11 can be rewritten as Equation 5.14 for the Basic product and Equation 5.15 for the SVR product.

$$\begin{aligned}\Delta br_{i,t}^B = \mu_i^B + \rho_i^B br_{i,t-1}^B + \delta_i^{B,+} mr_{i,t}^+ + \delta_i^{B,-} mr_{i,t}^- + \tau_i^{B,+} bpi_{i,t}^+ + \tau_i^{B.-} bpi_{i,t}^- \\ + \sum_{j=1}^{p-1} \lambda_i^B j \Delta br_{i,t-j}^B + \sum_{j=0}^{q-1} (\pi_{ij}^{B,+} \Delta mr_{i,t-j}^+ + \pi_{ij}^{B,-} \Delta mr_{i,t-j}^-) \\ + \sum_{j=0}^{q-1} (\theta_{ij}^{B,+} \Delta bpi_{i,t-j}^+ + \theta_{ij}^{B,-} \Delta bpi_{i,t-j}^-) + \epsilon_{it}^B\end{aligned} \tag{5.14}$$

$$\begin{aligned}\Delta br_{i,t}^S = \mu_i^S + \rho_i^S br_{i,t-1}^S + \delta_i^{S,+} mr_{i,t}^+ + \delta_i^{S,-} mr_{i,t}^- + \tau_i^{S,+} bpi_{i,t}^+ + \tau_i^{S.-} bpi_{i,t}^- \\ + \sum_{j=1}^{p-1} \lambda_i^S j \Delta br_{i,t-j}^S + \sum_{j=0}^{q-1} (\pi_{ij}^{S,+} \Delta mr_{i,t-j}^+ + \pi_{ij}^{S,-} \Delta mr_{i,t-j}^-) \\ + \sum_{j=0}^{q-1} (\theta_{ij}^{S,+} \Delta bpi_{i,t-j}^+ + \theta_{ij}^{S,-} \Delta bpi_{i,t-j}^-) + \epsilon_{it}^S\end{aligned} \tag{5.15}$$

For the Basic product, the parameters $\upsilon_i^{B,+} = -\tau_i^{B,+}/\rho_i^B$ and $\upsilon^{B,-} = -\delta_i^{B,-}/\rho_i^B$ are representative of the long run impact of *bpi* on mortgages rate while the parameters $\theta_{ij}^{B,+}$ and $\theta_{ij}^{B,-}$ correspond to short run impacts. For the SVR product, the parameters $\upsilon_i^{S,+} = -\tau_i^{S,+}/\rho_i^S$ and $\upsilon^{S,-} = -\delta_i^{S,-}/\rho_i^S$ are representative of the long run impact of *bpi* on mortgages rate while the parameters $\theta_{ij}^{S,+}$ and $\theta_{ij}^{S,-}$ correspond to short run impacts. The equation for the long run impacts of *mr* on mortgages rate remain the same, with the same denotation of β_i^{B+}, β_i^{B-}, β_i^{S-} and β_i^{S-}. Similarly, the short-run parameters for impact of cost-of-funds are represented by the symbols $\pi_{ij}^{B,+}$, $\pi_{ij}^{B,-}$, $\pi_{ij}^{S,+}$ and $\pi_{ij}^{S,-}$.

- **Hypothesis 3a: Long run symmetrical BPI shocks for Basic rates:** H_0^{3a} : $\upsilon_i^{B,+} = \upsilon_i^{B,-}$ vs $H_A^{3a} : \upsilon_i^{B,+} \neq \upsilon_i^{B,-}$
- **Hypothesis 3b: Long run symmetrical BPI shocks for Standard Variable rates:** $H_0^{3b} : \upsilon_i^{S,+} = \upsilon_i^{S,-}$ vs $H_A^{3b} : \upsilon_i^{S,+} \neq \upsilon_i^{S,-}$
- **Hypothesis 3c: Long run positive BPI shock same between both products:** $H_0^{3c} : \upsilon_i^{B,+} = \upsilon_i^{S,+}$ vs $H_A^{3c} : \upsilon_i^{B,+} \neq \upsilon_i^{S,+}$
- **Hypothesis 3d: Long run negative BPI shock same between both products:** $H_0^{3d} : \upsilon_i^{B,-} = \upsilon_i^{S,-}$ vs $H_A^{3d} : \upsilon_i^{B,-} \neq \upsilon_i^{S,-}$

Hypotheses 3a and 3b are equivalent to Hypothesis 1, which focused on the asymmetry of cost-of-funds, and test the existence of asymmetry in the impact of BPI changes on prices. These hypotheses are divided into 3a and 3b to separately analyse asymmetry for Basic rates and SVR rates, respectively. Rejecting the null hypothesis for Hypothesis 3a indicates that customer perception plays a role in the overall pricing strategy of a bank. The extent of this role can be determined by examining the statistical significance and magnitude of the coefficients.

Hypotheses 3c and 3d, similar to Hypotheses 2c and 2d, test whether Basic product and SVR product pricing are affected differently by BPI. However, unlike Hypotheses 2c and 2d, these hypotheses do not evaluate the equivalence of cost-of-funds impacts across products. The relationship between asymmetry in cost-of-funds and BPI will also be

examined to identify variations. This includes determining whether increases in cost-of-funds elicit different responses than decreases, and comparing these dynamics to similar scenarios involving BPI.

5.4 Results

Utilising the elements discussed in Chapter 5.3, Figure 5.2 summarises how the proposed approach varies from the state-of-the-art approach. This proposed approach, illustrated in the figure, is implemented in this section. The key differences between the state-of-the-art approach and the proposed approach are found in the model features, which now incorporate perception-based pricing, perception asymmetry, and the splitting of price points into back-book and front-book. To achieve this, the BPI was developed as an additional input to capture perception, differentiating it from the state-of-the-art approach. Another key difference is the focus on the Australian market and the data period. Finally, the choice of statistical methodology—based on a panel NARDL approach—offers a modern advancement in banking pricing analysis, setting this study apart from prior works.

5.4.1 Statistical Analysis

The results for the models without asymmetric shocks are presented in Table 5.1, the models with asymmetry in Table 5.2, and overall diagnostic tests in Table 5.3.

Table 5.1 is significant at the 5% level, suggesting that the drivers are explanatory for all coefficients except $L_{BPI}(\upsilon)$ under the dependent variable of SVR. Notably, the coefficient for $L_{BB}(\beta)$ is close to 1 for the Basic product and less than 1 for the SVR product. A coefficient close to 1 indicates that the price for the Basic product closely tracks changes in cost-of-funds over the examined period. Conversely, a value less than 1 suggests that the SVR product lags in adjusting price relative to changes in cost-of-funds.

During the period analysed, the cash rate reduced more often than it increased. This may partly explain the lag in SVR price movements, highlighting the limitations of models that exclude asymmetry.

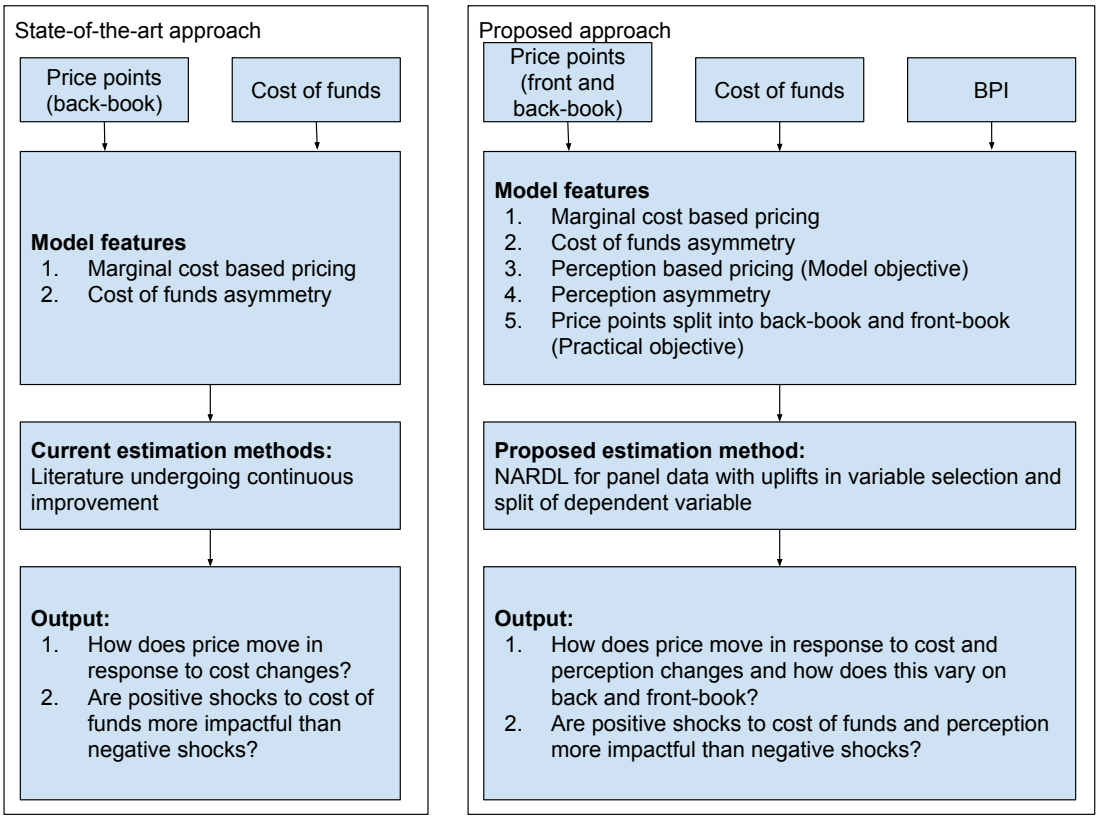

FIGURE 5.2: State-of-the-art relative to proposed approach for modelling pricing strategy.

Without asymmetry, the BPI is found to be statistically significant and meaningful for the front-book (Basic) product, but not for the SVR product ($L_{BPI}(v)$). As the front-book targets new customers, it is logical that perception would play a larger role in influencing these prices. Notably, the coefficient of 0.242 implies that a 1-point increase in the BPI index would lead to a price increase in the long-run, and vice versa if the BPI decreases. This indicates that if banks perceive declining customer satisfaction due to poor reviews, negative headlines, or reduced volume, they may respond by lowering prices to compensate. This result aligns with intuition and underscores the importance of including perception in the pricing model.

The constant (μ) in the model is interpreted as the mark-up due to other factors, such as risk, in the marginal cost model. After including the additional variable of BPI, the constant is observed to be lower for the Basic product than for the SVR product. This potentially reflects the lower dependence of the SVR product on BPI. In other words,

	Price Basic BB, BPI	**Price SVR BB, BPI**
$L_{BB}(\beta)$	1.019***	0.715***
	(0.066)	(0.035)
$L_{BPI}(\upsilon)$	0.242**	0.056
	(0.118)	(0.046)
$Constant(\mu)$	0.138***	0.470***
	(0.023)	(0.120)
ρ	-0.085***	-0.139***
	(0.016)	(0.033)
$\Delta BB(\pi_{I,0})$	0.606***	0.675***
	(0.103)	(0.039)
$\Delta BPI(\theta_{I,0})$	-0.020***	-0.011*
	(0.003)	(0.007)
Obs	664	664

TABLE 5.1: Change in price without asymmetry split by product type (Basic, SVR). BB is the BBSW 1 month representative of cost-of-funds. BPI is the Banking Perception Index. Coefficients represent effect sizes for a one-unit increase in the independent variable, with standard errors shown in parentheses. *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively.

back-book pricing is driven more by the risk associated with the loan, whereas front-book pricing relies more heavily on customer perception.

The value ρ is expected to be negative, capturing the regression to the mean effect that the lagged bank rate has on the dependent variable representing the change in bank rate. If ρ were positive, the equation would not function effectively. A larger absolute value of the coefficient indicates faster regression to the mean. While ρ does not provide substantial interpretation directly related to the thesis hypothesis, it is a necessary inclusion to ensure the NARDL model captures the required dynamics.

The coefficients for $\Delta BB(\pi_{I,0})$ and $\Delta BPI(\theta_{I,0})$ represent the short-run dynamics for BBSW and BPI, respectively. Although these coefficients are not central to the analysis [6], it is important to acknowledge the presence of short-run dynamics in the model.

Table 5.2 introduces the asymmetry dynamic to both BBSW (BB) and BPI (BPI). For the Basic product, the level of asymmetry in cost-of-funds appears minimal, as indicated by the long-run coefficients L^{+}_{BB} and L^{-}_{BB} with values of 1.043 and 0.988, respectively. In

	Price Basic BB, BPI	**Price SVR BB, BPI**
$L^{+}_{BB}(\beta^{+})$	1.043***	1.289***
	(0.200)	(0.146)
$L^{-}_{BB}(\beta^{-})$	0.988***	0.774***
	(0.200)	(0.044)
$L^{+}_{BPI}(\upsilon^{+})$	0.167**	0.020
	(0.082)	(0.042)
$L^{-}_{BPI}(\upsilon^{-})$	0.170**	0.052
	(0.080)	(0.042)
$Constant(\mu_i)$	0.635***	0.830***
	(0.115)	(0.140)
ρ_i	-0.115***	-0.144***
	(0.022)	(0.023)
$\Delta BB^{+}_{0} = \pi^{+}_{I,0}$	-0.558***	-0.504***
	(0.111)	(0.139)
$\Delta BB^{-}_{0} = \pi^{-}_{I,0}$	0.773***	0.888***
	(0.127)	(0.061)
$\Delta BPI^{+}_{0} = \theta^{+}_{I,0}$	-0.005	-0.002
	(0.003)	(0.009)
$\Delta BPI^{-}_{0} = \theta^{-}_{I,0}$	-0.031***	-0.008
	(0.006)	(0.008)
Obs	656	656

TABLE 5.2: Change in price with asymmetry split by product type (Basic, SVR). BB is the BBSW 1 month representative of cost-of-funds. BPI is the Banking Perception Index. Coefficients represent effect sizes for a one-unit increase in the independent variable, with standard errors shown in parentheses. *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively.

contrast, there is a stark asymmetry for the SVR product. Positive increases in cost-of-funds lead to banks increasing their rates more than the cost-of-fund movement (1.289), while reductions in cost-of-funds result in smaller rate decreases in the long-run (0.774).

This indicates an asymmetry favouring the bank from a margin perspective, consistent with prior Australian studies [5–7]. However, this asymmetry is not observed for the Basic product, which was not examined in those studies. This finding suggests that banks' pricing strategies, from a cost-of-funds perspective, vary based on the nature of the product. A natural question arises as to whether such practices are justified from a fairness perspective.

If we further incorporate the perception index, which relates to the long-run coefficients of L^{+}_{BPI} and L^{-}_{BPI}, it is observed to be significant for the Basic product but not for the SVR

	Price Basic	**Price SVR**
	BB, BPI	**BB, BPI**
$W_{LR}H_0 : \beta^+ = \beta^-$	0.132	21.23***
	[0.717]	[0.000]
$W_{LR}H_0 : \upsilon^+ = \upsilon^-$	0.003	1.442***
	[0.954]	[0.230]

TABLE 5.3: Diagnostics of asymmetry tests for BPI and BBSW 1 month (BB). Chi-square reported, p-value shown in square brackets. *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively.

product. Compared to Table 5.1, it is worth noting that asymmetry is not meaningful when perception is considered in the context of the Basic product. This indicates that banks tend to adjust their prices symmetrically in response to BPI shocks, both upwards and downwards. The difference in coefficients is minimal, with values of 0.167 and 0.170, respectively.

The trend with the constant or mark-up factor remains when asymmetry is taken into account. This refers to the fact that the SVR product has a higher mark up factor of 0.830 in comparison to the 0.635 of the Basic product. ρ_i remains with a negative coefficient and the short-run drivers of ΔBB_0^+, ΔBB_0^-, ΔBPI_0^+ and ΔBPI_0^- are generally significant. The exception being the short-run dynamics of BPI, which implies that the shocks are more evident in the long-run than in the short-run. This makes sense as cost-of-funds would be expected to cause a faster reaction than BPI.

Table 5.3 uses the Wald test to determine whether the positive and negative coefficients, for the purpose of assessing asymmetry, are equal. The null hypothesis assumes equality between positive and negative coefficients, meaning that failing to reject the null indicates insufficient evidence to support the presence of asymmetry.

From the results of this test, we observe that SVR has statistically significant values, while the Basic product does not. This finding aligns with the earlier analysis of coefficient values and indicates that greater emphasis is placed on asymmetry in back-book pricing than in front-book pricing.

This result confirms findings from prior Australian studies [5–7] regarding back-book pricing, using a more up-to-date dataset. It also extends these findings by demonstrating that the relationship does not hold for the Basic product.

It is also worth noting that asymmetry in BPI is not relevant for the SVR product, as the variable itself was not found to significantly contribute to explaining SVR price movements, as shown in Table 5.2.

5.4.2 Hypothesis Testing

Hypothesis were formed in Section 5.3, the results of these are summarised in Table 5.4.

TABLE 5.4: A summary of hypothesis and results

Hypothesis	Details	Outcome
2a	$H_0^{2a} : \beta_i^{B,+} = \beta_i^{B,-}$ vs $H_A^{2a} : \beta_i^{B,+} \neq \beta_i^{B,-}$	Basic product does not have clear asymmetry for cost-of-funds
2b	$H_0^{2b} : \beta_i^{S,+} = \beta_i^{S,-}$ vs $H_A^{2b} : \beta_i^{S,+} \neq \beta_i^{S,-}$	Standard Variable product does have clear asymmetry for cost-of-funds
2c	$H_0^{2c} : \beta_i^{B,+} = \beta_i^{S,+}$ vs $H_A^{2c} : \beta_i^{B,+} \neq \beta_i^{S,+}$	Basic product increases less than Standard Variable Product in reaction to cost-of-funds increases
2d	$H_0^{2d} : \beta_i^{B,-} = \beta_i^{S,-}$ vs $H_A^{2d} : \beta_i^{B,-} \neq \beta_i^{S,-}$	Basic product increases more than Standard Variable Product in reaction to cost-of-funds decreases
3a	$H_0^{3a} : \upsilon_i^{B,+} = \upsilon_i^{B,-}$ vs $H_A^{3a} : \upsilon_i^{B,+} \neq \upsilon_i^{B,-}$	Basic product does not have clear asymmetry for Banking Perception Index
3b	$H_0^{3b} : \upsilon_i^{S,+} = \upsilon_i^{S,-}$ vs $H_A^{3b} : \upsilon_i^{S,+} \neq \upsilon_i^{S,-}$	Standard Variable product does have clear asymmetry for Banking Perception Index
3c	$H_0^{3b} : \upsilon_i^{B,+} = \upsilon_i^{S,+}$ vs $H_A^{3b} : \upsilon_i^{B,+} \neq \upsilon_i^{S,+}$	Basic product increases less than Standard Variable Product in reaction to Banking Perception Index increases
3d	$H_0^{3c} : \upsilon_i^{B,-} = \upsilon_i^{S,-}$ vs $H_A^{3c} : \upsilon_i^{B,-} \neq \upsilon_i^{S,-}$	Basic product increases more than Standard Variable Product in reaction to Banking Perception Index decreases

Hypothesis 1 has been excluded as it has been superseded by Hypotheses 2a and 2b, which address asymmetry in the context of the Basic product and SVR product, respectively. Hypothesis 2a examines the viability of asymmetry for cost-of-funds in the Basic product. The Wald test results from Table 5.3 indicate no asymmetry in price. This conclusion is further supported by the coefficients for L_{BB}, where the positive and negative values are approximately equal to 1 in both Table 5.1 and Table 5.2.

Hypothesis 2b addresses the viability of asymmetry for cost-of-funds in the SVR product. For the SVR product, asymmetry is statistically significant, as demonstrated by the Wald test in Table 5.3. Overall, the conclusions from these two hypotheses indicate that cost-of-funds asymmetry is evident for the back-book proxy (SVR product), but not for the front-book Basic product.

Hypothesis 2c tests whether the positive long-run estimates are comparable between the Basic product and the SVR product, while Hypothesis 2d evaluates the same for negative long-run estimates. The results indicate that for the SVR product, asymmetry is statistically significant at the 1% level. Additionally, the coefficients exceed 1 for positive shocks to cost-of-funds and are less than 1 for negative shocks, as shown in Table 5.2. In contrast, the Basic product exhibits coefficients for both positive and negative shocks that are approximately equal to 1, while also being statistically significant at the 1

The results for the SVR product align with existing literature on the Australian market, including the existence of asymmetry and the magnitude of the coefficients [5–7]. However, the results for the Basic product differ, suggesting a distinct pricing strategy for front-book products.

Hypotheses 3a and 3b examine whether BPI (customer perception) has an asymmetric impact on price movements. The Wald test in Table 5.3 indicates no asymmetry for the Basic product (3a), but asymmetry exists for the SVR product (3b). This implies that sentiment impacts Basic products symmetrically: a 1-unit increase in BPI has approximately the same impact as a 1-unit decrease. In contrast, for the SVR product, a 1-unit increase in BPI is more likely to result in a greater-than-1 increase in price, while a 1-unit decrease in BPI is likely to lead to a decrease of less than 1.

Hypotheses 3c and 3d test for the equivalence of long-run positive and negative BPI shocks between Basic and SVR products. An examination of the coefficients shows that BPI is significant for the Basic product but not statistically significant at the 5% level for the SVR product.

For the Basic product, an increase or decrease in BPI leads to a corresponding change in price in the same direction. This suggests that improved customer sentiment allows

banks to increase margins, a phenomenon consistent with brand loyalty and findings in the literature for non-mortgage products [22, 23].

Interestingly, this relationship does not hold for the SVR product, implying that banks may apply different pricing strategies for new front-book customers compared to back-book customers. As highlighted by ACCC [8], this approach does not favour existing customers and may be driven by a lack of transparency regarding discounts applied to back-book rates.

5.5 Discussion

There have already been studies on asymmetric pricing for mortgages, including those specific to the Australian market, such as [5–7]. These studies have a broader scope, examining all bank product loans using aggregated models and, in some cases, relying on more difficult-to-obtain bank-level data. However, these studies do not incorporate the concept of perception or distinguish between front-book and back-book pricing. This omission represents a limitation, as highlighted in Section 5.4, where the results underscore the importance of these features. This section will further explain why these elements are valuable additions.

ACCC [8] conducted an analysis of banks in Australia and identified a significant lack of transparency in their pricing approaches. This means that while banks charge customers specific rates, customers do not have visibility into the rates charged to other customers. Conducting research on this type of data is challenging, as the lack of transparency for customers often extends to the data available for research purposes. This creates a barrier to entry for understanding how pricing strategies function.

Using its position as a regulator, the ACCC was able to obtain proprietary data for its analysis and concluded that this lack of transparency is a fundamental issue in the market. This regulatory access highlights the inherent difficulty for researchers attempting to analyse pricing mechanisms without similar access to privileged data.

This is problematic, however, since if researchers do not have the full picture, how can they accurately understand the pricing mechanisms? There are several models that could perform well given adequate data, such as marginal cost pricing and the Industrial Organisation Approach [6]. However, without visibility into the actual prices charged to end customers, it becomes challenging to address hypotheses concerning the differential treatment of new and existing customers.

This differential treatment is central to the transparency discussion. In other words, a lack of transparency would only benefit a bank if it enabled them to engage in price differentiation.

This is where this study innovates: it explores how to proxy the treatment of new customers relative to existing customers. Rather than relying on an overall bank rate, as in prior Australian studies [5–7], this study separates the analysis into front-book pricing, represented by the Basic product, and back-book pricing, represented by the SVR product.

This focus on Australia is particularly relevant due to the country's emphasis on variable-rate mortgages, as discussed in Section 1.1.4, which highlights what makes the Australian market unique. By splitting the analysis into front- and back-book rates, this study fits a model to each and demonstrates that pricing dynamics vary significantly between the two.

The Basic product, which typically represents the price charged to new customers without further discounts, exhibits no asymmetry in its response to changes in BBSW. This suggests that the Basic product closely mirrors cash rate movements, aligning with what the market would prefer.

In contrast, the SVR product shows a clear deviation in treatment based on whether cost-of-funds increase or decrease. This deviation works in the bank's favour in both scenarios: when the cost-of-funds increases, banks raise rates by more than the increase; when the cost-of-funds decreases, banks reduce rates by less than the decrease. This asymmetric behaviour enhances the bank's profitability relative to the alternative direction in both cases.

Here's the refined version of the text with corrections highlighted using bold with underscores:

This analysis aligns with the findings of ACCC [8], but it is conducted at a more granular level and supported by statistical evidence grounded in theory. It highlights a clear deviation in treatment between new and existing customers, raising the question of whether this behaviour aligns with principles of fair treatment.

In a competitive market, it would be possible for another organisation to provide the transparency that customers desire. Indeed, smaller start-ups in the Australian market, such as Athena Home Loans, have emerged with this goal in mind. However, the eight banks examined in this study account for more than 85% of the market. While start-ups may have good intentions, they are often acquired by larger organisations, potentially altering their behaviour over time.

This is characteristic of an oligopolistic market. Given the centrality of banking to consumers' livelihoods, there is a need for broader discussions on whether governments could do more to ensure transparency. One potential short-term measure is requiring banks to post the average rates for existing customers relative to new customers on their websites regularly. Such a move would encourage discussions about refinancing.

This transparency could enable smaller banks to offer more competitive rates compared to the now-visible pricing across the market, reducing the oligopolistic bias and fostering a more competitive environment.

Thus far, the discussion has focused on one key finding from the study: asymmetry in pricing. However, the other pivotal finding relates to understanding pricing strategy from a broader perspective.

Traditional studies using the marginal cost pricing approach of De Bondt [25] have predominantly focused on pricing as being driven by marginal cost. Risk and other factors are typically treated as incorporated within the constant term of the equation. This study builds on this framework by incorporating the concept of perception.

It is understandable why prior research [5–7, 34, 48, 51, 53, 58] has not incorporated this element, as measuring perception using standard methodologies is inherently challenging. To address this limitation, this study employs machine learning techniques to derive the

concept of perception through the Banking Perception Index (BPI), as demonstrated in Chapter 4.

By using this unique measure and including BPI in the marginal cost pricing model, an interesting dynamic emerged. The front-book rate was influenced by sentiment, while the back-book rate was not. This suggests that adjusting rates based on perception is logical when it can influence new flows, but less so for sticky customers [51].

New flows drive volume growth, whereas changing rates on the back-book would be prohibitively expensive to justify based solely on perception. This is because adjusting rates for the back-book would affect all customers, yet the benefit would primarily accrue from retaining non-sticky customers. Given ACCC [8]'s recommendation for customers to refinance, it is likely that the majority of customers to date have been sticky, making this dynamic even more pronounced.

Another notable aspect of including BPI was its statistical significance. This demonstrates that perception does drive pricing decisions during the examined time period. Moreover, the relationship was not asymmetric for the Basic product, meaning that price movements aligned with perception changes: when perception decreased, prices decreased, and when perception increased, prices increased.

This dynamic is particularly intriguing because it suggests that banks do not reward customers for positive perception, which could signal loyalty. Instead, they use positive perception to justify higher margins, akin to leveraging an intangible brand value. Conversely, banks compensate for negative perception—potentially driven by bad headlines or other factors—by reducing rates.

This behaviour, while rational and not unexpected, reflects the nature of an oligopolistic market. In an ideal scenario, would it make more sense for a bank to hold rates constant when observing improved sentiment, rather than increasing rates? Additionally, should the SVR rate also be influenced by sentiment, instead of relying predominantly on cost-of-funds considerations?

5.6 Summary

The purpose of this chapter was to estimate the impact of perception on pricing, with a focus on front- and back-book differentiation. The chapter began by introducing a stylised model and approach to be applied, which was then formulated statistically using the NARDL model as a base. The base model incorporated the element of asymmetry in cost-of-funds, and it was subsequently extended to include perception and front- and back-book price differentiation.

Three overarching hypotheses were formulated in alignment with the model's notation. These models were then tested in the results section, and their output was compared against the proposed hypotheses. The discussion section explored the implications of the findings, highlighting why these results are both novel and significant.

The data used spanned the period from 2012 to 2020, aligning with the availability of data for the derived BPI. The first key novelty of this study lies in recognising that pricing strategy varies by product, with each product representing the concept of front- and back-book—Basic product for front-book and SVR product for back-book, respectively. The second key novelty is the inclusion of the concept of BPI to account for perception in pricing strategies.

The overall findings suggest that both inclusions are worthwhile. Perception significantly influences the pricing of the Basic product but does not impact the SVR product. The SVR product aligns with what prior Australian studies have identified when analysing the factors influencing pricing [5–7]. This indicates that for back-book prices, those studies are appropriately formulated and not missing a critical driver.

However, those studies did not address front-book pricing. When considering front-book pricing, perception emerges as a key driver that warrants inclusion in pricing models. The differentiation between front- and back-book pricing is a pivotal improvement because, as the results clearly demonstrate, pricing strategies vary between the two.

Overall, while front-book pricing represents only a small portion—approximately 1% of volume per month for banks, as discussed in Section 1.1.2—this smaller share accumulates

significantly over time. As 1% of flows shift monthly, the cumulative effect becomes substantial, highlighting the importance of understanding and optimising front-book pricing strategies.

Chapter 6

Discussion

6.1 Introduction

This thesis set out to explore whether customer perception significantly influences the pricing behaviour of banks. The literature review in Chapter 6.2 identified key research gaps and highlighted the need for a study that bridges the divide between perception and pricing in the banking sector. Through a systematic review of existing methodologies in Chapter 3, the development of the Banking Perception Index (BPI) in Chapter 4 provided a novel metric for quantifying perception. This index was then applied to pricing models in Chapter 5, offering a comprehensive approach to understanding the relationship between customer perception and bank pricing strategies.

By examining the results within the framework of the objectives laid out in the introduction, this discussion synthesises key findings, as outlined in Section 6.3, and demonstrates how perception influences front-book and back-book pricing dynamics. Section 6.4 further contextualises the research outcomes, linking them to knowledge contributions and practical implications for the banking industry.

6.2 Current State of Research

The core focus of this thesis has been on pricing behaviour within the banking sector, specifically examining the distinction between front and back-book pricing, the concept of customer perception, its measurement, the impact of the HRC, and whether perception influences pricing. Current research offers a substantial analysis of bank pricing mechanisms but lacks integration of these components into a unified framework.

Two dominant approaches in the literature are marginal cost pricing and industrial organisation pricing [6]. Studies in Australia have predominantly employed marginal cost pricing [5–7], consistently concluding that pricing asymmetry exists, favouring banks. Specifically, when the cost of funds increases, prices tend to rise more, and when the cost of funds decreases, prices fall less. While offering a broader perspective, industrial organization pricing, is more restrictive due to its need for extensive bank-level data, limiting the scope of analysis to fewer institutions [6].

The marginal cost pricing model has been extended to incorporate the degree of asymmetry, which has been a staple in pricing literature since De Bondt [25]. However, these models often remain relatively simple, with marginal cost as the primary explanatory variable, while other considerations, such as loan risk, are captured in the constant. Despite the widespread use of this approach, there is a notable gap in the literature in separating front-book pricing (pricing for new customers) from back-book pricing (pricing for existing customers) in the literature. In Australia, deviations between these two are expected, with back-book pricing generally less competitive than front-book pricing [8]. Allen and McVanel [53] examined a similar dynamic in the Canadian mortgage market, distinguishing between posted and discounted rates, revealing disparities between the prices shown to customers and what they ultimately pay.

The concept of perception has been explored in banking literature, but mostly through point-in-time survey data [17–20, 60], focusing on why customers choose specific banks. More advanced methods, such as NLP and text mining, have been applied in other industries to extract insights from unstructured data, like reviews and headlines [62–64, 66–68, 70–72], but these techniques have yet to be fully utilised in banking. This presents an

opportunity to apply machine learning approaches to analyse customer perception more dynamically in the banking sector.

There are examples in other industries where perception directly impacts pricing, such as REIT and oil markets [22, 23]. In banking, the HRC has likely influenced customer perceptions due to scandals like money laundering, yet studies related to the HRC have predominantly focused on legal and ethical consequences at the industry level rather than examining the perception and pricing impacts on individual banks [13–16].

In summary, while the literature addresses the concepts of pricing, perception, their relationship, and the HRC impact, these elements have not been thoroughly integrated within the context of banking. This study aims to bridge this gap, offering a more nuanced understanding of how perception, and cost inform pricing strategies. By combining these elements, this research highlights the strategic decisions banks can make by incorporating perception, offering greater insights into market behaviour beyond a purely cost-driven model.

6.3 Results Synthesis

Section 1.4 outlined the research aims and objectives, identifying three primary objectives for this thesis. These objectives were designed to address six key contributions targeted by the study. Table 6.1 summarises of these contributions, detailing the actions taken to achieve each objective, along with references to the chapters where these contributions are discussed in depth. In this section, each objective is examined in relation to its corresponding contributions, providing a straightforward synthesis of how the research aligns with the original aims.

6.3.1 Objective 1: Quantitative Index for Perception

Objective 1 aimed to develop a quantitative index model of banking perception, labelled the Banking Perception Index (BPI), and validate this model by applying it to the Haynes Royal Commission (HRC). This objective was fulfilled in Chapter 4, building on the

TABLE 6.1: A summary of key contributions and action taken

#	Objective	Contribution	Action taken	Chapter reference
1	1	Banking Perception Movement	Model BPI by bank and month	3, 4
2	1	Banking Perception and the HRC	Use modelled BPI and see how HRC influenced it	4
3	1	Idiosyncratic movements in Banking Perception	Use modelled BPI and compare by bank	4
4	2 & 3	Asymmetric Pricing	Model price with positive and negative shocks with more recent data in the Australian market	5
5	2 & 3	Front and Back-Book Pricing	Model price with varying front and back-book outcome variables	5
6	2 & 3	Behavioural Element of Pricing	Incorporate perception into the model	5

comprehensive systematic review in Chapter 3. The achievement of this objective involved three key contributions.

Contribution 1 focuses on developing the BPI model, a quantitative index of banking perception. This novel model captures month-on-month changes in perception, contrasting with the existing literature, which largely relies on point-in-time surveys. By using machine learning techniques, this study contributes a more dynamic and granular understanding of perception shifts over time. Unlike traditional methods, which depend on restricted bank-level data, the BPI utilises publicly available unstructured data such as reviews and headlines, making the model more adaptable and scalable.

Contribution 2 involved applying the BPI to assess perception shifts during the HRC period. While most prior studies focus on qualitative analysis, this thesis applies a quantitative lens to track how banks' perceptions fluctuated during and after the HRC. Statistical tests revealed that some banks underperformed during this period (e.g., Bank 1, Bank 7), while others performed well (e.g., Bank 4, Bank 6). The detailed analysis at

the index level (MRS, MHS, MGS) provided deeper insights into specific factors driving performance, offering a data-driven basis for understanding bank-specific impacts.

Contribution 3 incorporates insights from the BPI analysis that offer a more nuanced view of the banking sector. The study highlights significant variations in perception across individual banks, challenging the industry-wide focus prevalent in previous research. This bank-level granularity reveals key differences in how banks responded to the HRC, with some banks facing scandals (e.g., Bank 7) underperforming compared to others (e.g., Bank 4), which remained relatively unaffected. Such insights demonstrate the free market's role in incentivising better behaviour among banks, independent of government intervention.

The BPI model provides a significant methodological advancement in understanding how banking perception evolves over time and its impact on pricing behavior. The novel approach of combining unstructured data sources with machine learning techniques allows for a flexible, scalable, and dynamic measurement of perception, applicable not only in the context of the HRC but also across different countries and regulatory environments. In conclusion, the development and application of the BPI contribute to advancing the literature on banking perception while informing broader discussions on transparency, market dynamics, and policy implications.

6.3.2 Objective 2: Pricing Behaviour Model Framework

Objective 2 aimed to develop a robust pricing behaviour model by incorporating the BPI and addressing the distinction between front-book and back-book pricing. Chapter 5 explores this objective with the foundational methodology in the relevant sections.

The framework developed under this objective sets the stage for analysing pricing asymmetry and incorporating perception into pricing models. The concept of asymmetry in pricing behaviour is introduced using the NARDL approach, as described by Shin et al. [59], which allows for modelling differential price responses depending on whether cost-of-funds increase or decrease, particularly for back-book pricing. This modelling approach has been applied in similar studies, such as Apergis and Cooray [5] and Valadkhani and Anwar [7], who investigated asymmetric pricing in the Australian banking sector.

Additionally, the model accounts for the differing behaviours between new customers (front-book) and existing customers (back-book). This distinction, as highlighted by ACCC [8], is critical in understanding the market segmentation strategies banks use to attract new customers while maintaining higher rates for existing customers. Applying this framework to the Australian market is significant but is also relevant to other markets where this front-back book differentiation exists.

Finally, the model integrates the BPI into pricing strategies, capturing how customer perception influences pricing decisions—an often overlooked factor in previous models, such as those discussed by Ruscheinsky et al. [22] and Qadan and Nama [23] in non-banking sectors. Including of perception into the pricing model extends the traditional cost-based pricing model by accounting for how public perception of banking practices impacts rate setting, particularly for new customers.

This framework laid the groundwork for analysing how banks balance perception and price asymmetry, setting the stage for the more detailed analysis discussed in Objective 3.

6.3.3 Objective 3: Strategic Implications

Building on the framework established in Objective 2, Objective 3 focuses on evaluating the quantitative impact of the BPI on pricing behaviour, particularly in the context of front-book and back-book differences. This is discussed in detail in Chapter 5, where the results and statistical analyses are presented.

Contribution 4 examines the use of the NARDL approach, as outlined by Shin et al. [59], to quantify asymmetric pricing impacts. The results indicate that banks tend to raise back-book rates more aggressively than they lower them in response to changes in the cost of funds. This "rockets and feathers" effect, as coined by Bacon [50], is particularly evident for back-book products like the SVR. This finding is consistent with prior Australian studies by Apergis and Cooray [5] and Holland et al. [6], which similarly noted that back-book rates do not decrease as rapidly as they increase, especially post-GFC.

Contribution 5 highlights the distinction between front-book and back-book products, with front-book rates, such as those for the Basic product, showing less asymmetry compared to

back-book rates. The findings suggest that front-book rates, which are more transparent and market-driven, tend to align more closely with cost-of-funds movements. This aligns with conclusions from studies like ACCC [8], which emphasize the competitive pressures banks face when marketing front-book rates. In contrast, back-book rates are more flexible, allowing banks to benefit from customer inertia, which is supported by Lowe et al. [51], who discussed the stickiness of existing customers in the Australian banking market.

Contribution 6 focuses on the behavioural aspect of pricing, revealing that perception (captured through the BPI) significantly influences front-book rates but not back-book rates. Including perception in the pricing model introduces a new dimension, showing that banks adjust front-book prices to attract new customers while being less concerned with perception when setting back-book rates. This aligns with findings by Qadan and Nama [23] on how perception influences pricing in other sectors and extends these insights to the banking sector. This unique contribution adds to the traditional marginal cost pricing model by demonstrating that perception influences pricing decisions, especially for front-book products, as banks seek to optimize volume growth and manage public sentiment [51].

These insights reveal the complex interplay between market conditions, customer perception, and pricing strategy, particularly concerning customer retention and acquisition.

Contributions 4 to 6 can be summarised by considering an example of the RBA moving the cash rate by 25 bps. If, hypothetically, the RBA increased the rate by 25 bps, on average, banks are expected to increase their back-book rate by 32 bps (1.289×25 bps). Conversely, if the RBA decreased the cash rate by 25 bps, banks are expected to decrease their back-book rate by 19 bps (0.774×25 bps). In contrast, for the Basic product, if the RBA increased the rate by 25 bps, this would lead to an increase of 26 bps (1.043×25 bps), whereas a decrease would lead to a reduction of 25 bps (0.988×25 bps). This highlights a tendency to favour front-book customers, likely driven by a desire for volume growth and the low risk of back-book attrition due to customer stickiness. Perception, meanwhile, has a significant impact on front-book pricing, with approximately a 4 bps (0.167×25 bps) movement in rates for each change in perception. This suggests that banks are more

attuned to how they are perceived in pricing for new customers but less concerned about perception for existing customers.

In summary, Objective 3 successfully demonstrates the impact of perception on front-book pricing, the differential treatment of front-book and back-book customers, and the asymmetric pricing behaviour of banks. These findings provide a deeper understanding of bank pricing strategies and their implications, further explored in the Policy Implications section.

6.4 Implications for Knowledge and Practice

6.4.1 Knowledge

One of the primary knowledge contributions of this study is the development of a novel perception index, as discussed in Objective 1. Traditionally, perception in the banking sector has been assessed through survey-based methods. This study introduces an alternative approach that utilises publicly available data, offering several advantages. This new perception index enhances the applicability of perception measurement across various industries and provides researchers with a more dynamic tool to investigate how perception evolves. Such an approach supports strategy-oriented research by elucidating how actions impact perception and how shifts in perception can influence subsequent strategic decisions.

Furthermore, publicly available data addresses a significant barrier in banking research, namely the restricted access to private sector data. By providing a more accessible data source, this study facilitates further exploration into the impact of perception within the banking industry. Given the importance of banking products in everyday life, expanding research in this domain has broader societal implications and benefits.

Objective 2's introduction of a new pricing behaviour model framework represents another contribution to knowledge. This framework extends previous studies by highlighting the differences in pricing behaviour between front-book and back-book products. While earlier research focused predominantly on marginal costs and asymmetric pricing, this study

reveals that banks exhibit distinct pricing dynamics for new versus existing customers. This differentiation underscores the necessity for future research to consider the unique dynamics of front-book pricing, which prior studies did not address adequately.

Moreover, incorporating perception into the pricing model, facilitated by the BPI, underscores its role as a significant explanatory variable for front-book pricing. This novel inclusion suggests that future pricing analyses should integrate perception measures to enhance their accuracy. The study's exploration of BPI asymmetry, which found no significant asymmetry, further contributes to the literature by identifying an area that has been relatively underexplored and warrants further investigation.

6.4.2 Policy

The introduction of the BPI offers valuable insights into the impact of the HRC and provides a methodological framework for future assessments of regulatory actions. The BPI integrates reviews, headlines, and growth data, offering a comprehensive perspective on customer perception. From a monitoring perspective, it enables an evaluation of how regulatory changes affect customer perception of banks. This method reveals the broader impact of the HRC, demonstrating how increased transparency can influence market behaviour.

The findings suggest that increased transparency, facilitated by the BPI, can be a valuable regulatory tool. By enhancing market information, governments can reduce the need for more intrusive regulatory measures while ensuring that customers can make informed decisions. This aligns with the concerns raised by ACCC [8], which highlighted the importance of transparent pricing practices.

The study's results indicate that back-book pricing tends to be less transparent than front-book pricing. For example, the Basic product, characterised by its transparency, aligns more closely with marginal costs, while the SVR product allows banks greater discretion in pricing, potentially benefiting their margins. From a policy perspective, this suggests that the government might consider measures to increase transparency in back-book pricing. Options include mandating that all products adhere to transparency standards similar

to the Basic product or regularly publishing aggregated pricing information to facilitate customer comparison and refinancing decisions. Both approaches aim to protect consumers by ensuring they receive fair and transparent pricing for essential financial products.

Additionally, the RBA can leverage the findings to understand better the impact of BBSW on both front-book and back-book pricing. For instance, if the RBA increases the cash rate by 25 basis points, this could lead to a corresponding increase in back-book pricing. Understanding these dynamics can help the RBA make more informed decisions regarding cash rate adjustments, considering the immediate and long-term impacts on consumers.

6.4.3 Bank Strategy

The BPI provides a multi-dimensional view of customer perception, incorporating reviews, headlines, and growth data. This approach addresses a limitation of traditional Net Promoter Score (NPS) measures, which, as noted by Zaki et al. [69], may only partially capture customer loyalty. NPS surveys, assessing customer satisfaction after interaction, can be biased and intrusive. In contrast, the BPI offers a less intrusive, more comprehensive assessment of public perception, allowing for meaningful comparisons between banks.

The BPI also provides actionable insights for banks by breaking down perception into three indicators: MRS, MHS, and MGS. By analysing changes in these indicators over time, banks can adjust their strategies to address weaknesses and leverage strengths. For example, if a low BPI score is primarily due to MRS, banks might focus on improving their reputation through enhanced marketing strategies highlighting positive headlines and growth. Conversely, if MGS is weak despite strong MRS and MHS, banks could intensify their product promotions to capitalise on positive public perception.

The study also highlights that banks price differently for front-book versus back-book customers. Front-book pricing is more responsive to changes in the cost of funds and public perception, while back-book pricing is less transparent and more advantageous to banks. As discussed by ACCC [8], addressing this discrepancy could provide a competitive edge. Banks that proactively improve transparency and align back-book pricing with

front-book pricing might gain goodwill and differentiate themselves from competitors, as demonstrated by emerging players like Athena Home Loans.

6.4.4 Customer

From a customer perspective, the study confirms that back-book customers often receive less favourable treatment than front-book customers. This finding is consistent with the analysis by ACCC [8] and provides empirical evidence of pricing disparities. The study highlights that banks are more sensitive to public perception when setting front-book prices, suggesting that customers might benefit from monitoring public perception to secure better rates.

During periods of negative perception, banks may offer more attractive front-book rates to mitigate reputational damage. Customers should know these dynamics and consider refinancing options during such times. However, customers need to weigh the benefits of potentially lower rates against the reasons behind the bank's poor reputation. This cost-benefit analysis is crucial for making informed decisions that balance the advantages of lower rates with the risks associated with diminished bank reputation.

Chapter 7

Conclusion

7.1 Aim

The overarching aim of this thesis was to explore and explain how perception influences the pricing behaviour of banks, with a particular focus on the Australian mortgage market. This research aimed to bridge a significant gap in the literature, where pricing models traditionally focused on cost-based variables, such as the cost of funds, but often overlooked the critical role that market perception plays in determining pricing strategies. Given that nearly two-thirds of Australians own a home with a mortgage or are renting and that banks' pricing strategies heavily influence mortgage rates, understanding these dynamics is both timely and necessary.

The motivation behind incorporating perception into pricing models arises from the complexity of the banking industry, particularly in the context of front-book versus back-book pricing, where banks often charge new customers different rates than existing ones. The hypothesis driving this research was that an overreliance on cost-based variables, without considering perception, might lead to omitted variable bias, potentially skewing conclusions drawn from prior models.

By including perception, this study sought to develop a more holistic framework for analysing how banks set prices, particularly in markets like Australia, where a few dominant banks control the majority of mortgage lending. These banks often adjust their rates

asymmetrically in response to changes in the cost of funds, raising rates more readily than lowering them, a behaviour that both profit margins and public perception could influence.

This thesis also investigated how banks balance profit maximization and maintaining a favourable market perception, particularly in the wake of significant regulatory changes, such as those introduced following the HRC. Understanding this balance has broader implications for the banking sector, consumers, policymakers, and future academic inquiry.

By systematically breaking down the objectives into a BPI, a more refined pricing model, and an evaluation of their combined effects, this research aims to provide new insights that can influence both theoretical and practical approaches to bank pricing in the future.

7.2 Objective Conclusion

This thesis set out to achieve three main objectives, each contributing to a broader understanding of how perception influences the pricing behaviour of banks. Each objective was approached systematically, with the results offering knowledge and practical contributions to the field.

The first objective was to develop a quantitative index for measuring banking perception, the BPI. This index was designed to capture public and market sentiment towards individual banks, moving beyond traditional reliance on survey data. Using publicly available data, the BPI is both scalable and adaptable to other sectors. The index was validated through its application to an example, the HRC, where it demonstrated its capacity to reflect real-time shifts in public perception during significant regulatory scrutiny. This breakthrough offers a more accessible, data-driven approach for future researchers and practitioners interested in banking perception and its influence on pricing.

The second objective aimed to improve existing models of pricing behaviour by integrating the BPI into a more comprehensive framework. Previous models had predominantly focused on asymmetric pricing, particularly the role of marginal costs and cost-of-funds in determining bank rates. However, this study introduced a critical distinction between front-book and back-book pricing – the rates banks charge new customers versus existing

ones. By incorporating perception into this model, this thesis highlighted how banks might alter their pricing strategies for new customers, driven by cost factors and how they wish to be perceived in the market. This enhanced model offers a more nuanced understanding of pricing dynamics, accounting for economic and behavioural drivers of bank decisions.

The third objective was to quantitatively assess the impact of the BPI on pricing behavior, specifically within the front-book and back-book contexts. Applying econometric models demonstrated that perception, as captured by the BPI, is a significant explanatory variable for front-book pricing. This finding suggests that banks are more sensitive to public perception when attracting new customers, but that perception may play a less pronounced role in back-book pricing. The study also found that the BPI did not exhibit asymmetry, offering a novel contribution to existing research on behavioural pricing asymmetries. This insight provides a foundation for future studies on perception-based pricing models and offers practical implications for bank strategies.

In conclusion, this thesis has made substantial strides in advancing our understanding of how perception impacts bank pricing behaviour. By developing the BPI, integrating it into an enhanced pricing model, and assessing its effects within different pricing contexts, the study has provided valuable insights and tools for both knowledge and practical applications. The BPI offers a novel approach to capturing public sentiment and its influence on banking strategies, surpassing traditional survey-based methods. Integrating perception into the pricing model adds depth to our understanding of how banks adjust their strategy in response to market sentiment. The quantitative assessment of the BPI's impact on front-book and back-book pricing enriches existing research and opens new avenues for exploring behavioural pricing dynamics. Overall, the findings contribute to a more comprehensive view of pricing behaviour in the banking sector, underscoring the importance of perception in shaping market strategies and offering a robust framework for future research in this field.

7.3 Limitations and Future Studies

The limitations of developing a quantitative index for perception primarily arise from the study's reliance on literature and intuition. As a result, the BPI is not a robust statistical measure but rather an index intended to evaluate organisational performance based on reviews, headlines, and growth. It does not explicitly control for the interrelationships among these factors, such as how headlines might influence both reviews and growth. Furthermore, the BPI does not account for strategic factors such as product offerings, broker attitudes, economic conditions, and interest rates. The assumption is that these elements are captured at the bank-specific level, where financial institutions maintain consistent strategies. For instance, if Bank A focuses its pricing strategy on retail banking while Bank B targets commercial customers, the BPI does not adjust for these strategic differences. Consequently, fluctuations in the BPI are attributed to variable factors influenced by the HRC rather than changes in individual bank strategies. Future research could address this limitation by incorporating strategic variables into the analysis.

A further limitation arises from the potential endogeneity between perception and pricing behaviour. While the study assumes that perception (as measured through BPI) influences pricing strategy, it is also possible that pricing decisions shape customer sentiment and media coverage. For instance, if a bank consistently offers competitive interest rates or fee waivers, this may improve its reputation, thereby influencing reviews and headline sentiment. This feedback loop suggests a bidirectional relationship, where perception and pricing co-evolve rather than follow a strict cause-effect structure. The current model does not explicitly account for this endogeneity, which may bias estimates of perception's influence on pricing. Future research could address this issue using models such as Vector Auto-Regressive approaches used by Ruscheinsky et al. [22] in the context of oil prices—that allow for simultaneous relationships between perception and pricing behaviour.

One potential oversight is that if Bank A is criticised for poor treatment of retail customers during the HRC, this might change its strategic direction. To mitigate this, the analysis was limited to 2019 to capture short-term impacts and avoid conflating results with the COVID-19 pandemic. As additional data becomes available, extending the study

period and controlling for the effects of COVID-19 would provide a more comprehensive understanding of long-term strategic changes and their impacts.

The study used data from 2013 due to the increasing prominence of online reviews. This limitation means the study did not consider the impact of transparency initiatives on illegal banking activities before 2013. Future studies could avoid using review data and focus exclusively on headlines and growth, although this approach would forgo insights provided by individual customer experiences.

Another limitation is the reliance on a single website for reviews and headlines, which may introduce bias due to the audience characteristics of these websites. While Product Review and ABC Headlines were chosen for their substantial volume of data, expanding the scope to include a broader range of sources could provide a more balanced perspective. Additionally, examining how different news outlets presented similar headlines during the HRC could offer further insights.

Measuring front-book and back-book rates is challenging in practice. Ideally, access to back-book rates via public sources would be advantageous, but this is not feasible due to non-public marketing practices. The study employed proxies, using Basic Product rates to represent front-book rates and SVR movements to represent back-book rates. While this proxy approach is logical, it remains a limitation. Future research could explore ways to enhance transparency in pricing, potentially through regulatory measures, to improve the accuracy of multi-bank analyses.

The study adopted a marginal cost pricing approach rather than an industrial organisation approach due to the latter's requirement for more granular bank data, which would have reduced the number of banks included in the analysis. The marginal cost approach, being less data-intensive, was therefore preferred. Future research might explore how an industrial organisation approach could incorporate the BPI or differentiate between front-book and back-book pricing.

A final consideration relates to the generalisability of the BPI and modelling framework to markets outside Australia. While this study focuses on Australian data and regulatory

conditions, the underlying structure of the BPI—combining customer reviews, media sentiment, and growth measures—could be adapted to other banking systems with appropriate local data. However, differences in mortgage product composition (such as the prevalence of fixed versus variable rates), regulatory settings, and media environments may influence both perception dynamics and pricing strategies. As such, future studies applying the BPI framework internationally should consider these contextual differences when interpreting results.

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