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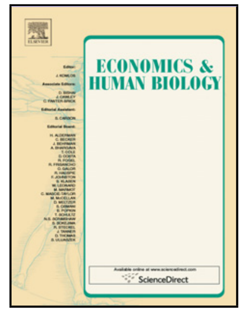

Title: Obesity and Health Expenditures: Evidence from Australia

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Highlights

- We estimate the relationship between obesity and health expenditures in Australia.
- Obese adults have higher expenditures for all types of health care.
- A similar relationship holds for men and women and for all age groups.
- Much, though not all, of the effect appears to be related to chronic conditions.
- Type II/III obesity is also associated with more costly recovery from health shocks.

Obesity and Health Expenditures: Evidence from Australia

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Keywords: obesity; healthcare costs; healthcare utilization; health expenditures; medical care

JEL codes: C3, I1

Obesity and Health Expenditures: Evidence from Australia

Abstract

Rising rates of obesity are a public health concern in every industrialized country. This study investigates the relationship between obesity and health care expenditure in Australia, where the rate of obesity has tripled in the last three decades. Now one in four Australians is considered as obese, defined as having a Body Mass Index (BMI, kg/m^2) of 30 or over. The analysis is based on a random sample survey of over 240,000 adults aged 45 and over that is linked at the individual-level to comprehensive administrative health care claims for the period 2006-2009. This sub-population group has an obesity rate that is nearly 30 percent and is a major consumer of health services. Relative to the average annual health expenditures of those with normal weight, we find that the health expenditures of those with a BMI between 30 and 35 (obese type I) are 19 percent higher and expenditures of those with BMI greater than 35 (obese type II/III) are 51 percent higher. We find large and significant differences in all types of care: inpatient, emergency department, outpatient and prescription drugs. The obesity-related health expenditures are higher for obese type I women than men, but in the obese type II/III state, the men's obesity-related expenditures are higher. When we stratify further by age groups, we find that obesity has the largest impact among older men aged above 75 and women aged 60-74 years old. In addition, we find that obesity impacts health expenditures not only through its link to chronic diseases, but also because it increases the cost of recovery from acute health shocks.

Keywords: obesity; healthcare costs; healthcare utilization; health expenditures; medical care
JEL codes: C3, I1

1. Introduction

According to the World Health Organization (WHO), the worldwide rate of obesity has doubled since 1980 and today it is estimated that over 500 million adults are obese (WHO, 2013). Although the highest rates of obesity are found in the US, some data suggest that obesity is growing faster in other countries. This is particularly true in Australia, where between 1980 and 2008, the percentage of adults who are obese tripled, from 8 percent to 24 percent (Australian Institute of Health and Welfare, 2010).

Because obesity is related to a variety of medical conditions, rising rates of obesity contribute to increased health expenditures. Several US studies using cross-sectional survey data find evidence of such an effect (Sturm 2002; Finkelstein et al 2003; Thorpe et al 2004; Finkelstein et al 2009; Cawley and Meyerhoefer 2012). The results of some of these studies also suggest that spending is higher for overweight adults as compared to those of normal weight, though in some cases this difference is not statistically significant (Finkelstein et al 2003; Thorpe et al 2004). Similarly, sub-group analyses testing for differences across weight categories, demographic groups or types of health care spending, often yield imprecise results because of small sample sizes.

In addition to having higher rates of obesity than other countries, the US is unique in terms of the financing and delivery of health care. In particular, private insurance plays a much more important role in the US than in any other country. In theory, the public financing of health care in other countries may contribute to obesity since individuals do not bear the incidence of higher health care utilization in the same way they would in a system based on risk-rated insurance premiums (Bhattacharya and Sood 2011). Even if this type of “ex ante moral hazard” effect is not important empirically, the public financing of health care means that obesity-related health spending has important fiscal and distributional consequences. Therefore, it is important to understand how obesity and health expenditures are related in non-US countries where health care is financed predominantly by the public sector.

Research on the relationship between obesity and health expenditures from such countries is quite limited. Most non-US studies use a prevalence-based cost-of-illness methodology that indirectly estimates the weight-expenditure relationship by assuming a relationship between obesity and specific diseases and attributing a portion of the treatment cost of those diseases to obesity (e.g., Anis et al, 2010; Wang et al, 2011; Detournay et al, 2000; Muller-Riemenschneider et al, 2008). There are fundamental limitations to this approach, which pieces together information on obesity, disease prevalence and health spending from prior studies conducted in different countries in different years. Studies that use individual-level data to estimate multivariate regression models provide much stronger evidence on the relationship between obesity and health expenditures.

In this paper, we directly estimate the relationship between body mass index (BMI) and health care spending in Australia, focusing on adults aged 45 and older, an age group that includes heavy utilizers of health care services. The main aims of the study are to document the relationship between obesity and health expenditures for this population and to investigate how this relationship varies with age and gender and type of health care service.

Australia is an interesting case to study, given its rapidly growing rates of obesity and the fact that its health system is representative of many systems outside the US.[1] In addition, our analysis is based on a uniquely rich data set that links several years of administrative claims

[1] Australia's universal public health system, known as Medicare, provides comprehensive coverage for inpatient hospital treatment, out-of-hospital medical services and pharmaceuticals. In 2009, health spending in Australia accounted for 8.7% of total GDP. This is slightly below the average for OECD countries (9.5%) and roughly half the amount that the US spent as a share of GDP (OECD, 2011).

databases with a survey of over 240,000 individuals, selected randomly from the 45+ population. The combined data set has several important advantages over the data used in prior studies, including those from the US. The administrative databases, which are obtained from public and private hospitals and the public insurance system that covers all Australians, provide comprehensive information on spending for inpatient care, ambulatory care and prescription drugs. Moreover, unlike the self-reported utilization data that are typically used in this literature (e.g., Wolfenstetter, 2012 for Germany), administrative claims data are not subject to recall error and do not impose assumptions that an individual's cost is equal to the average costs, and therefore provide more accurate measures of an individual's health expenditures. The survey data, the 45 and Up Study, includes an extensive set of questions on individual characteristics, allowing us to condition on various demographic and socioeconomic factors that are often missing in past studies.

Another important strength of the survey data is its size. Our sample is more than ten times as large as the largest sample size used by previous studies (Finkelstein et al, 2009). This large sample makes it possible to estimate differences between narrowly defined BMI categories. We are also able to obtain precise estimates for specific types of care and to stratify the analysis by relatively narrow age groups. For instance, 16 percent of our sample is aged 75 and over (over 38,000 individuals), allowing us to accurately estimate the health care cost of obesity in older age.

Our empirical strategy centers on prospective models in which health spending is regressed on BMI-based weight categories measured in a previous year. The model is similar to ones used for the purpose of risk-adjusting payments to insurers or providers (see, for example, Van de Ven and Ellis 2000; Pope et al, 2004). Because a prospective model is more useful for predicting future expenditures than a concurrent model it is more informative for health sector budgeting. In the context of our analysis, an important advantage of a prospective model is that it mitigates potential bias arising from reverse causality running from acute health shocks to weight.[2]

The association between obesity and chronic conditions such as diabetes and hypertension is an important explanation for a positive relationship between obesity and health expenditures. Additionally, obese individuals may have more difficult recoveries from acute health shocks, even if those shocks were not directly related to obesity. For example, after breaking a bone due to an accident, obese individuals may recover more slowly, require more physical therapy and experience more complications than non-obese patients. Numerous medical studies have found that obesity is negatively related to the recovery and rehabilitation process (e.g., Vincent and Vincent, 2008; Naylor et al., 2008; Gendall et al., 2007). Because we are able to link a survey respondent's BMI to multiple years of claims data we can test for this type of interaction effect. To our knowledge, no prior study on the relationship between obesity and health expenditures has attempted to distinguish between acute and chronic conditions in this way.

Consistent with studies based on US data, we find a strong relationship between BMI and health expenditures in Australia. Holding constant observed demographic and socioeconomic characteristics, annual total health expenditures are 19 percent higher for an obese individual with BMI between 30 and 35 (obese type I) and 51 percent higher for individuals with BMI above 35 (obese type II/III) compared to the average expenditures of someone of normal weight. We find statistically significant and economically meaningful differences in expenditures on all types of care: inpatient care, emergency department visits, outpatient medical care and

[2] Bias from reverse causality can be positive or negative. On one hand, the onset of severe illness may lead to significant weight loss either directly or as a side effect of treatment—e.g., cancer and chemotherapy. Alternatively for other conditions, such as depression, the effect may go in the opposite direction (Cawley and Meyerhoefer 2012).

prescription drugs. The additional expenditures associated with type II/III obesity is greater for men more than women, especially above the age of 75.

In general, our preferred prospective model produces larger estimated effects than the corresponding concurrent model—in some cases over 50 percent larger. We find that individuals who are hospitalized in one year tend to have higher than average expenditures in the following year. The magnitude of this effect is similar for normal weight, overweight and obese type I individuals, but is significantly larger for individuals in the obese II/III category. This suggests that while much of the elevated spending for obese individuals can be linked to chronic medical conditions, severe obesity also amplifies the effect of acute shocks on health spending.

2. Data and Descriptive Analysis

The 45 and Up Study was fielded between 2006 and 2010 in New South Wales (NSW), Australia's most populous state.[3] The sample accounts for 10 percent of the state's population age 45 and older, with key demographic characteristics that are comparable to the overall 45+ population (Johar et al, 2012). Although the 45 and Up Study is a cross-sectional survey with only one observation per respondent, the survey data can be linked at the individual-level to medical claims data for the years 2006 to 2009. This means that we can link an individual's survey variables to his/her medical care utilizations in the year of the survey as well as adjacent years. We utilize this feature of the data to obtain information about previous health shocks and future medical spending. Because in our preferred prospective model we regress spending in one year on weight and other individual characteristics measured in the previous year, we are not able to use respondents who completed the survey in 2009 and 2010. However, because most 45

[3] For details on the survey methodology, see http://www.45andup.org.au/aboutthestudy.aspx and 45 and Up Study Collaborators (2008). New South Wales has over 7 million residents.

and Up respondents were surveyed in 2008, this causes us to lose only 4,279 respondents (1.6 percent). We further exclude 28,507 respondents (10.7 percent) with incomplete survey information. The final sample consists of 241,635 respondents.

The survey provides self-reported data on height and weight, which we use to calculate each respondent's BMI (kg/m^2), A common concern with self-reported data is that heavier individuals are more likely to underreport their weight leading to attenuation bias in the estimated relationship between BMI and health spending (Sherry et al, 2007). Courtemanche, Pinkston and Stewart (2014) propose a correction method that can be implemented using data that includes both self-reports and direct measures of height and weight.[4] We apply this correction using data from the 2007/08 Australian National Health Survey, which includes both measured and self-reported height and weight. See the Appendix for details on the adjustment procedure and a summary of how it affects individual BMI. Effectively, the adjustment shifts the BMI distribution to the right (Appendix Figure A3), producing an overall obesity rate of 28.6 percent, 6.6 percentage points higher than the obesity rate implied by self-report data. All the analyses that we report are based on the corrected BMI series.

The survey provides a number of individual characteristics, which enter our analysis as control variables. Table 1 presents the full sample selected summary statistics for these variables, tabulated by the standard BMI categories as defined by the National Heart, Lung and Blood Institute: underweight (BMI<18.5), normal weight (18.5≤BMI<25), overweight (25≤ BMI< 30), obese type I (30≤BMI<35) and obese type II/III (BMI ≥ 35).[5] The modal category is overweight, which accounts for 41.4 percent of the full sample. Roughly the same fraction of the sample falls

[4] We also ran the analyses using an alternative correction method proposed by Cawley (2004). The two correction methods produce similar results.

[5] The 45 and Up Survey does not supply survey weights; it is a random survey, not stratified by socioeconomic status or location. As shown in Johar et al (2012) the means for key demographics are comparable to the general population in this age group.

into the normal weight category (29.3 percent) as in the two obese categories combined (28.6 percent). Less than one percent of the sample is underweight.

[Insert Table 1]

Differences among people in the different BMI categories points to the importance of controlling for individual characteristics. Similar to what has been found for the U.S. (Wang and Beydoun 2007; McLaren 2007; Baum and Ruhm 2009), the summary statistics in Table 1 indicate that compared to normal weight individuals, obese adults have less education and lower incomes. Underweight individuals have less education and lower incomes than the other groups. Immigrants, who tend to use fewer health care services, are under-represented in the higher BMI categories.

Although the universal public Medicare program provides comprehensive coverage for all types of health care, more than half of all adults in Australia also hold private health insurance (Australian Bureau of Statistics 2013). The primary benefit of private insurance is the ability to obtain more timely access to elective services through private hospitals. Previous research has documented "advantageous selection" in Australia's market for private health insurance whereby individuals with private insurance tend to be in better health than those without such coverage (Johar and Savage 2012; Buchmueller et al. 2013). The figures in Table 1 are consistent with this pattern: obese adults are less likely to have private insurance than those in the normal and overweight categories. Thus it is important to control for insurance status.[6]

In any analysis of health expenditures it is essential to control for the effect of age. Data from the US indicate that obesity rates increase up through middle age—between the ages of 40 and 59—and then decrease at higher ages (Hedley et al 2004; Ogden et al 2006). In our sample,

[6] We also control for whether an individual is eligible for a "health card", a means-tested program that provides additional coverage for out-of-pocket medical expenses.

the percentage of men with BMI above 30 increases up to around age 61 and falls thereafter. For women the percent classified as obese is highest around age 76. Overall, the mean age for the normal, overweight and both obese categories are similar.

The survey includes detailed information on self-reported health conditions, which are reported in Table 2. Because we are interested in the "total" cost of obesity, we do not include these conditions as covariates in our main regression analyses. However, they will use them in supplementary analyses as they are informative regarding the mechanisms by which obesity affects health expenditures. A cross-tabulation of health conditions and BMI categories shows that, compared to individuals in the normal weight category, obese individuals report worse health on several dimensions. They are substantially more likely to be diagnosed with heart disease, stroke, diabetes and high blood pressure. They are also more likely to have recently experienced a fall. In contrast, differences in the prevalence of cancer, asthma/hay fever and broken bones are smaller and statistically insignificant. Underweight individuals are more likely than any other group to report a diagnosis of heart disease or stroke and to describe their health as fair or poor. This suggests that simple comparisons that combine underweight and normal weight individuals in a single "non-obese" category will tend to understate the effect of obesity on health expenditures, though because the prevalence of underweight is very low, this bias would be small.

[Insert Table 2]

There are three sources of claims data: (1) hospital registers from NSW Health, which provide information on admission and emergency department (ED) presentations in all public and private hospitals in the state; (2) the Medical Benefits Schedule (MBS) from Medicare (the Department of Human Services), which contains individual expenditures on outpatient medical services such as physician consultations, imaging and diagnostic tests; and (3) the Pharmaceutical Benefits Scheme (PBS) by Medicare, which contains individual data on prescription drugs provided under Medicare.[7] Annual total health expenditure is given by the sum of expenditures on all four components, normalized to 2009 $AUD.[8] To cost services in hospitals, we apply the NSW Department of Health's hospitalization and ED costing rules.[9] For hospitalizations, cost varies by diagnosis group, type of hospital, type of admission (overnight, same day, transfer, in mental health unit, non- or sub-acute care units such as rehabilitation), length of stay, ICU hours and the use of ventilation machine. Similarly, for ED visits, cost varies by hospital type, triage category (more urgent categories are more expensive) and whether the visit led to an admission.

Table 3 reports summary statistics for each type of expenditure tabulated by BMI category. Consistent with the differences in the prevalence of health conditions, obese individuals have significantly higher total health expenditures than individuals in the normal weight category. Above the underweight category, there is a monotonically positive relationship between BMI and total expenditures. Total expenditures for obese type I and obese type II/III adults are AU$1,023 higher (23 percent) and AU$1,989 higher (45 percent) than the mean expenditure for normal weight category. For the various components of health expenditures, we see significant differences in the utilization of inpatient care, outpatient care and prescription drugs. People in the overweight and obese type I categories are more likely to present at an ED but they have slightly lower emergency department spending than normal weight individuals.

[7] The linkage to the hospital data was performed by the Centre for Health Record Linkage (http://www.cherel.org.au/), a government initiative which maintains record linkage infrastructure for the health and human services sectors. The linkage to the MBS and PBS data was performed by Medicare. The linked data are provided under ethics approval from the NSW Population and Health Services Research Ethics Committee and the Department of Human Services Departmental Ethics Committee.
[8] On January 31, 2009, the Australian dollar was worth 0.94 US dollars.
[9] Details of the hospital cost algorithm and its validity can be found in the Appendix of Ellis et al. (2013).

Higher spending on inpatient care is the reason that individuals in the underweight category have higher than average spending. This may reflect dramatic weight loss due to serious illness.

[Insert Table 3]

Figure 1 presents the results of non-parametric regressions showing the relationship between BMI and health expenditures. The results correspond to a prospective model in which expenditures in one year are regressed on BMI measured in the prior year. We report separate models by gender and for three age groups: 45 to 59, 60 to 74 and 75 and older. As expected, the graphs show that age has a strong independent effect on expenditures; expenditures for the oldest age group are much higher than those of the 45 to 59 year old group, regardless of BMI. Within each age group, the graph is U-shaped, declining as weight increases from underweight to normal weight and increasing thereafter. Beyond the minimum point the relationship between BMI and expenditures is approximately linear. The gradient is less steep for the oldest age category, particularly for women.

[Insert Figure 1]

3. Econometric Methods

3.1. Primary Specification

To adjust for the effect of observable individual characteristics, we estimate regression models of the form:

$$(1) \qquad y_{it+1} = \alpha + \sum_1^4 \beta_k \, BMI_{ikt} + \gamma_2 X_{it} + \varepsilon_{it+1},$$

where y_{it+1} is total or specific health expenditure, BMI_{ikt} represents a set of indicator variables for four BMI categories based on weight in the prior year: underweight, overweight, obese type I, and obese type II/III. Note that these variables are based not on self-reported height and weight, but measures that have been adjusted according to the method described in the Appendix. The coefficients β_k represent the difference in adjusted mean expenditures for individuals in category *k* and normal weight individuals, which is the omitted category. The nonparametric regressions in Figure 1 suggest expenditures decrease with BMI initially and then increase monotonically above a certain level of BMI. Therefore, as an alternative specification we also estimate models that specify a quadratic relationship between expenditures and BMI.

The vector X_{it} includes demographic characteristics (age, marital status, country of birth, arrival years, skin color, language spoken at home, education, smoking status and eligibility for means-tested health care subsidies), socio-economic status (income, labor force participation and private health insurance) and dummy variables for geographic region (3 categories).[10]

Among the unobserved factors represented by the error term, individual preferences or personality traits are potentially important confounders. A number of studies have found that obesity varies significantly with risk aversion or time preference, and non-cognitive skills, such as willpower, future orientation, and self-efficacy (see, for example, Anderson and Mellor 2008; Zhang and Rashad 2008; Chiteji 2010; Ikeda, Kang and Ohtake 2010; Courtemanche, Heutel and McAlvanah 2011). Dodd (2014) finds a positive link between BMI and individual's intertemporal discount factor in monetary domain. These individual traits are also correlated with other health behaviors, such as smoking, drinking, and the demand for preventive medical services (Picone, Sloan and Taylor 2004; Khwaja, Silverman and Sloan 2007; Ida and Goto

[10] Controlling for geographic location helps to control for correlation between access and socio-economic status. Unfortunately, we do not have a variable that may capture the strength of a person's relationship with health practitioner that is not independent of actual utilization.

2009). Unobserved variables relating to an individual's social networks and living environment are additional confounding factors (Christakis and Fowler 2007; Cohen-Cole and Fletcher 2008). Because our obesity measures may pick up the effect of these other factors, the β coefficients cannot be interpreted as causal effects. Of course, this limitation is not unique to our analysis, but rather is a general issue pertaining to studies in this literature. [11]

Because the empirical distribution of health expenditures often has a significant mass at zero, researchers analyzing expenditure data commonly use two-part models that separately estimate the probability of use and conditional mean expenditures (see for example Jones, 2011; Mullahy, 2009; Manning and Mullahy, 2001). The results we report are from a two-part model that estimates the probability of having positive expenditures as a probit and uses OLS to estimate the conditional expenditure equation. We also estimated an alternative specification that is commonly used to estimate health expenditures: a Gamma Generalized Linear Model (GLM) with log link. The results from the GLM model are not reported, but are available upon request. The two models produce similar results, though the Gamma GLM model produces larger marginal effects of obesity. This is consistent with the finding of other studies that GLM tends to over-predict high expenditures (Griswold et al 2004; Ellis et al 2013).

We view the results from the OLS two-part model as conservative. In terms of prediction errors (Mean Squared Error), the OLS two-part model has slightly smaller in-sample and out-of-sample prediction errors, though the differences are small. In addition, we conducted Hosmer-Lemeshow test of goodness of fit which regresses the prediction errors on the deciles of the predicted expenditure for the full sample and sub-samples; a model that is a good fit if the

[11] One recent study by Cawley and Meyerhoefer (2012) attempts to address this endogeneity problem by using the weight of a person's biological children as an instrument. The maintained assumption is that the weight of a person's child captures genetic determinants of obesity and not shared environmental or lifestyle factors. In contrast, Gronniger (2005) makes the opposite assumption. He treats the obesity of family members as a proxy for omitted variables that are a potential source of bias in a model like equation (1).

differences between the observed and fitted values are small and if there is no systematic contribution of the differences to the error structure of the model. We find that for our 45+ population, the null hypothesis of good fit cannot be rejected for all expenditure types (p-values ranging from 0.213 to 0.815), and for the sub-samples by age and sex, there are only 3 cases where the null is rejected at the 5 percent significant level.

3.2. Obesity and the Cost of Health Shocks

Although we would expect the relationship between BMI and expenditures to be strongest for chronic conditions, obesity may also be associated with higher expenditures after an acute health shocks if obese individuals recover less quickly. We are aware of no prior studies on obesity that have been able to draw a distinction between expenditures related to chronic conditions and those resulting from an acute shock. With multiple years of detailed hospitalization data, we are able to trace out how a health shock experienced in one year affects health spending in subsequent years. Specifically, with expenditure in year *t*+1 as the outcome, we create an indicator variable (*Shock*) that takes a value of one for individuals who were hospitalized in year *t* and zero for others. We then add this variable to our regression model, interacting it with the categorical obesity variables:

$$(2) \qquad y_{it+1} = \alpha_0 + \sum_1^4 \alpha_{1k} BMI_{it} + \alpha_2 X_{it} + \alpha_3 Shock_{it} + \sum_1^4 \alpha_{4k} (Shock \times BMI)_{it} + \varepsilon_{it+1}$$

If high BMI exacerbates the impact of an adverse health shock, the coefficient on the interactions between the health shock variable and the obesity indicators will be positive and significant.

4. Regression Results

4.1. Total Expenditures

Table 4 reports results for equation (1) where total annual health expenditures is the dependent variable.[12] Panel A reports results from the model in which BMI enters categorically; panel B reports the specification where BMI enters quadratically. For each model, we report marginal effects, which combine the impact of each explanatory variable on the extensive and intensive margins.[13] Because only few individuals have zero total expenditures, however, for this outcome the marginal effects are effectively driven by the differences in conditional expenditures, (i.e., the intensity of use). The results in the odd-numbered columns are from our preferred prospective model. For the purpose of comparison, results from concurrent models, where BMI and health expenditures are measured in the same year, are reported in the even-numbered columns. Because men and women tend to have different patterns of health care utilization, in addition to the pooled sample we estimate separate models by gender. As it turns out, however, the relationship between BMI and health expenditures is broadly similar for men and women.

[Insert Table 4]

The marginal effects for the underweight indicator are all large, positive and statistically significant, though the magnitudes are smaller than raw differences reported in Table 3. For the

[12] The full results of all models are available from the authors upon request.

[13] The contribution of each part of the two-part model is derived from: $E(y|x_d = 1) - E(y|x_d = 0) =$

$$\{Pr(y > 0|x_d = 1) - Pr(y > 0|x_d = 0)\} \times E(y|y > 0, x_d = 1) + Pr(y > 0|x_d = 0) \times \{E(y|y > 0, x_d = 1) - E(y|y > 0, x_d = 0)\}$$

where y is expenditure and x_d is the BMI category. All other covariates are evaluated at their respectively value. The first term gives the marginal impact of the BMI category on the probability of positive expenditure (use) and the second term gives the marginal impact of BMI category on the level of expenditure (intensity).

pooled sample, the prospective model in Panel A implies a difference of just under AU$1,436, or 55 percent of the unadjusted difference of AU$2,588 ($AUD6795- $AUD4387, see Table 3). The main reason for the difference between the unadjusted and adjusted estimates is that the underweight category includes a disproportionate number of very old individuals.

Above the underweight category, the prospective model indicates a strong positive relationship between BMI and health expenditures. In the pooled (male and female) sample, overweight adults have expenditures that are AU$189, or 4 percent greater than the mean for the normal weight category. This estimate is smaller than the unadjusted difference reported in Table 3 ($443). Interestingly, the regression-adjusted differences for the two obese categories are very close to the corresponding raw differences, despite the extensive control variables. The prospective model estimated on the pooled sample implies that obese type I individuals spend over AU$800 per year more than otherwise similar normal weight adults. For the obese type II/III category, the regression-adjusted difference is AU$2,233, or 51 percent of the mean total expenditures for the omitted category.

For the quadratic specification, we report the marginal effect of an additional BMI unit at different points in the BMI distribution. Consistent with the nonparametric regressions in Figure 1, these models indicate a U-shaped relationship between BMI and spending, with spending minimized in the normal weight range for women and the overweight range for men. At a BMI of 30—the cutoff between the overweight and obese type I categories—the prospective model implies that an additional unit of BMI is associated with an additional AU$121 of health spending for men and an additional AU$114 for women.[14] The estimated gradients are larger at a BMI of 35, which is the cutoff between obese type I and obese type II.

For both men and women, the concurrent model produces a smaller BMI coefficient and a smaller gap between the obese and normal categories, though the difference is larger for men. According to the concurrent model (Panel A, column 4), men in the obese type I category spend $453 more per year than those in the normal weight category. The prospective model implies a differential that is more than twice as large ($804). Similarly, the concurrent model implies that the obese type II/III category is associated with an additional AU$1,574 in expenditures per year while the prospective model implies a difference of AU$2,299.

Although several factors complicate comparisons with results from prior studies, our results are roughly similar to, though slightly smaller than the most widely cited US studies. These studies tend to use a single obese category, comprising all individuals with BMI >30. In their regression analysis of data from 2006, Finkelstein et al (2009) find an overall 42 percent difference between obese and normal weight individuals. The difference is larger among those with private health insurance (58 percent) and smaller among the Medicare population (36 percent). Cawley and Meyerhoefer's (2012) non-IV model generates a slightly smaller estimate (US$656 or about 37% of the non-obese mean expenditure), while the estimate from their IV model is substantially larger than (US$2,741 or about 160 percent). When we combine our two obese categories into one for the sake of comparability (results not shown in the table), the prospective model generates an estimated difference between obese and normal weight individuals of AU$1,205, or 28 percent relative to the normal weight mean. The concurrent model implies a difference of AU$921, or 21 percent.

[14] We also estimated a third specification in which BMI enters linearly along with an indicator variable for the low weight category. Prospective models using this specification imply that an additional BMI unit is associated with an additional AU$129 of spending for men and an additional AU$118 for women.

Table 5 reports separate estimates for three age categories: 45-59, 60-74 and 75 and older. For brevity, we report results from the prospective model only. For each age group, we see a significant positive relationship between BMI and total expenditures. However, the estimates for the oldest age group may be biased downwards if obese individuals are more likely to die before the age of 75 and are more likely to have high health expenditures during the end of their lives. For this oldest group, the marginal cost of obesity is much higher for men than it is for women, driving up the men's all-age results in Table 4. On the other hand, for the 60 to 74 year olds, obese women are more costly. The quadratic model implies that at a BMI of 30 an additional unit of BMI is associated with AU$149 in additional spending for men and AU$175 for women. In this age category the regression-adjusted difference between obese type II/III and normal weight men is roughly AU$2,700, and AU$2,900 for women.

[Insert Table 5]

4.2. Expenditures by Category

To provide greater insight regarding the positive relationship between BMI and health expenditures, we estimated separate regressions for each of four categories of health spending: inpatient care, emergency department, outpatient medical and prescription drugs. Results from these regressions are reported in Table 6. Again, for brevity, we report only the results from our preferred prospective models, separately for males and females.

[Insert Table 6]

The results indicate a statistically significant and economically meaningful relationship between obesity and expenditures for all types of care. Inpatient care is the category with the highest mean, accounting for roughly half of total expenditures. Relative to normal weight adults, inpatient expenditures are AU$372 higher for obese type I individuals and over AU$1,300 higher for the obese type II/III category. When we combine our two obese categories into a single category, we estimate a difference of AU$663 for men and AU$717 for women (results not shown). Relative to the mean for normal men and women, these estimates represent differences of roughly 25 and 40 percent, respectively. As a point of comparison, in their full sample, Finkelstein et al (2009) find an obese/normal difference of 46 percent for inpatient expenditures. However, their estimates vary substantially across payer categories. Among Medicare enrollees the difference is a statistically insignificant 4 percent, whereas for privately insured patients they find a difference of 90 percent.

In squared brackets, we report the proportion of the overall marginal effects related to the impact of excessive weight on the probability of health care utilization—i.e., the extensive margin. For inpatient expenditures we see that roughly three quarters of the difference between the obese type I and normal weight categories and roughly half of the difference between obese type II/III and normal weight individuals comes from the fact that obese individuals have a higher probability of admission. Similarly, for prescription drugs, differences between obese and normal weight individuals come from both a higher probability of having any spending and higher levels of conditional spending. In contrast, since nearly everyone in the sample has some spending for outpatient medical care, for this category higher spending levels for obese individuals are related almost entirely to differences on the intensive margin.

The results in Table 4 indicate that overweight adults have significantly higher health expenditures than individuals in the normal weight category. When we estimate separate regressions by spending category we see that this result is driven by higher spending on outpatient medical care and prescription drugs. There are no significant differences between these two weight categories in terms of inpatient or emergency department care. In contrast, the higher total expenditures for underweight adults are driven largely by higher inpatient spending, with most of this effect coming from the intensive margin.

As noted, because we are interested in capturing the total effect of obesity on health expenditures, we purposefully did not condition on any measures of health status or health conditions. The hypothesis here is that the main way that obesity is related to higher health expenditures is that obese individuals are more likely to have chronic conditions, such as diabetes, hypertension or heart disease. Therefore, a model including health conditions as explanatory variables would greatly understate the effect of obesity on health expenditures. That said, a comparison of our main specification with a model that controls for observable health conditions would be informative on the importance of chronic conditions in explaining the BMI-expenditure gradient. Results from such a model are reported in Table 7.

[Insert Table 7]

As expected, the estimated relationship between BMI and expenditures is substantially attenuated when we condition on health status. The regression-adjusted difference between the overweight and normal weight categories, which was statistically significant in our main model, disappears in the augmented specification. The higher expenditures associated with obesity declines from AU$800 to AU$900 per year to essentially zero. Individuals in the obese type II/III category are still estimated to have significantly higher expenditures than otherwise similar normal weight adults, but the difference is much smaller when we control for health conditions (AU$372) than when we do not (AU$2,233).

4.3. Obesity and the Cost of Health Shocks

The results in Table 7 suggest that a greater prevalence of chronic conditions explain much, but not all of the higher expenditures associated with obesity. Although the remaining difference may be attributable to differences in severity or other unmeasured conditions, another possibility is that acute health shocks, which are less likely to be captured by the self-reported information on medical conditions, are more costly for obese individuals. As described above, we test for this possibility using a model that includes a binary measure for whether the person was recently hospitalized and this variable interacted with the weight category indicators.[15] The coefficient on the interaction term tells us whether health shocks that result in hospitalization increase subsequent health expenditures more for obese than normal weight individuals.

Table 8 reports selected marginal effects from the interaction model (Equation 2). The first four rows report the "main effect" of being overweight or obese—i.e., the difference in expenditures associated with weight among individuals who did not have a prior health shock. The next four rows report the effect of prior shocks by weight category. For normal weight individuals, a hospitalization in one year is associated with an additional AU$2,819 in health expenditures the following year. Note that because of the prospective framework, this higher spending is not for the inpatient admission we are using to define the shock. An acute health shock has a slightly smaller effect on subsequent spending for overweight individuals. In the full sample, expenditures increase by AU$2,761 for this group. The difference between normal weight and overweight men is even larger (AU$3.233 vs. AU$2903), whereas for women the effect of a shock on future spending is essentially identical.

[15] Overall, 22.5 percent of the sample is considered to have had a health shock according to this definition. There is a positive relationship between BMI and the probability of having a shock. Whereas, 20% of normal weight individuals had a prior health shock, 24% of obese type I and 26% of obese type II/III individuals did.

In the pooled sample, acute health shocks experienced by individuals in the obese type I category raise subsequent expenditures by AU$3,155, or 12 percent more than the effect of a shock for adults in the normal weight category. In percentage terms, the difference between obese I and normal weight individuals is smaller for men (3 percent) than for women (13 percent). The cost of a shock is substantially larger for individuals in the obese type II/II category. In the pooled sample, being hospitalized in year t leads to AU$4,092 higher spending in year t+1.. For men in the highest BMI category, an acute health shock in t raises spending by AU$4,223 in year t+1. For women in the obese type II/III category spending increases by AU$3,991, which is more than 50 percent larger than the effect of a prior hospitalization for normal weight women.

[Insert Table 8]

5. Discussion

Although rising rates of obesity are a health concern worldwide, empirical evidence on the relationship between obesity and health expenditures is limited to a small number of studies based on data from the U.S. We extend the literature by examining this relationship for adults in Australia, where the proportion of the population who are considered as obese has risen dramatically in recent years. The Australian experience provides insight on the fiscal impact of obesity in a universal, public health care system.

Our analysis is based on a unique data set that combines information from a large, random-sample survey with several administrative health databases. The administrative data provides accurate information on an individual's expenditures for inpatient and emergency hospital care, outpatient medical services and prescription drugs. With a final sample size of over

240,000 adults, we are able to precisely estimate differences between finely defined BMI categories, something that most prior studies are not able to do. In addition to estimating the relationship between BMI and total health expenditures, we estimate separate models by type of expenditure. In this more detailed analysis we examine the extent to which differences in spending between obese and normal weight individuals is explained by differences in the probability of having positive expenditures and differences in expenditures conditional on use.

Similar to studies using US data, we find that obesity is associated with substantially higher expenditures for all types of health care. Among individuals who are not classified as underweight, expenditures increase monotonically with BMI. Annual spending for adults who meet the standard definition of obesity—BMI of 30 or greater—is roughly 30 percent higher than spending for otherwise similar individuals whose BMI falls in the normal range. However, this simple comparison obscures significant differences within the obese groups. Nearly 30 percent of obese individuals (8 percent of the population) have a BMI above 35 which is classified as a more severe class of obesity, obese type II/III. We find that these very obese individuals have an average annual health spending that is roughly 50 percent greater than that of normal weight individuals (AU$2,233 higher). The remaining 70 percent of obese individuals with a BMI between 30 and 35 or obese type I have annual health spending that is nearly AU$850, or 19 percent, higher than people of normal weight.

For both obesity categories, we find significantly elevated spending for inpatient hospital care, emergency department visits, outpatient medical care and prescription drugs. For inpatient and emergency department care and prescription drugs, the difference in expenditures comes from both a higher probability of having any expenditure and greater conditional expenditures. The obese type I individuals, the spending gap with normal weight individuals is explained entirely by the fact that they are more likely to have costly medical conditions, including diabetes and hypertension. For obese type II/III individuals, chronic conditions are also an important part of the explanation for their high level of expenditures compared to the normal weight individuals , but this is not the entire story. Results from a model that accounts for whether or not a person was hospitalized in the prior year suggest that obese type II/III individuals have significantly more costly recoveries from acute health shocks. This interaction between extreme obesity and acute health shocks is a promising area for future research.

An important limitation of our analysis as well as previous studies in this literature relates to omitted variables. A comparison of unadjusted and regression-adjusted results suggests that much of the difference in spending between overweight and normal weight individuals is explained by other differences between these two groups. In contrast, the estimated spending gap between obese and normal weight individuals is quite insensitive to adjustment for covariates. Still, our results may be affected by other important factors that remain unmeasured and therefore cannot be interpreted as causal effects.

It is important to note, however, that there is some debate about whether it is even meaningful to talk about a single causal effect of obesity (DiNardo 2007). From a policy perspective, it may be more relevant to consider the effects of specific strategies for reducing obesity. Not only will some approaches be more effective than others in reducing BMI, but different strategies may have different consequences for health expenditures. And, as with many health interventions, the issues of timing are important. A full analysis of alternative strategies should consider how quickly an initiative can affect obesity as well as its effects on lifetime health costs. To the extent that obesity leads to premature mortality, savings from a policy that successfully reduces obesity at younger ages may be partially offset by higher lifetime expenditures caused by increased longevity. With these caveats noted, the magnitude of our point-in-time estimates suggests that interventions that are successful in reducing obesity rates may also have the effect of reducing health expenditures.

Even if the empirical relationship between obesity and health expenditures is clear, the policy implications of this relationship are subtle and complex. Economic arguments for government intervention depend importantly on the extent to which these higher costs represent social rather than private costs (Philipson and Posner 2008; Bhattarya and Sood 2011; Cawley 2014).[16] In the context of a private insurance system with risk-rated premiums, the higher health spending related to obesity may largely represent a private cost that is borne directly by obese individuals themselves (Bhattacharya and Bundorf 2009). Recently in employer-sponsored health plans in the US, there has been an increase in the use of wellness programs with financial incentives targeted at obesity and other conditions with strong behavioral determinants. The Affordable Care Act allows for an expansion of such incentives (Madison, Volpp and Halpern 2011; Horwitz, Kelly and DiNardo 2013; Cawley 2014). This approach can be seen as moving even further in the direction of a system whereby the health care costs associated with obesity are fully internalized.[17]

In a publicly financed system, such as that of Australia or most European countries, increases in health care costs related to obesity will be spread more broadly. Whether or not this pooling affects individual behavior, increases in these costs will put strain on public budgets, potentially crowding out other policy priorities or generating deadweight loss as taxes are increased to fund the higher health spending. Thus, although our results suggest that obesity may

[16] Several studies have focused on reducing childhood obesity including Cawley (2008), Moodie et al. (2008) and Breitfelder et al. (2011).
[17] However, because of significant exemptions, it is not clear that the new regulations will have much "bite". See Cawley (2014) for a thoughtful discussion.

increase health spending less in percentage terms in Australia than in the US, because the vast majority of health spending in Australia is publicly financed, the obesity epidemic might be viewed as a more pressing public policy issue in Australia and other countries with similar health systems.

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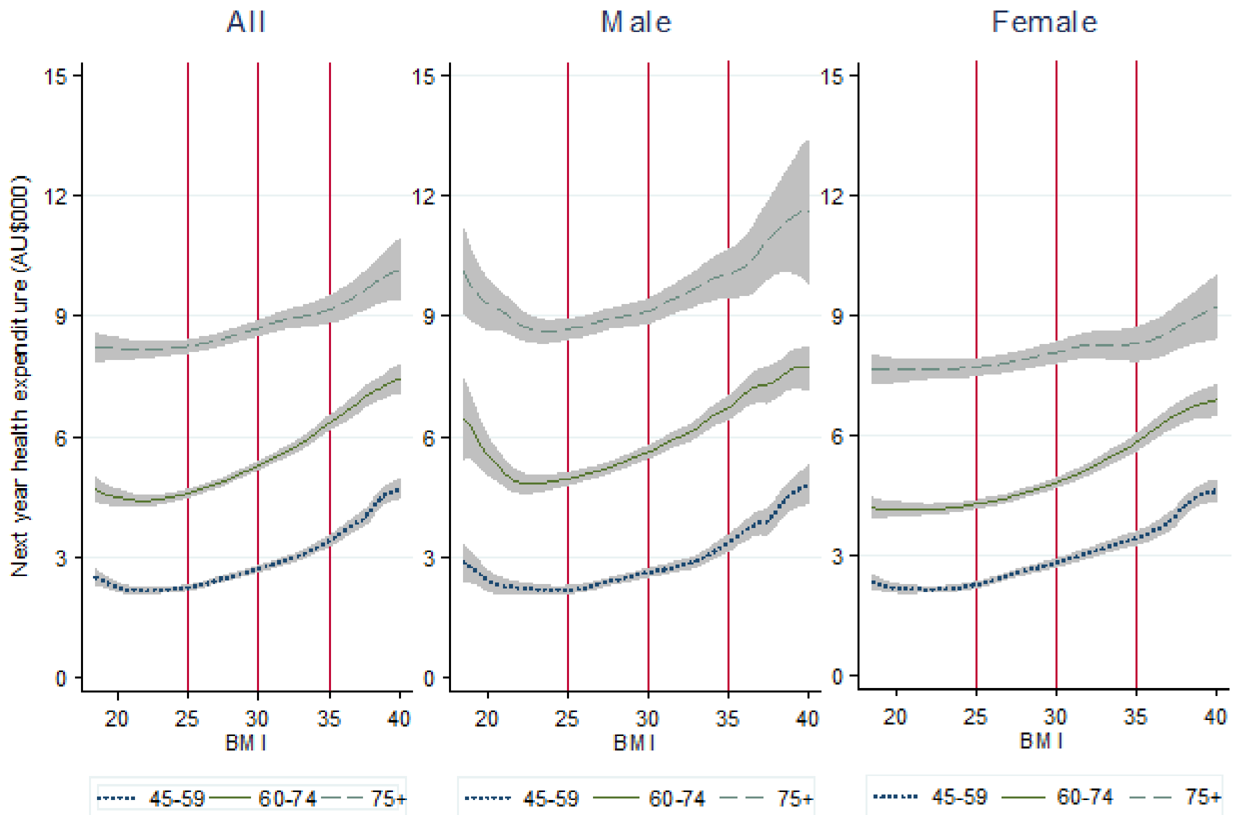
Figure 1: Non-parametric plot between prospective health expenditure and BMI



Note: Plots are based on lowess regressions of health expenditures on BMI. To provide clearer graphs on the bulk of observations, observations in the top 0.1% health expenditure are excluded and the expenditure of those with BMI over 40 is grouped with BMI 40 (top-coded). BMI is corrected for self-reporting error (see Appendix). Shaded region indicates 95% Confidence Interval. On January 31, 2009, the Australian dollar was worth 0.9 US dollars.

Table 1. Selected summary Statistics by BMI Category

	All	Under-weight	Normal Weight	Over-weight	Obese type I	Obese type II/III
BMI Range		< 18.5	18.5-25	25-30	30-35	>35
N	243,894	1,685	71,345	101,021	49,249	20,594
(Sample %)		(0.7)	(29.30)	(41.40)	(20.2)	(8.04)
Demographics						
Age[a]	62.123	65.791	61.870	62.748	62.031	59.857
(s.d.)	(11.107)	(12.782)	(11.983)	(11.030)	(10.313)	(9.516)
Male	0.470	0.266	0.363	0.528	0.540	0.407
Foreign born	0.095	0.098	0.114	0.090	0.084	0.081
Foreign language	0.253	0.274	0.290	0.254	0.224	0.191
High school	0.128	0.157	0.110	0.122	0.146	0.175
Certificate	0.318	0.376	0.312	0.311	0.327	0.342
Trade diploma	0.320	0.274	0.301	0.328	0.331	0.319
University	0.235	0.193	0.276	0.239	0.197	0.164
Married	0.693	0.556	0.659	0.716	0.710	0.667
Never married	0.062	0.131	0.073	0.053	0.056	0.079
Widowed	0.084	0.134	0.096	0.079	0.077	0.077
Divorced	0.073	0.095	0.078	0.066	0.073	0.091
Separated	0.028	0.039	0.030	0.026	0.026	0.032
Partner	0.054	0.039	0.059	0.053	0.051	0.048
Missing marital status	0.006	0.007	0.005	0.006	0.007	0.005
Mean income[b]	$47,726	$36,088	$48,616	$48,611	$46,676	$43,707
(s.d.)	($28,895)	($27,326)	($28,990)	($28,799)	($28,769)	($28,845)
Health card	0.292	0.402	0.270	0.286	0.308	0.345
Private Health Insurance	0.639	0.542	0.642	0.657	0.632	0.563
Current smoker	0.072	0.182	0.089	0.063	0.064	0.072
Past smoker	0.355	0.255	0.297	0.362	0.407	0.404
Major city	0.452	0.461	0.488	0.452	0.423	0.396
Inner region	0.352	0.334	0.332	0.353	0.366	0.377
Outer region	0.177	0.183	0.165	0.176	0.187	0.196
Remote	0.020	0.022	0.015	0.019	0.023	0.031

Note: Obese type I has a BMI between 30 and 35 and Obese type II/III has a BMI of over 35. [a] in the regression, age enters as categorical variables in the age bands of 5 years up to 80 years old and the top band is 80 years and above. [b] income is reported in (irregular) bands. In estimation, we use the categorical variables in the regression, but for brevity, we report the continuous income here replacing the income bands with the mid-point of the bands. For the top income band, we assume a top of about one standard deviation from the lower bound. Also included as covariates are dummy variables for skin colour, ancestry, country of birth and survey year.

Table 2. Self-reported health conditions by BMI category

	All	Under-weight	Normal Weight	Over-weight	Obese type I	Obese type II/III
Specific Conditions (0,1)						
Skin cancer	0.286	0.291	0.278	0.302	0.284	0.245
Breast/prostate cancer	0.058	0.055	0.054	0.061	0.059	0.052
Other cancer	0.063	0.104	0.062	0.061	0.067	0.066
Heart disease	0.119	0.128	0.097	0.124	0.134	0.135
Stroke	0.031	0.055	0.028	0.031	0.033	0.036
Diabetes	0.089	0.049	0.044	0.074	0.131	0.217
Asthma/ hay fever	0.024	0.025	0.024	0.024	0.024	0.030
Depression	0.129	0.151	0.115	0.118	0.145	0.194
Broken bone	0.114	0.195	0.120	0.110	0.109	0.122
Other health measures						
Physical health index	3.224	4.779	2.557	2.850	3.845	5.752
Mental health index	3.804	4.915	3.644	3.509	4.046	5.139
Fall in the last 12 months	0.482	0.774	0.455	0.433	0.526	0.685
High blood pressure	0.356	0.234	0.237	0.347	0.463	0.563
Fair/poor health	0.135	0.245	0.105	0.108	0.165	0.286
Fair/poor quality of life	0.099	0.205	0.088	0.083	0.112	0.180
N	243,894	1,685	71,345	101,021	49,249	20,594

Notes: Obese type I has a BMI between 30 and 35 and Obese type II/III has a BMI of over 35. Mental health score is computed based on the Kessler-10 instrument. The score for each symptom ranges from zero to four, where zero indicates not experiencing the symptom at all, and five indicates experiencing the symptom all the time. The mental health score is the sum across the symptoms. The physical health score is based on the Medical Outcomes Score Physical Functioning which is a sub-score of the SF-36 instrument. A score of zero indicates no limitation, a score of one indicates a little limitation, and a score of two indicates a lot of limitation for the activity. The physical health score is the sum of this score across the 10 physical activities. The reported chronic conditions are based on ever diagnosed conditions asked in the survey, and the corresponding figures in the table are the sample proportions who reported ever diagnosed with a given condition. The self-assessed health and quality of life are asked in the survey in a five-point scale reflecting excellent, very good, good, fair and poor. The corresponding figures in the table are the sample proportions of those reporting fair or poor level.

Table 3. Mean Prospective Health Expenditures by BMI Category (AU$)

		All	Under-weight	Normal Weight	Over-weight	Obese type I	Obese type II/III
Total Expenditure	% >0	96%	97%*	97%	97%*	98%*	98%*
	Mean| >0	$4,964	$6,795*	$4,387	$4,830*	$5,410*	$6,376*
	(Std. dev.)	(11,084)	(18,839)	(10,415)	(10,977)	(11,434)	(13,285)
Hospital Inpatient	% >0	28%	31%*	25%	28%*	30%*	31%*
	Mean| >0	$8,449	$12,431*	$8,318	$8,224	$8,496	$9,902*
	(Std. dev.)	(16,636)	(29,147)	(15,830)	(16,315)	(16,448)	(19,022)
Emergency Department	% >0	14%	21%*	13%	14%*	16%*	18%*
	Mean| >0	$660	$785*	$676	$645*	$650*	$689*
	(Std. dev.)	(642)	($714)	(687)	(622)	(570)	(722)
Outpatient Medical	% >0	96%	95%*	96%	96%*	97%*	98%*
	Mean| >0	$1,346	$1,521*	$1,255	$1,327*	$1,424*	$1,508*
	(Std. dev.)	(1,757)	(1,661)	(1,739)	(1,732)	(1,761)	(1,908)
Prescription Drugs	% >0	67%	73%*	60%	68%*	74%*	78%*
	Mean| >0	$1,557	$1,557*	$1,391	$1,508*	$1,673*	$1,946
	(Std. dev.)	(3,000)	(2,276)	(2,970)	(2,982)	(2,878)	(3,409)

Notes: Obese type I has a BMI between 30 and 35 and Obese type II/III has a BMI of over 35. % >0 rows report the sample proportion with positive value of various types of health expenditure for the full sample (All) and by sub-samples of BMI categories. Mean| >0 rows report the full sample and sub-samples mean of various types of health expenditure conditional on positive values. (Std.dev.) rows report the respective standard deviation of the conditional mean of various types of health expenditures. * indicates statistically different from normal weight individuals at the 1 percent significance level.

Table 4. Regression Results: Total Health Expenditures (AU$000)

	(1) All Prospective	(2) All Concurrent	(3) Male Prospective	(4) Male Concurrent	(5) Female Prospective	(6) Female Concurrent
A: BMI categories						
Underweight	1.436***	1.426***	3.659*	1.924**	0.738*	1.339***
	(0.455)	(0.241)	(2.042)	(0.780)	(0.385)	(0.297)
Overweight	0.189***	0.049	0.201*	-0.068	0.203***	0.133**
	(0.061)	(0.043)	(0.104)	(0.076)	(0.069)	(0.051)
Obese type I	0.843***	0.685***	0.804***	0.453***	0.911***	0.903***
	(0.061)	(0.047)	(0.116)	(0.093)	(0.076)	(0.077)
Obese type II/III	2.233***	1.752***	2.299***	1.574***	2.196***	1.871***
	(0.110)	(0.095)	(0.173)	(0.133)	(0.119)	(0.096)
B: Quadratic BMI						
Marginal effect calculated at						
BMI = 18	-0.036**	-0.056**	-0.097**	-0.141***	-0.005	-0.012
	(0.017)	(0.013)	(0.038)	(0.024)	(0.019)	(0.014)
BMI = 25	0.052***	0.030***	0.028	-0.011	0.064***	0.052***
	(0.008)	(0.007)	(0.019)	(0.011)	(0.008)	(0.006)
BMI = 30	0.116***	0.093***	0.121***	0.085***	0.114***	0.098***
	(0.006)	(0.005)	(0.009)	(0.007)	(0.006)	(0.004)
BMI = 35	0.181***	0.156***	0.216***	0.183***	0.164***	0.145***
	(0.010)	(0.008)	(0.016)	(0.014)	(0.012)	(0.009)
N	234,981	243,894	113,534	114,692	128,101	129,202

Notes: Obese type I has a BMI between 30 and 35 and Obese type II/III has a BMI of over 35. Estimates in the tables are average partial effects calculated at individual covariates (i.e., not marginal effects at sample means). In Panel A, the estimates represent the difference in spending between each category and the omitted normal weight category. In Panel B, the estimates represent the change in spending associated with a unit change in BMI evaluated at each particular value of BMI. Bootstrapped standard errors with 50 replications are reported in parentheses; in each replication, the adjustment equation is also result of a bootstrapped NHS sample. All models include covariates as in Table 1 as well as dummy variables for skin colour, ancestry, country of birth and survey year.

* p<.10; ** p<.05; *** p<0.01

Table 5. Regression Results: Health Expenditures by Age group (AU$000)

	Male			Female		
	45-59	60-74	75+	45-59	60-74	75+
A: BMI Categories						
Underweight	2.132	3.232*	5.365	0.431	0.657	1.190
	(1.930)	(1.828)	(5.272)	(0.264)	(0.523)	(0.918)
Overweight	0.308***	0.288*	-0.042	0.233***	0.210*	0.208
	(0.081)	(0.151)	(0.243)	(0.062)	(0.121)	(0.207)
Obese type I	0.656***	1.068***	0.639*	0.758***	1.205***	0.750**
	(0.099)	(0.183)	(0.348)	(0.089)	(0.165)	(0.308)
Obese type II/III	1.737***	2.703***	3.088***	1.757***	2.938***	1.927***
	(0.146)	(0.272)	(0.665)	(0.125)	(0.218)	(0.604)
B: Quadratic BMI						
Calculated at:						
BMI = 18	-0.032	-0.007	-0.449***	0.022	-0.115**	-0.042
	(0.031)	(0.040)	(0.133)	(0.016)	(0.054)	(0.067)
BMI = 25	0.042***	0.082***	-0.091*	0.622***	0.054**	0.040
	(0.016)	(0.022)	(0.054)	(0.009)	(0.023)	(0.030)
BMI = 30	0.097***	0.149***	0.176***	0.092***	0.175***	0.106***
	(0.009)	(0.015)	(0.031)	(0.007)	(0.013)	(0.024)
BMI = 35	0.154***	0.216***	0.440***	0.121***	0.297***	0.173***
	(0.016)	(0.021)	(0.079)	(0.010)	(0.030)	(0.046)
N	45,156	43,772	20,590	63,240	44,140	18,083

Notes: Obese type I has a BMI between 30 and 35 and Obese type II/III has a BMI of over 35. Estimates in the table are average partial effects. In Panel A, the estimates represent the difference in spending between each category and the omitted normal weight category. In Panel B, the estimates represent the change in spending associated with a unit change in BMI evaluated at each particular value of BMI. Bootstrapped standard errors with 50 replications are reported in parentheses; in each replication, the adjustment equation is also result of a bootstrapped NHS sample. All models include covariates as in Table 1 as well as dummy variables for skin colour, ancestry, country of birth and survey year.

* p<.10; ** p<.05; *** p<0.01

Table 6. Regression Results: Health Expenditures by Category

	Hospital Inpatient (AU$000)	Emergency Department (AU$00)	Outpatient Medical (AU$00)	Prescription Drugs (AU$00)
A. MALE				
Underweight	3.049*	0.600**	1.801*	0.824
	(1.807)	(0.236)	(0.989)	(1.198)
	[26%]	[76%]	[1%]	[68%]
Overweight	0.064	-0.035	0.565***	1.261***
	(0.091)	(0.032)	(0.120)	(0.191)
	[135%]	[-2%]	[18%]	[66%]
Obese type I	0.372***	0.085**	1.617***	3.164***
	(0.098)	(0.041)	(0.150)	(0.242)
	[78%]	[122%]	[12%]	[59%]
Obese type II/III	1.319***	0.374***	3.709***	6.894***
	(0.162)	(0.051)	(0.246)	(0.296)
	[53%]	[84%]	[8%]	[50%]
B. FEMALE				
Underweight	0.490	0.310***	0.967**	0.487
	(0.302)	(0.112)	(0.423)	(0.502)
	[46%]	[77%]	[-10%]	[21%]
Overweight	0.061	0.030*	0.480***	1.208***
	(0.061)	(0.015)	(0.124)	(0.152)
	[150%]	[154%]	[9%]	[57%]
Obese type I	0.425***	0.150***	1.710***	3.353***
	(0.058)	(0.025)	(0.174)	(0.236)
	[76%]	[98%]	[5%]	[49%]
Obese type II/III	1.269***	0.411***	3.378***	6.443***
	(0.100)	(0.044)	(0.199)	(0.379)
	[60%]	[85%]	[5%]	[44%]

Note: Obese type I has a BMI between 30 and 35 and Obese type II/III has a BMI of over 35. Estimates in the tables are average partial effects, representing the difference in spending between each category and the omitted normal weight category. Bootstrapped standard errors with 50 replications are reported in parentheses; in each replication, the adjustment equation is also result of a bootstrapped NHS sample. In squared brackets we report the approximate proportion of the marginal effect that can be attributed to the probability of use (extensive margin). Additional covariates are the same as in Tables 4 and 5.

* $p<.10$; ** $p<.05$; *** $p<0.01$

Table 7. Regression Results: Total Health Expenditures (AU$000), Controlling for Health Conditions

	All	Male	Female
Underweight	0.837**	2.672	0.271
	(0.419)	(1.991)	(0.336)
Overweight	-0.064	0.003	-0.078
	(0.062)	(0.108)	(0.066)
Obese type I	-0.002	0.002	0.047
	(0.063)	(0.119)	(0.078)
Obese type II/III	0.372***	0.406**	0.386***
	(0.115)	(0.198)	(0.118)
N	234,981	113,534	128,101

Note: Obese type I has a BMI between 30 and 35 and Obese type II/III has a BMI of over 35. Dependent variable is total annual prospective health expenditures, measured in AU$000. Estimates in the tables are average partial effects. Bootstrapped standard errors with 50 replications are reported in parentheses; in each replication, the adjustment equation is also result of a bootstrapped NHS sample. The regression model includes all the independent variables as the regressions reported in Table 4 plus a set of controls for health conditions. The health status variables include indices for mental health and functional limitations (activities of daily living) plus an indicator variable for whether the individual experience fall in the last twelve months and a series of indicator variables for the following conditions: skin cancer, breast/prostate cancer, other cancer, heart disease, stroke, diabetes, asthma/hay fever, depression, broken bones and high blood pressure.

* p<.10; ** p<.05; *** p<0.01

Table 8. The Effect of a Health Shock by Weight Category (AU$000)

	All	Male	Female
No Prior Health Shock, Overweight	0.145**	0.141	0.165**
	(0.061)	(0.103)	(0.069)
No Prior Health Shock, Obese type I	0.703***	0.666***	0.764***
	(0.061)	(0.112)	(0.075)
No Prior Health Shock, Obese type II/III	1.922***	2.003***	1.867***
	(0.104)	(0.172)	(0.111)
Prior Health Shock, Normal Weight	2.819***	3.233***	2.598***
	(0.076)	(0.135)	(0.083)
Prior Health Shock, Overweight	2.761***	2.903***	2.551***
	(0.074)	(0.109)	(0.107)
Prior Health Shock, Obese type I	3.155***	3.318***	2.930***
	(0.108)	(0.173)	(0.141)
Prior Health Shock, Obese type II/III	4.092***	4.223***	3.996***
	(0.199)	(0.314)	(0.195)

Note: Obese type I has a BMI between 30 and 35 and Obese type II/III has a BMI of over 35. Results are based on a regressions in which total health expenditures is regressed on an indicator for having been hospitalized in the prior year (*Shock*) interacted with each of the BMI categories (equation 2 in the text). The estimates presented are the average partial effects of the interaction terms and represent the additional spending in year t+1 (measured in thousands of dollars) for someone in a given weight category who had been hospitalized in the prior year relative to the average person in the same weight category who was not hospitalized. Results for the underweight are not reported as we focus on heaviness and the prevalence of underweight is very low. Bootstrapped standard errors with 50 replications are reported in parentheses; in each replication, the adjustment equation is also result of a bootstrapped NHS sample.
* p<.10; ** p<.05; *** p<0.01

Appendix

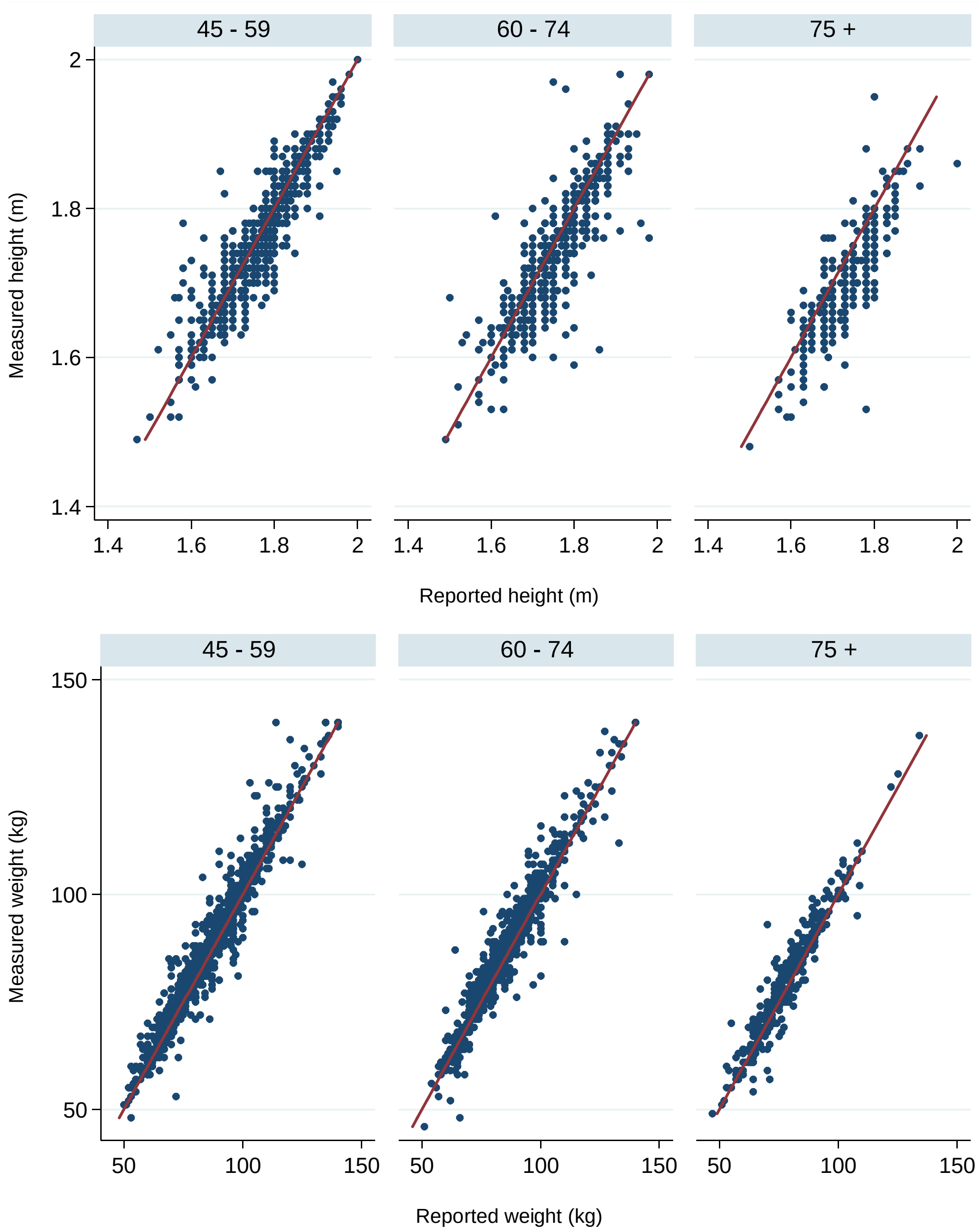
To correct for reporting bias in self-reported height and weight, we implement a procedure outlined by Courtemache, Pinkston and Stewart (2014). The correction relies on an external data source where both self-reported and measured data are available: the 2007-08 Australian National Health Survey (NHS). Assuming that measured height and weight in the NHS represent the true values for each variable, we regress each measured variable on the percentile of its self-reported counterpart. Parameter estimates from these regressions are then used to adjust the self-reported variables in the 45 and Up data.

In the 2007-08 NHS there are 8,531 adults over age 45; of these 5,034 (60 percent) have valid data on both self-reported and measured height and weight; we exclude those with self-reported or measured height less than 1 meter and self-reported or measured weight less than 20 kilograms. Conditional on age and sex, having non-missing values for both types of data is not correlated with such things as education, labor force status or private health insurance status. Summary statistics for observations with complete data are similar to those with only self-reported or measured. The self-reported mean height and weight of the NHS sample are very similar to those in the 45 and Up sample: 1.68 meters tall and 77 kilograms.

We stratify the NHS data into six age-gender groups. For males, scatter plots of self-reported and measured height and self-reported and measured weight are presented in Figure A1. The corresponding plots for females are provided in Figure A2. We add a 45 degree line which indicates equality between measured and self-reported values. Following Courtemache, Pinkston and Stewart (2014), we use spline with 11 knots (0, 0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95, 1) to allow a flexible relationship between measured and self-reported data. Predicted weight and height are obtained and using this, we compute the predicted or corrected BMI. Table A2 summarizes the effect of applying the regression-based correction to height and weight in the 45 and Up sample. We also report the percent of the sample falling into each BMI category based on unadjusted (self-reported) and adjusted (corrected) height and weight. As expected, the results suggest that individuals tend to report themselves taller and slimmer. Overall, there is a 6.6 percentage point difference in the self-reported and measured obesity rates. According to the adjusted data, 28.6 percent of the sample is classified as obese, compared to an obesity rate of 22 percent based on self-reports. Figure A3 show the distribution of self-reported and corrected

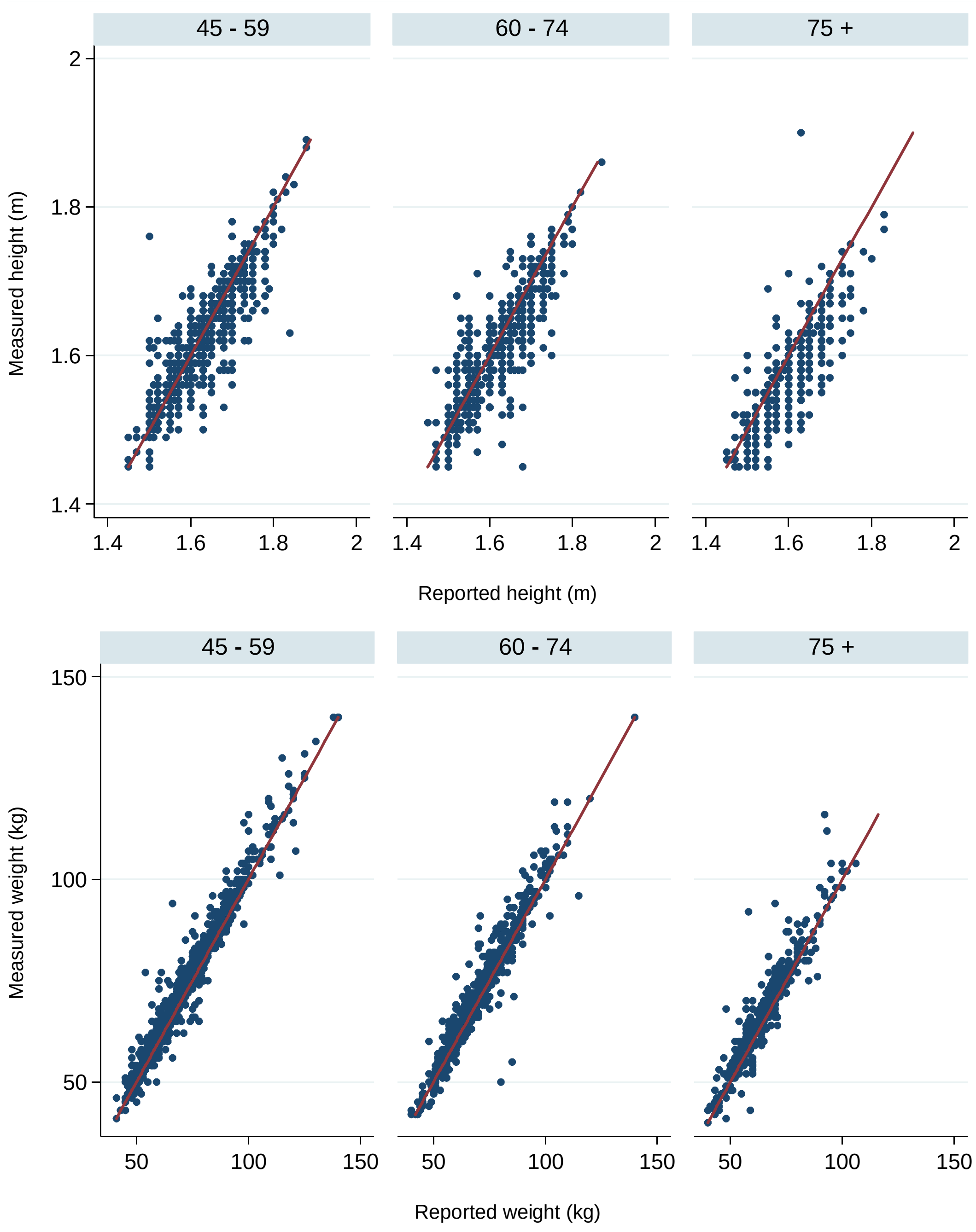
BMI from the 45 and Up sample.

Figure A1: Scatter plot of measured height and weight and self-reported height and weight for males by age group (NHS sample)



Note: each marker indicates an observation in the NHS sample for the respective sub-group. The straight line is a 45 degree line indicating equality between measured and self-reported values.

Figure A2: Scatter plot of measured height and weight and self-reported height and weight for females by age group (NHS sample)



Note: each marker indicates an observation in the NHS sample for the respective sub-group. The straight line is a 45 degree line indicating equality between measured and self-reported values.

Figure A3: Kernel density of self-reported and corrected BMI by age-sex group

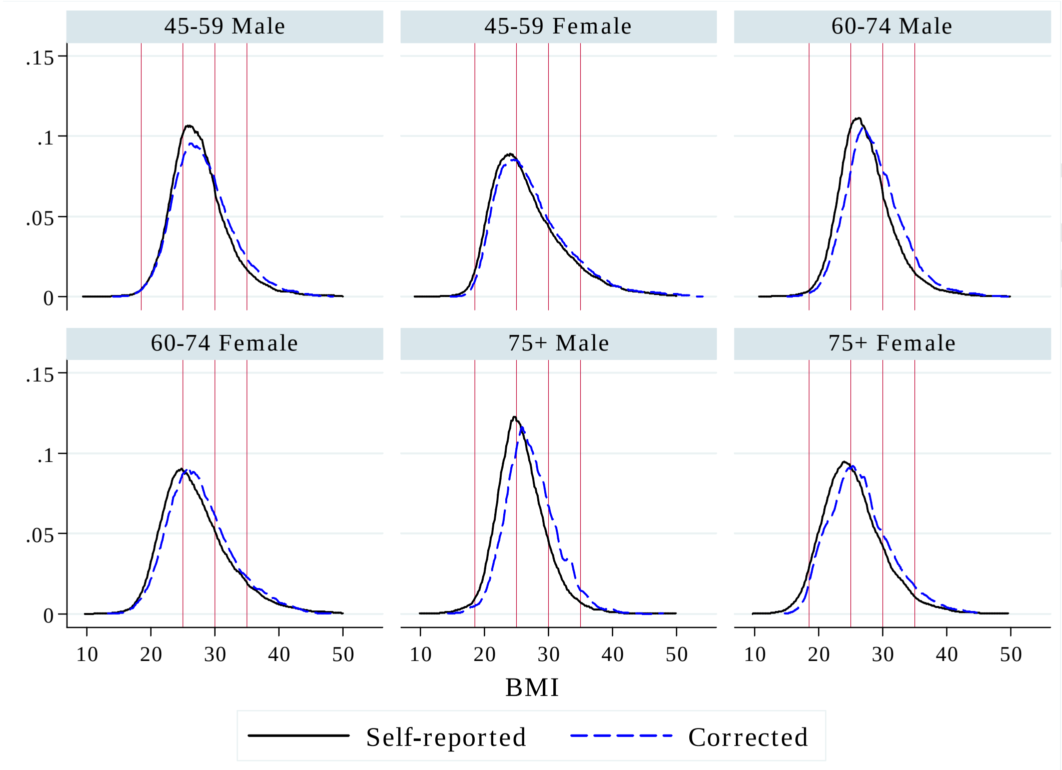


Table A1: Height and weight adjustments for reporting bias in the 45 and Up sample

Age-sex group	Unadjusted				Adjusted			
	Height	Weight	Obese type I	Obese type II/III	Height	Weight	Obese type I	Obese type II/III
45 – 59 Male	1.771	86.689	0.185	0.059	1.753	87.015	0.225	0.083
45 – 59 Female	1.633	71.291	0.151	0.088	1.618	72.166	0.167	0.106
60 – 74 Male	1.757	84.793	0.180	0.050	1.735	86.600	0.261	0.080
60 – 74 Female	1.620	71.018	0.168	0.080	1.600	71.111	0.193	0.092
75+ Male	1.735	77.625	0.105	0.019	1.704	79.365	0.187	0.037
75+ Female	1.595	64.701	0.121	0.037	1.574	66.934	0.162	0.058