An empirical investigation of a weight-wage penalty due to taste-based discrimination in Australia

Phillip Robert CHARHILL

100272614

A dissertation submitted to the School of Economics, University of East Anglia, in partial fulfilment of the MSc in Economics

Word Count: 12,798

An empirical investigation of a weight-wage penalty

due to taste-based discrimination in Australia

I certify that the work contained in this dissertation, submitted for the degree of the MSc in Economics is my own original work except where explicitly stated otherwise, and has not been previously submitted for a degree at this or any other University.

This dissertation either does not use data collected by the researcher from human participants, or uses secondary data obtained elsewhere.

I agree that this dissertation can be used as an example for the instruction of future UEA students.

Acknowledgements: My thanks and appreciation for the advice of my supervisor Dr. Ritchie Woodard. In dedication of S.K. and the future.

Phillip Robert CHARHILL

Date: 14th August 2023

Table of Contents

Section I: Introduction

In this paper we assess the evidence of a weight-wage penalty that is due to taste-based discrimination in Australia. A weight-wage penalty is where workers with greater weight, or those classed as obese, earn less than their counterparts of healthy weight. Taste-based discrimination is where employers treat workers differently due to personal taste (or distaste) for certain characteristics and not for economic reasons such as differences in productivity.

Our research questions are: is there empirical evidence of a weight-wage penalty in the Australian labour market? How much of this can be explained by differences in employment, that is, is there a weight-wage penalty between workers in similar jobs? How much of the remaining penalty can be explained by differences in productivity? And is there is still an unexplained penalty that can suggest the presence of taste-based wage-discrimination?

Research on this penalty is of interest as the obesity crisis grows in developed economies, having tripled since 1975 according to the World Health Organisation. As an increasing percentage of the population becomes obese, more workers will suffer this penalty and thus enjoy a lower standard of living due to reduced incomes which may worsen their health if they are less able to afford healthy food and exercise. Further, our analysis which decomposes the penalty is of use to policy makers seeking to minimise a weight-wage penalty. If we find the penalty is largely due to differences in productivity, attention should be paid to reducing the productivity gap by increasing productivity of obese workers. While if the penalty is due to discrimination, regulation aimed at protecting workers may be called for.

To analyse the penalty we utilise a subsample of the Household, Income, and Labour Dynamics in Australia (HILDA) dataset - a penal survey of Australian households. Our subsample consistent of employed persons surveyed between 2006 and 2021, the first year BMI is measured to the most recently available year. Our methodology consists of regression analysis on a baseline model to test the existence of a penalty (the effect of BMI on earnings) before adding controls and utilising fixed-effects estimation to hold constant differences in employment and productivity, which attributes the remaining effect of BMI on earnings to discrimination.

Prior research has established a consistent finding of a penalty in developed economies, but has neglected to study Australia's labour market, focusing on Europe and North America. We contribute to the literature by testing for the penalty in Australia and studying the cause through our approach to decompose the penalty.

This paper follows a traditional style; beginning with a review of literature on the presence and causes of the penalty in developed economies, followed by a detailed review of our methodological approach, a discussion of our data source, and closes with a presentation of the results and concluding remarks.

Our findings are in summary, evidence exists for a weight-wage penalty, some of which can be explained by employment and productivity, but that a remaining penalty exists suggesting discrimination, women face a smaller penalty then men, contrary to prior works, and our results may be subject to the time period studied.

Section II: Literature Review

In this section we discuss the existing literature to demonstrate a weight-wage penalty is a consistent finding in western developed economies that varies by gender, with women generally facing greater penalties, and by ethnicity, with minority groups facing smaller penalties. Further, we examine the work that has decomposed this penalty into three sources, differences in employment, differences in productivity, and taste-based discrimination, which inform our methodology, and conclude with the contributions this paper makes to the literature which include being the first paper to study the Australian labour market.

Evidence of the existence of a weight-wage penalty, of varying magnitudes, has been found by a wide array of studies in Europe and the United States over the last thirty years: Charles & Williams (1990), Cawley (2000), Maranto & Stenoien (2000), Saporta & Halpern (2002), Baum & Ford (2004), Brunello & d'Hombres (2007), Greve (2008), Gregory & Ruhm (2009), DeBeaumont (2009), Reece (2019), Böckerman *et al* (2019). While by no means an exhaustive listing, it demonstrates this penalty to be a consistent finding that has persisted over time. Thus we can examine these studies, and more, in greater depth to begin to review how this penalty varies by demographic and geography, and discuss decomposing it to identify and isolate taste-based discrimination.

We begin by examining how the penalty varies by sex, to which the overall consensus is that women face greater penalties than men do, or that men face no penalty. Maranto & Stenoien (2000) found penalties for women were 5% higher than for men, Baum (2004) 1.5-2.5% larger, and d'Hombres (2007) 1.4% larger. Other works have found men face no penalty: Charles & Williams (1990), Conley & Glauber (2006), Han, Norton, & Stearns (2009), and Mocan & Tekin (2011) find penalties of 12, 18, 7.5, and 7% for women respectively, while finding no evidence of a penalty for men. In light of this, some studies have elected to ignore men and focus solely on the effect of obesity for women, such as Cawley (2000). The explanations offered for this finding vary, and we shall discuss some of them later, but in summary, it has been suggested that the effect of physical appearance on wages is greater for women, and obese women face slower career progression than their counterparts of healthy weight. The finding is not universal however, Dou *et al* (2020) found men face a 2.5% larger penalty than women do. This may be explained by geography as Dou studied China while the other cited research is focused on Europe and the US. To further explore how the gender difference exists in Asia we can look to Lee *et al* (2019) who found a penalty for women and a *premium* – obesity causing greater earnings - for men in Korea. The number of studies in Asia is dwarfed by the volume of work conducted in western economies and more research is required before a consensus on the nature of the penalty in Asia can be reached. With this in mind we can ask whether we predict our findings to be line with western results or those from Asia. Due to Australia's greater cultural similarity to Europe and the US, compared to Asia, we might predict that if a weight-wage effect is found, it will be negative, and this is indeed what our findings suggest. Further, the existence of gender differences regardless of geography inform our methodology by encouraging the use of an interaction between BMI and sex in our regressions, which proves significant. Evidence has been presented that the shape of the relation between BMI and earnings vary by sex as well, with Greve (2008) finding a linear effect for women and an inverted-U shape for men, supported by Duo *et al* (2020). Gregory & Ruhm (2009) agree men follow an inverted-U but find women's earnings follow a cubic pattern. This suggests it may be beneficial to model the functional form of BMI differently for males and females, however we find an inverted-U shape fits the data for both sexes best.

Another demographic by which the penalty varies is ethnicity. It has been a consistent finding that ethnic minorities suffer a smaller penalty or no penalty, compared to whites in western economies. Cawley (2000, & 2004) found white workers face penalties but that Black and Hispanic workers do not, supported by Reece (2019). Cawley (2003) suggests various explanations including productivity and discrimination differences that vary by ethnicity. Kernper *et al* (1994), Poran (2002) and Fletcher (2014) offer a specific explanation, that ideal body weight (and thus BMI) is higher for blacks than whites, implying that a weight-wage penalty may began at a higher BMI for black workers, which drives insignificant results when comparing earnings between standard definitions of obesity. Other papers have suggested the lower sample size for ethnic minorities has driven insignificant results. Turning to those studies that find all ethnicities face some penalty, Maranto & Stenoien (2000) and Maralani & McKee (2017) find white workers face greater penalties than black workers do. While Slade (2017) agrees that whites face a greater penalty than blacks, Slade finds Hispanics suffer the largest penalty. As such any work on measuring the weight-wage penalty should control for ethnicity and examine interactions between BMI and ethnicity. In our data we do not observe ethnicity directly but attempt to proxy it, see section IV for more details.

Having examined evidence for the existence of a penalty and how it varies across, sex, ethnicity, and geography, we seek to explain the source of the penalty by decomposing it into three elements. We propose that obese workers having lower incomes stems from three causes: obese workers being discriminated against in hiring and promotion which leads them to lower paid jobs compared to similar workers of healthy weight, obesity negatively correlating with productivity which reduces pay, and taste-based discrimination where employers pay equally productive workers differently based on obesity. We present evidence for each of these causes in turn.

A meta-analysis by Puhl & Heuer (2009) concluded hiring discrimination based on obesity is a consistent empirical finding. Campos-Vazquez & Gonzalez (2020) observed obesity reduced the likelihood of a job applicant receiving a call-back for an interview[1]. Rooth (2009) studied this issue experimentally, sending applications that included photographs of the job seeker, in one application the photo showed someone of healthy weight, in another otherwise identical application the photo was digitally altered to show the person to be obese. These latter applications were less likely to receive call-backs, which is supported by Roehling's *et al* (2008) meta-analysis of thirty-two similar studies finding excess weight reduced likelihood of employment, promotion, and salary assignments. Further, Härkönen, Räsänen, & Näsi (2011) find obesity is negatively associated with career progression for women, and Caliendo & Lee (2013) found obese women were also less likely leave unemployment despite making more applications. Overall this suggests that obese people are less likely to obtain employment or progress in their careers compared to those of healthy weight, meaning they may remain in unemployment or not advance to new roles with greater pay, driving a weight-wage penalty. However this type of penalty can be accounted for by controlling for employment characteristics, then we can ask, does a weight-wage penalty exist between obese and non-obese workers in the same job. Sapota & Halpern (2002) analyse data of earnings in the legal profession, finding overweight attorneys were paid less. This suggests a penalty exists even in the same profession, so productivity and discrimination must be considered as well.

[1] This study is particularly interesting as it uses Mexican data, which has one of the highest rates of obesity in the world, perhaps discrediting the theory that obesity discrimination is negatively related to national obesity rates.

Evidence suggests obesity correlates negatively with productivity, Goetzel *et al* (2010) found presenteeism and taking time from work for medical appointments were positively associated with obesity, the latter is supported by Tsai *et al* (2008); presenteeism and absenteeism are often used as proxies for productivity. Komlos, Smith, & Bogin (2004) suggest obese workers have higher discount rates - that cause overeating and a lack of physical activity – and employers use weight as a signal of this unobservable trait that may affect productivity. Obesity in childhood may affect productivity as an adult if obesity reduces academic performance (the root of human capital). A meta-analysis by Santana *et al* (2017) found some evidence that obesity affects performance even after controlling for parental education and socio-economic status. Wu *et al* (2017) found obese children had worse short-term memories and suggested this as a source of lower academic achievement. Bagully (2017) argued obesity worsens mental health which damages performance, while Asirvatham *et al* (2019) suggest obesity caused stigmatisation from peers that leads to lower peer support and engagement with schoolwork. Returning to adult obesity, Averett (2019) notes research on obesity's physiological effect on cognitive skills as a reason for lower productivity and wages, implying obesity may affect productivity more in professions that rely on these mental skills. It has also been suggested that obesity impacts productivity in jobs that rely on interpersonal skills or interacting with customers. Han, Norton, & Stearns (2009) find larger weight-wage penalties in this type of employment, supported by DeBeaumont (2009) who find this is true for both employed and self-employed workers. The presence of this penalty for the self-employed (whose earnings are defined by their customers not an employer) suggests this penalty can be imparted by both employers and customers. The effect of obesity on productivity may be subject to sex, with Shinall (2015) and Lee *et al* (2019) finding obese women were less likely to be employed in service jobs and those requiring interpersonal tasks, but that men followed no such pattern. Further, Bozoyan & Wolbring (2018) attempt to decompose penalties in productivity and discrimination and find productivity differences explain penalties for men but not for women, suggesting women suffer more from discrimination. As such more research is required to fully identify the interplay between obesity's effect on productivity and one's sex.

It has further been suggested that in physically active roles obesity may decrease productivity more than in sedentary desk-based jobs. While we are unable to find studies that compare the weight-wage penalty between "active" and "non-active" jobs, we posit that physical activity is related to workplace productivity using the following research. Pereira *et al* (2015) and Grimani, Aboagye, & Kwak (2019) conduct meta-analyses of randomised control trails on workplace interventions to increase physical activity and find some evidence that such interventions improve productivity. The weakness of this research is the use of within variation in activity and productivity, while a penalty would be based on between variation in these factors. However, if obesity is (at least partially) due to low physical activity we can suggest obese workers are less productive, particularly in roles requiring such activity, but more specific research is required before a conclusion can be made. Further, Gates *et al* (2008) found obese workers suffered a productivity loss of 4% due to their weight, and Rodbard, Fox, & Grandy (2009) found evidence that obese workers are more impaired when completing tasks at work. But once again, a distinction between active and sedentary jobs is not made. Using the occupation variable in our sample we create dummy variables for whether a person's job requires social interaction or physical activity and use these as controls in our analysis, as Stinebricker & Sullivan (2019) do, see section IV for more details.

Taste-based discrimination in the context of obesity is an under studied one. However it is strongly linked to the phenomena of attractiveness and wages - where those deemed more attractive earn more – so to examine evidence for taste-based discrimination we can study this research. Kaczorowski

(1998) and Gvozdenodic (2013) find a positive association between subjective beauty and earnings in the North America, supported by a meta-analysis by Liu & Sierminska (2014), suggesting attractiveness does influence earnings. Stinebricker & Sullivan (2019) found attractiveness increased wages only in jobs where social interaction was considered important, and suggested attractiveness improves these interactions. An interesting result by Fidrmuc & Paphawasit (2018) shows more attractive researchers were more likely to be published in higher quality journals despite the researcher's appearance not being seen during review process, implying attractiveness correlates with work quality, at least for academics. It can further influence success in job applications and career progression, Hammer (2017) found attractiveness increased the likelihood of hiring after an interview, and Nault, Pitesa, & Thau (2020) found, through meta-analysis, attractive workers were more likely to be promoted and less likely to be considered for redundancy. It has been argued that attractiveness is used to infer productivity which should be rewarded, however Mobius & Rosenblat (2006) conducted an experiment where subjects assigned wages to workers who they watched completing a task and found the more attractive workers received higher wages despite the task being designed so attractiveness did not affect one's ability to complete the task. This implies attractiveness affects earnings even in the absence of productivity differences; and if obesity affects attractiveness we may find evidence of taste-based earning discrimination against obese workers.

To close this section we highlight the contribution we make to the existing literature. This study is the first (to the best of our knowledge) to examine evidence for the weight-wage penalty in Australia. We measure the size of each of the three components of the penalty; employment differences, productivity differences, and taste-based discrimination, allowing us to see which is the largest source of the penalty in Australia, which informs policy. In our estimation of discrimination, we attempt to control for productivity more fully than has been done previously by combining fixed-effects estimation with proxies for the time-varying determinants of productivity, making our results more robust measures of discrimination. We introduce and explain our methodology fully in the next section.

Section III – Methodology

In this section we explain our methodological approach to addressing our research question. We open with an explanation of how to measure taste-based discrimination despite not directly observing it, followed by regression specifications that aim to do this. We then discuss endogeneity that our regression may be subject to and how we correct for it, and close with details of robustness checks to examine the sensitivity of our findings.

The goal of our research is to examine whether evidence exists for a weight-wage penalty due to taste-based discrimination. We posit that a worker can be discriminated against at two points in time: while they are applying for a new job/position, and after they have been employed and during pay or contract negotiations. At each time they may face two types of discrimination, (defined as being treated differently from another person for any reason), which we will term justified and unjustified discrimination. Justified discrimination is based on differences in inferred or actual productivity, during hiring or after hiring respectively, it is usual and expected that workers with differing productivities receive different positions or pay. Unjustified discrimination, or taste-based as we have called it thus far, is not based on productivity but the preferences of the employer punishing those with characteristics they do not like with interview failure or lower pay. It is this last form of pay discrimination we seek to measure. We begin with a baseline model to test for a penalty before accounting for any of the above forms of discrimination. This is augmented to control for job characteristics to eliminate the discrimination at the hiring stage and test for discrimination between workers in the same job but cannot disentangle justified and unjustified pay discrimination. Thus we add productivity controls to hold productivity constant, meaning any remaining penalty can be attributed to unjustified discrimination.

To generate a model that can be most informative regarding discrimination, we use a lagged measure of obesity. This is to account for current income being determined some time ago, such as during the last pay negotiations or annual performance reviews surrounding employment contract renewal. If today's pay is decided upon yesterday's performance, it is yesterday's obesity that will be discriminated against, not today's obesity. As such our research question is best answered by measuring the effect of obesity in the prior period, on income in the current period, holding productivity constant.

Section 3.1: Regression Specifications

Having discussed the basis of our approach, we now explicitly present our regression specification and layout how we shall develop it in three stages to explore the evidence that relates to our research question. We begin with what we shall term the "baseline" model, a simple random-effects regression of lagged obesity (measured by BMI) to explain earnings (weekly income and hourly wage, estimated separately, and measured in natural logs to account for reduced sensitivity of earnings at larger values). This naïve regression shows the penalty for greater BMI on earnings before any controls are added. It is to this baseline that we experiment with non-linear forms of BMI and the interaction with sex. This baseline model is presented below in Equations 1, 2, and 3:

$$\ln(Earnings) = \beta_0 + \beta_1 BMI_{it-1} + \epsilon_{it}''' \quad (1)$$

$$\ln(Earnings) = \beta_0 + \beta_1 BMI_{it-1} + \beta_2 BMI_{it-1}^2 + \epsilon_{it}''' \quad (2)$$

$$\ln(Earnings) = \beta_0 + \beta_1 BMI_{it-1} + \beta_2 BMI_{it-1}^2 + \beta_3 BMI_{it-1} * sex_t + \beta_4 BMI_{it-1}^2 * sex_t + \epsilon_{it}''' \quad (3)$$

Where ϵ''' is an error term containing all other determinants of earnings, specifically demographics, job characteristics, productivity, and taste-based discrimination. Our aim of developing the regression specification is to draw out all these factors except taste-based discrimination and measure the effect of this discrimination on pay. We maintain the quadratic form of BMI and gender interaction for all forthcoming regression specifications. Throughout our specifications we use clustered standard errors (using each unique individual as a cluster) to address heteroskedasticity and serial autocorrelation.

We now augment our baseline model to include a vector **D** of usual demographics[2] that relate to earnings, as informed by Marranto & Stenoien (2000), Shinall (2015) and Slade (2017). This measures the penalty between similar workers but does not control for any type of discrimination as outlined above. We present this demographic model in Equation 4:

$$\begin{aligned} ln(Earnings) = \beta_0 + \beta_1 BMI_{it-1} + \beta_2 BMI_{it-1}^2 + \beta_3 BMI_{it-1} * sex_t + \beta_4 BMI_{it-1}^2 * sex_t + \beta_5 sex_t \\ + \beta_6 state_{it} + \beta_7 marital\ status_{it} + \beta_8 highest\ qual_{it} + \beta_9 age_{it} + \beta_{10} age_{it}^2 \\ + \beta_{11} birth\ country_{it} + \beta_{12} socioeco\ backgound_{it} + \beta_{13} wave_t + \epsilon_{it}'' \qquad (4) \end{aligned}$$

Where state, marital status, highest qualification, birth country, and wave are vectors of dummies for these categorical variables, see Section III for detail on these. ϵ''_{it} is an error term of all income determinants we are not controlling for, specifically: employment characteristics, productivity, and taste-based discrimination. Finally, we also include a time index to account for time effects, such as national wage inflation. You will note age is measured in a quadratic form, motivation for which is provided in Section V.

In the second specification, we remove the employment characters from ϵ_{it}'' and control for them. We augment Equation 4 with a new vector **J** of these characteristics[3] such as hours worked and occupation, to generate Equation 5:

$$\begin{aligned} ln(Earnings) = \beta_0 + \beta_1 BMI_{it} + \beta_2 BMI_{it}^2 + \beta_3 BMI_{it-1} * sex_t + \beta_4 BMI_{it-1}^2 * sex_t + \beta_D \boldsymbol{D} \\ + \beta_{14} occupation + \beta_{15} industry + \beta_{16} hours\ worked + \beta_{17} choice\ at\ work \\ + \beta_{18} initive\ at\ work + \beta_{19} fast\ at\ work + \beta_{20} one\ job + \epsilon_{it}' \qquad (5) \end{aligned}$$

Where occupation and industry are again vectors of dummies. ϵ_{it}' is a new error term containing productivity and taste-based discrimination. Examining the marginal effect of BMI in this second specification tells us the weight-wage penalty for workers in similar employment, allowing productivity and discrimination to vary.

In the final specification we attempt to draw productivity out of ϵ_{it}' using our proxies of productivity and utilise these to augment Equation 5 to generate Equation 6:

$$\begin{aligned} ln(Earnings) = \beta_0 + \beta_1 BMI_{it} + \beta_2 BMI_{it}^2 + \beta_3 BMI_{it-1} * sex_t + \beta_4 BMI_{it-1}^2 * sex_t + \beta_D \boldsymbol{D} + \beta_J \boldsymbol{J} \\ + \beta_{21} tenure\ with\ employer + \beta_{22} tenure\ within\ occupation + \beta_{23} days\ absent \\ + \beta_{24} interpersonal\ work + \beta_{25} physcially\ active\ work + \epsilon_{it} \qquad (6) \end{aligned}$$

This specification will first be estimated via random effects and then again by fixed-effects to further control for time invariant determinants of productivity. Having removed employment characteristics and productivity from the error term, all we hope remains in ϵ_{it} is taste-based discrimination, making the interpretation of the marginal effect of BMI in this specification: the weight-wage penalty holding job characteristics and productivity constant. Thus this penalty can be attributed to taste-based discrimination and will directly address our research question.

[2] **D** = (sex, state. marital status, age, highest qualification, birth country, socio-economic background)
[3] **J** = (occupation, industry, hours worked, choice-; initiative-; fast-at work, one job)

Section 3.2: Endogeneity

Having laid out our regression equations that we shall draw results from, we must address potential endogeneity that would bias our findings and cast doubt on their reliability. We explain the issue of endogeneity in a general form first, before discussing specific causes of endogeneity in our context and our proposed solutions to them.

Suppose a simple, and general, multiple linear regression (MLR) model as below in Equation 7:

$$Y = \beta X + \varepsilon \tag{7}$$

Endogeneity can be defined as a violation of the fourth MLR assumption, often titled zero conditional mean, which states the expected value of the error term ε, conditional on the data matrix X, is equal to zero (Equation 8).

$$E(\varepsilon|X) = 0 \tag{8}$$

This is true when the error term can be described as mean independent, that is all the variables x_j within the data matrix X are uncorrelated with ε (Equation 9), and average value of the error term is equal to zero (Equation 10).

$$Cov(x_i, \varepsilon) = 0 \; for \; i = 0, 1, 2 \ldots, k \tag{9}$$

$$E(\varepsilon) = 0 \tag{10}$$

If the condition in Equation 8 is satisfied, the OLS estimator of β is unbiased. Should the condition in either Equations 9 or 10 be violated, β will be biased: if Equation 9 is not true, the coefficients of the explanatory variables will be biased; if Equation 10 is not satisfied, only b_0 (the intercept) will be biased. As the intercept of our model is not of interest to our research question, we will restrict ourselves to discussing violations of Equation 9. We will now discuss three sources of endogeneity in turn: reverse causality between income and obesity, true productivity being absent from our vectors of controls, and measurement error in the key explanatory variable BMI.

Using the equations below we define reverse causality (also known as simultaneity) and show how it violates Equation 9. Suppose BMI is a function of income (we present intuition as to why later), and a vector of determinants $\boldsymbol{Y}$ with an error term μ (Equation 11), and also that income is a function of BMI, and a vector of other determinants $\boldsymbol{Z}$ with an error term ϵ (Equation 12):

$$BMI = \alpha_0 + \alpha_1 Income + \alpha_2 \boldsymbol{Y} + \mu \tag{11}$$

$$Income = \beta_0 + \beta_1 BMI + \beta_2 \boldsymbol{Z} + \epsilon \tag{12}$$

By substituting Equation 11 into Equation 12 and rearranging terms we find the following result:

$$BMI = \frac{\alpha_0 + \alpha_1\beta_0}{1 - \alpha_1\beta_1} + \frac{\alpha_1\beta_2}{1 - \alpha_1\beta_1}\boldsymbol{Z} + \frac{\alpha_2}{1 - \alpha_1\beta_1}\boldsymbol{Y} + \frac{\alpha_1\epsilon + \mu}{1 - \alpha_1\beta_1} \tag{13}$$

Thus, BMI depends on the error term (the final term of Equation 13) which itself is a function of ϵ. Therefore, BMI is corelated with its error term and the condition in Equation 9 is violated and the estimation of BMI's effect on income ($\beta_1$in Equation 12) will be biased.

But is reverse causality an issue within our regression framework? It can be argued (as we have) that BMI is a determinant of income, however it can also be suggested that income determines BMI. Suppose a worker has a low income, for any reason such as poor education, which reduces their budget for purchasing food. As food is a necessity good, of which a certain quantity must be consumed, low-income consumers will likely buy cheaper foods than a high-income consumer might. If cheaper food is less healthy, this may link low incomes and greater BMI. Ward *et al* (2013) studied the affordability of a healthy basket of food for Australian consumers and found such a basket would cost a low-income household 30% of their income, while a high-income household would spend only 10% on it. This demonstrates a significant difference in affordability of healthy food and supports the suggestion that low incomes lead to an unhealthy diet. They further discuss the dangers this presents regarding health, noting cheaper foods are more likely to be high in sugar, fat, and salt, which contribute to weight gain. Love *et al* (2018), again studying Australia, agrees that a healthy diet would cost 30-32% of disposable income, but compared this to actual food expenditure on an unhealthy diet, which accounted for 59.5% of poorer households' disposable income. Love suggests that healthy food is not less affordable, but that the *perception* that a healthy diet is expensive discourages healthy consumption by poorer consumers, further exacerbated by poor access to healthy food options, particularly in rural areas. While this debates the affordability of a healthy diet for low-income consumers, it supports the hypothesis that low-income consumers *have* an unhealthy diet. Initially, this supports the presence of reverse causality as an issue within our model. However this links today's income to today's diet, and there exists a lag after a change in diet before weight subsequently changes. As such we argue there is no link between income at time t and BMI at time t, but instead between income at t and BMI at $t + 1$ due to the lag. Since our model is using a lagged form of BMI to better reflect what pay decisions are made upon, reverse causality could only be an issue if today's income determines yesterday's obesity. Further, Kim & von dem Knesebeck (2018) conduct a meta-analysis of 14 studies examining the effect of income on obesity, and though finding a statistically significant result, this significance is removed by accounting for publication bias, implying there is no empirical evidence of the proposed reverse causality. In addition, prior empirical work on the weight-wage penalty has attempted to address (assumed) reverse causality without presenting evidence that such an issue exists. As such we conclude that reverse causality should be limited in our investigation. But it should be noted that the most common solution to this proposed issue is to lag BMI[4], which we are doing for an alternative reason. Therefore, if our position is incorrect and reserve causality does plague our model, we have adopted a solution already.

The second cause of endogeneity is not directly including productivity in our vector of controls within our regression specification and proxying it instead. Measuring productivity has been the bane of much research in economics for many years and debate exists even on how to define productivity, Tangen (2005). Teague & Eilon (1973) suggest measuring productivity as some ratio of output to inputs but note that many professions utilise intangible input that themselves are difficult to measure, such as technical skill or charisma, making this ratio impossible to calculate. Schainblatt (1982) mentions the difficulty of calculating individual productivity when the resulting output is generated by a team effort, in their context research by scientific teams. Since almost every job in the modern world is part of a team or at least done in coordination with others, this again presents difficulties in measuring productivity. Rust *et al* (2004) highlight the difficulty of measuring productivity when work has long-term impacts, such as the lasting impact of marketing on a business' success, in their context. How can we measure the value of work completed today when its benefits may not fully be felt for years? They go on to describe the challenge faced by outputs which cannot be measured financially, such as brand awareness. This very brief discussion cannot hope to thoroughly describe the issue of measuring

[4] Debate exists on the preferred lag length however, with Alauddin Majumder (2013) using a one-year lag, Averett & Korenman (1996) and Cawley (2004) using a 7-year lag, while Gregory & Ruhm (2009) use a 13-year lag.

productivity, but, we hope, give a very slight impression of the extent of the difficulty of such a task. Further, you may notice a habit within research on measuring productivity to restrict itself to a single profession or occupation. This is indicative of another issue, that of how to create a comparable measure of productivity, how to compare the output of a car mechanic with that of a police officer, or any other combination. Our data contains workers from over eighty occupations so creating a comparable measure across all would be a herculean task. This justifies *why* productivity is omitted from our specification, allow us to now demonstrate why this generates endogeneity.

Omitting productivity (an inarguable determinant of labour income) from our regression generates omitted variable bias. Suppose we could measure productivity, we could produce a regression model as presented in Equation 14, where both BMI and productivity are included with a vector **Z** of other determinants and an uncorrelated error term δ.

$$Income = \gamma_0 + \gamma_1 BMI + \gamma_2 productivity + \gamma_3 \boldsymbol{Z} + \delta \tag{14}$$

By not controlling for productivity we relegate it to the error term of our model, as in Equations 15&16

$$Income = \beta_0 + \beta_1 BMI + \beta_2 \boldsymbol{Z} + \varepsilon \tag{15}$$

$$\epsilon = \delta + \gamma_2 productivity \tag{16}$$

If BMI correlates with productivity, and our literature review suggests it does, BMI now correlates with the regression error term of Equation 15, thus violating Equation 9 and creating a biased estimation of BMI's causal impact on labour income.

To address this source of bias we suggest decomposing the determinants of productivity into two groups; those that vary over time (education, familiarity with a business' processes, technical skill, etc) and those that do not vary over time (intelligence, discount rate, risk preferences, etc), and to attempt to control for these two groups. For the time varying elements, we shall use proxies of these factors: controlling for tenure with employers as a proxy for familiarity with business processes, and tenure with occupation as a proxy for technical skill, days away from work to proxy absenteeism, and whether work requires interpersonal tasks or physical activity (as informed by our literature review as determinants of productivity that correlate with obesity). For the time invariant determinants, we can adopt a fixed-effects estimation method which controls for all time-invariant heterogeneity between observations. It is our aim that by combining these methods we can control for much of the correlation between obesity and productivity to minimise the bias in our coefficient, this is one reason for advancing from the regression specification in Equation 5 to that in Equation 6.

The final root of endogeneity we shall discuss is that of measurement error in the self-reported BMI variable. We explain the reasons and evidence within the data section of the paper, but to summarise, self-reported BMI is likely to be an underestimate of true BMI, particularly among more obese people who either underestimate their own weight or report a lower weight than they know they are due to wishing to present themselves more favourably to an interviewer. Using the equations below we demonstrate how measurement error in BMI will bias our estimate of BMI's effect on labour income.

Suppose labour income is a function of true BMI, a vector of other determinants **Z** and an error term ϵ (Equation 17).

$$Income = \beta_0 + \beta_1 True\ BMI + \beta_2 \boldsymbol{Z} + \epsilon \tag{17}$$

Now suppose BMI is measured with error such that self-reported BMI is a function of true BMI and an error term τ (Equation 18), where $Var\ (\tau|reported\ BMI) = \sigma_\tau^2$

$$Reported\ BMI = True\ BMI + \tau \tag{18}$$

Substituting Equation 18 into Equation 17 and rearranging produces Equation 19.

$$Income = \beta_0 + \beta_1 Reported\ BMI + \beta_2 \boldsymbol{Z} + (\epsilon - \beta_1 \tau) \tag{19}$$

And the correlation between reported BMI and the error term of Equation 19 $(\epsilon - \beta_1 \tau)$ is:

$$Cov\big(reported\ BMI, (\epsilon - \beta_1 \tau)\big) = -\beta_1 \sigma_\tau^2$$

Thus, a self-reported BMI that differs from true BMI will correlate with the error term of the regression model estimating the effect of BMI on labour income, causing bias, see O'Neill & Sweetman (2013) for empirical support of measurement error introducing bias. To account for this we shall adjust the levels of BMI at which the obesity groups are defined, this approach is informed by Dauphinot *et al* (2009) and Lim, Seubsman, & Sleigh (2009) and further detailed later.

Section 3.3: Robustness Checks

Having discussed our approach to endogeneity, we deepen our analysis with some robustness checks to examine the sensitivity of our results which we detail below. The purpose and value of each is also laid out.

The first alteration to the model aids in addressing arguments that BMI often struggles to reflect weight-related healthiness (such as BMI not distinguishing between muscle weight and fat weight), by re-measuring BMI as the deviation from a person's desired BMI. If a person is healthy, they are likely happy with their weight and BMI, so there will be minimal deviation. However, if weight-related health is poor, a person may desire a lower BMI to address this, thus producing a deviation. Participants in 2019 were asked their desired weight, from which desired BMI is derived. We shall restrict our analysis to a five-wave panel around the 2019 wave (2017-2021) and assume that desired BMI is constant across this period, then calculate the deviation from desired BMI and re-run our model on the sub-sample. If this new form of measurement produces different conclusions, it may suggest BMI does not measure weight-related healthiness well, and that future research would be better suited to use another measure, such as body fat index.

The second alteration, used with respect to the measurement error problem, is to adjust the levels of BMI at which obesity groups are measured, Dauphinot *et al* (2009) found reducing the threshold at which obesity is defined from 30 to 29 reduced misclassification from 30% to 17%. Lim, Seubsman, & Sleigh (2009) found a reduction of 0.5 points corrected for approximately half of the error introduced by self-reported measurement. We shall experiment with both, defining obesity as both $BMI \geq 29$ and $BMI \geq 29.5$ and compare the results. We will run the model using in place of continuous BMI a categorical variable of obesity groups, and compare the weight-wage penalty for original and adjusted definitions of obesity. If our results are sensitive to this, it implies measurement error in self-reported BMI is a significant issue and that some additional endogeneity in our model has been corrected for.

As a final note on our methodology, we briefly discuss the use of survey weights for our data. HILDA provides various weights to improve representation of the Australian population and to correct for known errors in sampling, for more information on weights, please see the HILDA user manual[5]. As part of our research we applied the appropriate weights to our sample of the dataset and compared between weighted and non-weighted summary statistics and regression outputs. In both cases, there was no significant change in calculated values, however standard errors increased by a factor of two. Due to our conclusions not being sensitive to the use of weights, and the drop in precision of our estimates, we chose to use unweighted models throughout our analysis.

Having laid out our approach to answer our research question and the methods employed to ensure robust findings, we introduce the data that we will immerse the model into in the next section.

[5] Which can be found at: https://melbourneinstitute.unimelb.edu.au/hilda

Section IV: Data

In this section we will discuss the HILDA dataset that has been selected to address our research questions. We will conduct descriptive analysis to examine the presence of obesity in Australia and how labour market outcomes differ between workers of healthy weight and obese workers to obtain an impression of the context of our data, such as: whether there is a difference in average wages between healthy and obese workers, and whether obese workers in our sample are less likely to have been promoted recently - before using the model developed in the prior section to address our research questions more inferentially.

The Household, Income, and Labour Dynamics in Australia[6] (HILDA) dataset is a national longitudinal panel study of Australian households asking questions annually on topics including income, labour market outcomes, health, and family dynamics. It began in 2001, is funded by the Australian government, and managed at the University of Melbourne. We use a subset of the panel, from 2006 - the year when BMI was introduced as a question – to 2021 – the most recent available year, producing a sixteen-wave panel for our analysis. We further restrict our analysis to those categorised as employed (neither unemployed nor out of the labour force). We use a subset of the collected variables which can be divided into three groups: demographic characteristics, job characteristics, and productivity proxies. We shall define and explore these groups in turn, after exploring the extent of obesity in Australia and its labour market.

Section 4.1: Describing Variables

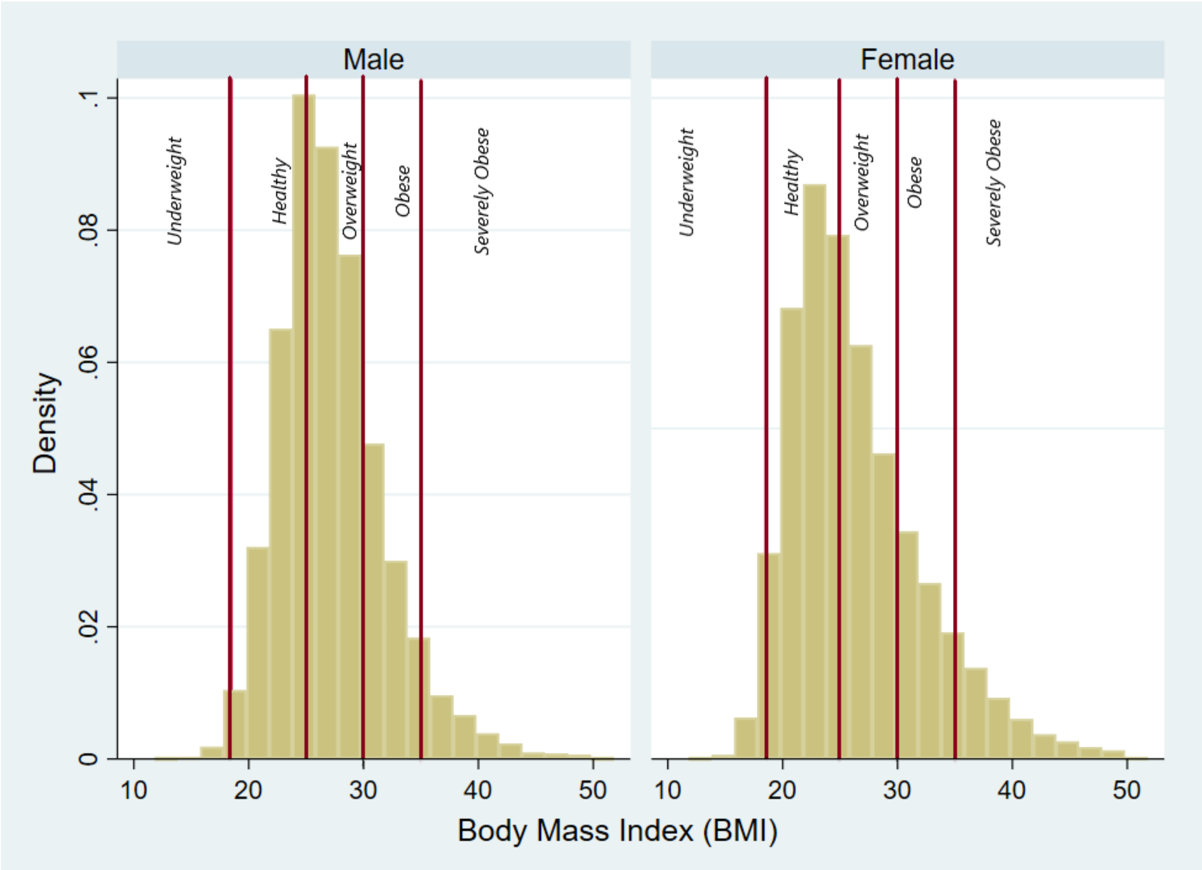
Beginning with obesity, as defined by the World Health Organization (WHO) as “abnormal or excessive fat accumulation that presents a risk to health”, is measured via a person’s body mass index (BMI) which is a statistic calculated as weight in kilograms divided by the square of their height in centimetres. A BMI of under 18.5 is considered underweight, between 18.5 and 25 is considered healthy, 25 to 30: overweight, 30 to 35: obese, and above 35 is considered severely or morbidly obese. HILDA measures BMI by asking participants to self-report their height and weight in preferred units, which are then standardised into kilograms and centimetres, which are then used to calculate BMI. The self-reported nature of the measure is important, Gosse (2014) conducted a meta-analysis of studies comparing self-reported and medically assessed BMI and found self-reported figures were under reported and participants were more likely to under reported at higher levels of BMI, supported by Davillas & Jones (2021). Hattori & Sturm (2013) found one in six medically obese individuals would be classified as non-obese when using self-reported measures and this under reporting was not associated with age, sex, or ethnicity. As such the reliability of our measure of obesity can be questioned due to downward bias from this measurement error. See Section III for a discussion on addressing this error. However, we continue to use self-reported measures as medically assessed BMI is unavailable in most economic surveys, including HILDA.

For the remainder of this section, unless stated otherwise, our sample is the regression sample from running our basic penalty model (Equation 4 in section III). The sample comprises of 124,200 observations from 18,461 unique participants. Figure 4.1 shows a histogram of BMI in our sample, showing a mostly bell-shaped distribution with mean of 27.25 (males), 26.5 (females) and positive

[6] For details on HILDA see: https://www.dss.gov.au/about-the-department/longitudinal-studies/living-in-australia-hilda-household-income-and-labour-dynamics-in-australia-overview

skew of 1.15 (males), 1.25 (females). The vertical lines mark the level of BMI that define the obesity groups laid out above.

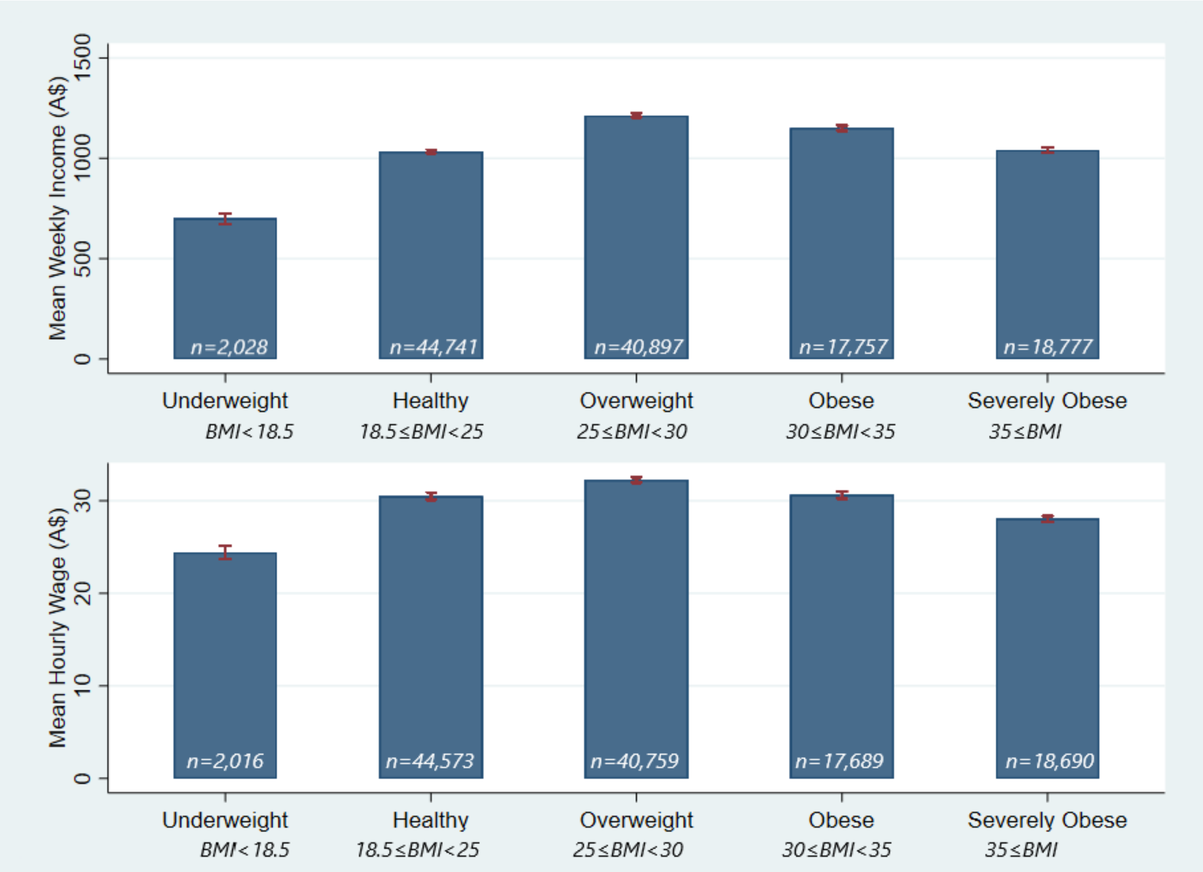
Figure 4.1: Histogram of BMI by sex



The proportion of our sample in each group is as follows: 1.6% are underweight, 36.0% are healthy, 32.9% are overweight, 14.3% are obese, and 15.1% are severely obese.

Turning to our dependent variable, labour income is measured as the weekly pre-tax income from all jobs a participant has. Participants are not asked this figure directly and instead are asked in what unit of time they would like to report their earnings in Australian dollars (A$), such as annually or monthly, before reporting the figure for each job they may have individually. This is then standardised into a single variable of total weekly income. We report the method of data collection as this method reduces measurement error that might arise if participants were asked to calculate their weekly income and sum from all their jobs, which requires mental effort, which may encourage estimation of income, or be prone to mistakes by participants with lower numerical ability. For a cursory impression of the data and presence of a weight-wage gap, we can conduct a t-test to compare the mean of weekly income between obese and non-obese workers. Comparing weekly income, we find obese workers have a mean A$17 less than healthy workers, significant at the 1% level. Further, by dividing weekly income by hours workers per week, we can test the difference an estimated hourly wage. This concludes obese workers have a mean hourly wage A$1.89 lower than healthy workers, again significant at 1%. Figure 4.2 shows the mean weekly income (above) and hourly wage (below) for each of the five previously defined obesity groups, and associated 95% confidence intervals, showing an increase in average earnings from underweight and healthy, which peaks in the overweight group before declining through the obese groups, suggesting a quadratic relation between obesity and earnings.

Figure 4.2: Average income and wage by obesity groups



This suggests a weight-wage penalty but is not a conclusive result as we are not controlling for other factors that drive wages and may correlate with obesity, such as demographics or productivity, which we do in our forthcoming regression analysis.

Using our data we can perform a similar test to examine the hiring differences as suggested in our literature review. Rescinding our data restriction to the sample from Equation 4 and returning to the full sample for this test only (as the regression sample only contains employed people), we can examine if obese people are less likely to be employed. A t-test concludes they are 1.9% less likely to be employed, or in reverse are 1.9% more likely to be unemployed, significant at the 1% level. Returning to our regression sample, we also find obese workers are 1.4% less likely to have been promoted at work in the last year. Again, these tests, while interesting as surface level investigation of differences between obese and non-obese workers, these tests are not conclusive, as we are controlling for other factors or addressing the inherent reverse causality between health and labour market outcomes; that is, does obesity cause lower wages or lack of promotion, or does less labour market success drive obesity? Such reverse causality is discussed in greater detail in our methodology section.

Having discussed our dependent and key explanatory variables, we turn now to defining our controls. Which are grouped as follows: demographics, job characteristics, and productivity proxies.

Beginning with demographics, we measure the following: Sex – whether the participant described themselves as male or female in the most recent survey. If a person changes their sex, their responses in prior waves are updated retroactively by HILDA to account for this, as such recorded sex does not vary across time for our sample. Socio-economic background – measured in deciles zero to ten, ten implying most advantaged background[7]. State of residence – the current area of Australia a person lives, see Table 4.2 for a listing of areas. Marital status – whether a person is married, living with a partner, separated, divorced, widowed, or single. Age – at last birthday in years. Highest qualification – achieved by the time of interview, see Table 4.2 for groups. Region/country of birth – ethnicity is not measured in national Australian surveys including the Australian census, Ranzaho (2023), so we proxy it by where a person was born. Originally coded as which country a person was born in, we have reduced the 160 different nations to the three most common, Australia, the United Kingdom, and New Zealand, and grouped the remaining nations into the regions of the world as defined by the UN[8].

Next, job characteristics, in which we measure: Weekly hours worked – the usual number of hours worked across all jobs each week. One or more jobs – whether a person is employed in only one job or is employed in multiple jobs. Industry – that the person is employed in. Occupation – type of work employed in, such as manager, labourer, technician, etc. Three similar variables, whether work involves Choice, Initiative, or Rapidity – where participants are asked if their job requires them to make decisions themselves, use their initiative, or work quickly, measured on a Likert scale with higher values implying greater agreement. These three responsibilities make work more difficult or require more skill or experience and thus may correlate with wages and act as determinants. This comes under the literature of efficiency wages, see Arai (1994) for a discussion on autonomy at work and wages, Ramaswamy (1991) who notes a role of initiative in efficiency wages, and Katz (1986) who notes correlations between the pace of work and wages.

Finally, our proxies for productivity: Tenure with employer – the number of years a person has been working for their current employer. Tenure with occupation – the number of years a person has been working within their current occupation. Days absent – the number of days within the last year that the person has spent away from work on worker's compensation (a form of insurance payment for sickness and injury offered in Australia), a measure of absenteeism but imperfect as it does not measure days away not covered by worker's compensation. Interpersonal work – whether a person's job requires interpersonal activity beyond usual interaction with managers or colleagues, such as salespeople, retail or hospitality workers. Physically active work – whether a person's job requires physical activity, defined as not being able to complete their work while remaining seated. These latter two variables are informed by our literature review suggesting these may play a role in the productivity of obese workers.

[7] For construction of scale see: ABS (2011) Census of Population and Housing: Socio-Economic Indexes for Areas (SEIFA), Australia (ABS Cat. No. 2033.0.55.001)
[8] See: https://unstats.un.org/unsd/methodology/m49/

Section 4.2: Sample Representativeness

Below, in Tables 4.1 to 4.4, we present descriptive statistics for the variables described above[9] that will be used in our regression analysis, with controls divided into the three groups. We can use these values to examine if our sample is representative of the wider Australian population, by making comparisons to national statistics where possible, and also explain any eccentricities in our sample. Table 4.1 summarises our dependent, and key explanatory, variables.

Table 4.1: Summary Statistics of Earnings and BMI

Variable	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Weekly income	1104.145	953.047	0	16,991
Hourly wage	30.598	32.651	0	3,275
BMI	26.877	5.442	11.8	76.2

Beginning with our dependent variable of income, average weekly pre-tax income is around A$1,100. The Australian Bureau of Statistics (ABS) reports average income was between A$1,400-1500 in 2014 – the middle of our panel. This may suggest our sample is poorer than the wider population, however this statistic is for fulltime employees, who in our sample have a mean of A$1,390. As such the parttime workers may be lowering our overall average. This links to income's minimum value of zero (also working hours' minimum value), which may seem strange considering our sample is restricted to employed persons. However this may be due to people on zero-hours contracts who are employed but currently are not working and thus earning, or those out of work while still employed (recall that our panel includes 2020 and 2021 where the pandemic caused many workers to have zero hours or income while still remaining legally employed).

Turning to our key explanatory variable of BMI, its average puts it just into the overweight category. As stated earlier, among our sample 1.6% are underweight, 36.0% are healthy, 32.9% are overweight, 29.4% are obese or severely. The ABS reports that in 2017-18, 1.3% were underweight, 31.7% were healthy, 35.6% were overweight, and 31.3% were obese, meaning our distribution is largely similar with slight differences in the proportion in the healthy and overweight groups.

Turning to our demographics, summarised in Table 4.2, women make up 49% of our sample and the average age is 41 years. Average age in 2015 was 36.3 years (Statista 2023), as our sample is of working people this excludes children and students who might draw this average down. Approximately 68.7% of our sample is married or living with a partner, and 22.5% are single. The proportions of our sample in each state of Australia are also representative, 2021 national figures from Statista are reported in parentheses, 28.5% (31.8) in New South Wales, 25.8% (25.8) in Victoria, 21.3% (20.4) in Queensland, 8.7% (6.9) in South Australia, 9.3% (10.4) in Western Australia, 3.1% (2.1) in Tasmania, 0.9% (1.0) in the Northen Territory, and 2.4% (1.7) in the Capital Territory. 81% are native born Australians, and 19% are both overseas, the ABS reporting 28% of the 2015 population was born outside Australia, this difference may again be due to our sample being of workers, as some immigrants may be students or non-working family. In our sample the nations with the largest migration to Australia are the United Kingdom, 4.6% of our sample born there, and New Zealand, 2.5%, who were the two nations Australia saw the greater influx from according to the same ABS report. Thus we can conclude our sample is

[9] Excluding occupation and industry, which have fifty and eighty-six groups respectively, we present a table of these variables in the appendix

largely representative of the wider Australian population, with some account for our focus on employed adults.

Table 4.2: Summary Statistics of Demographic controls

Variable	***Mean***	***Std. Dev.***	***Min.***	***Max.***
Female	0.491	0.500	0	1
Age	41.018	14.048	16	89
Socio-economic background	5.981	2.777	1	10
Marital Status:				
Married	0.509	0.500	0	1
Living together	0.178	0.383	0	1
Separated	0.025	0.156	0	1
Divorced	0.053	0.224	0	1
Widowed	0.010	0.098	0	1
Single	0.225	0.418	0	1
State:				
New South Wales	0.285	0.451	0	1
Victoria	0.258	0.438	0	1
Queensland	0.213	0.409	0	1
South Australia	0.087	0.283	0	1
Western Australia	0.093	0.290	0	1
Tasmania	0.031	0.173	0	1
Northern Territory	0.009	0.096	0	1
Australian Capital Territory	0.024	0.153	0	1
Highest Qualification:				
Postgraduate	0.070	0.254	0	1
Graduate Diploma	0.072	0.258	0	1
Bachelor or Honours	0.183	0.387	0	1
Adv. Diploma or Diploma	0.103	0.305	0	1
Cert. III or IV	0.236	0.424	0	1
Year 12	0.166	0.372	0	1
Year 11 or below	0.170	0.376	0	1
Undetermined	0.0001	0.011	0	1
Region of Birth:				
Australia	0.811	0.391	0	1
United Kingdom	0.046	0.208	0	1
New Zealand	0.024	0.154	0	1
Oceania	0.007	0.082	0	1
Europe	0.027	0.163	0	1
Asia	0.058	0.233	0	1
Africa	0.014	0.116	0	1
The Americas	0.013	0.114	0	1

Moving to job characteristics, presented in Table 4.3, mean weekly working hours is approximately 36 hours (35 being the ABS' definition of working fulltime) with a maximum value of 144, which suggests working 20.6 hours a day. This is likely a result of an error - we have only 41 observations reporting working from than 100 hours and the 95th percentile is 60 hours, due to this low rate of extreme values, they are unlikely to bias our results. The average response to if their work involved choice was 3.8, translating to between slightly disagree and neutral on a seven-point Likert scale; initiative at work averaged 5.5, between slightly agree and agree; and having a fast pace of work averaged 5, meaning slightly agree. This suggests the average person in our sample has a job that does not require much autonomy, must somewhat use their initiative, and demands some rapidity.

Table 4.3: Summary Statistics of Job Characteristics

Variable	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Hours worked	36.121	14.685	0	144
One job	0.921	0.271	0	1
Choice at work	3.765	1.865	1	7
Initiative at work	5.539	1.396	1	7
Rapidity at work	5.048	1.482	1	7

Finally discussing our productivity proxies, displayed in Table 4.4, average tenure with employer is 7.5 years and 10.2 years with their occupation. It is expected tenure with occupation to be higher as most workers do not change occupation without also changing employer. A note on the minimum value of the tenures, they are measured in years, so this minimum value represents one week (by multiplying the value by 365). The mean number of days away from work on compensation was 0.65 days, it is worth noting the 95th and 99th percentiles are zero and ten days respectively, suggesting this average is dragged up by a small number of workers with very long periods of illness or injury. Regarding interpersonal and physically active work, 53.5% and 41.6% respectively of our sample's jobs fall into these categories. Due to availability of similar national surveys it is difficult to compare these to the wider Australian population.

Table 4.4: Summary Statistics of Productivity proxies

Variable	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Tenure with employer	7.528	8.750	0.0192	73
Tenure with occupation	10.212	10.905	0.0192	75
Days absent	0.646	8.451	0	352
Interpersonal work	0.535	0.499	0	1
Physically active work	0.416	0.493	0	1

In conclusion, our subsample of HILDA is widely representative of the Australian population thus fitting our previously developed model with this data should produce informative results from which we can make inferences regarding discrimination in the Australian labour market. In the next section we present and discuss our empirical findings.

Section V: Results & Discussion

In this section we present the results of the regression models developed in Section III and discuss their implications for our research question. We begin with the results of our baseline model, Equations 1, 2, and 3 to investigate the shape of the relationship between BMI and earnings and any gender differences. We then present the results on the decomposition of the penalty and the implication for our research question. After this we conduct the sensitivity analysis discussed toward the close of Section III.

Section 5.1: Baseline Results

We begin by exploring how BMI and earnings are related, and the presence of gender differences. Our literature review suggested a non-linear effect of BMI on earnings and significant gender differences. In Table 5.1 we show a summary of estimating Equations 1,2 and 3.

Table 5.1: Results from the Baseline models

	Income			Hourly Wage		
Equation:	1	2	3	1	2	3
BMI	0.0358*** (0.00101)	0.149*** (0.00645)	0.149*** (0.00588)	0.0197*** (0.000588)	0.0777*** (0.00312)	0.0777*** (0.00304)
BMI^2		-0.00178*** (0.000107)	-0.00183*** (0.0000967)		-0.000957*** (0.0000511)	-0.000945*** (0.0000512)
BMI x female			-0.0203*** (0.00180)			-0.00306*** (0.00103)
BMI^2 x female			0.000251*** (0.0000585)			0.0000245 (0.0000333)
R^2	0.0140	0.0277	0.0722	0.0035	0.0089	0.0126
Observations	112,912	112,912	112,912	111,724	111,724	111,724

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Values rounded to three significant figures

Estimating Equation 1 produces a positive and significant coefficient for BMI, implying a weight-wage premium for both income and wage. Our visualisation of obesity groups and earnings in Figure 4.2 suggested this might be true in the lower groups but a penalty takes effect during obesity. As such we add a quadratic BMI term and estimate Equation 2, whose coefficient proves significant and negative, supporting the presence of a quadratic relationship of an inverted-U shape for both income and wage. Next we add an interaction between BMI and female to account for differences between the sexes and estimate Equation 3. For income, both interaction terms prove significant, implying women also follow an inverted-U shaped relation, but of lower magnitude than men. For wage, only the linear interaction term is significant, however they are jointly significant and as the quadratic term becomes significant upon adding controls we choose to retain it. In closing, our baseline model offers support for the use of a quadratic relation[10] between BMI and earnings, and the presence of gender differences that should be accounted for. This is in line with prior findings. As such our forthcoming models utilise this functional form and interaction in their modelling.

[10] It should be noted adding a cubic term produces a significant result, however plots of predicted earnings are unaffected by the inclusion of a cubic term. As such we choose to use the simpler quadratic model

Section 5.2: Decomposing the penalty

Now we seek to establish the presence of a penalty between similar workers, and then decompose the penalty to control for discrimination during hiring and justified discrimination due to productivity, to analyse the evidence for taste-based pay discrimination. We summarise our findings in Table 5.2 below before discussing the implications of each stage in turn, for full regression results see appendix.

Beginning with the estimation of Equation 4, which estimates the weight-wage penalty controlling for demographics included in **D**, the coefficients of BMI and the interaction terms remain significant implying a BMI does impact earnings and that the effect for women is smaller than it is for men when controlling for demographic characteristics. We can calculate the turning point in the relation between BMI and earnings (these are presented in Table 5.3 for all the models) which show us where the premium for weight ends, and the penalty begins. Controlling for demographics the penalty on income is similar between the sex, with the turning point in the middle of the obese category, suggesting incomes aren't penalised until high obesity or severe obesity. The penalty on wages follows a different path however, for women the penalty begins quickly once weight exceeds the healthy group, while for men the penalty, again, begins much later during the obese group. To better visualise this relationship we present predicted earnings, by sex, controlling for demographics in Figure 5.1 below:

Figure 5.3: Predicted earnings (Equation 4)

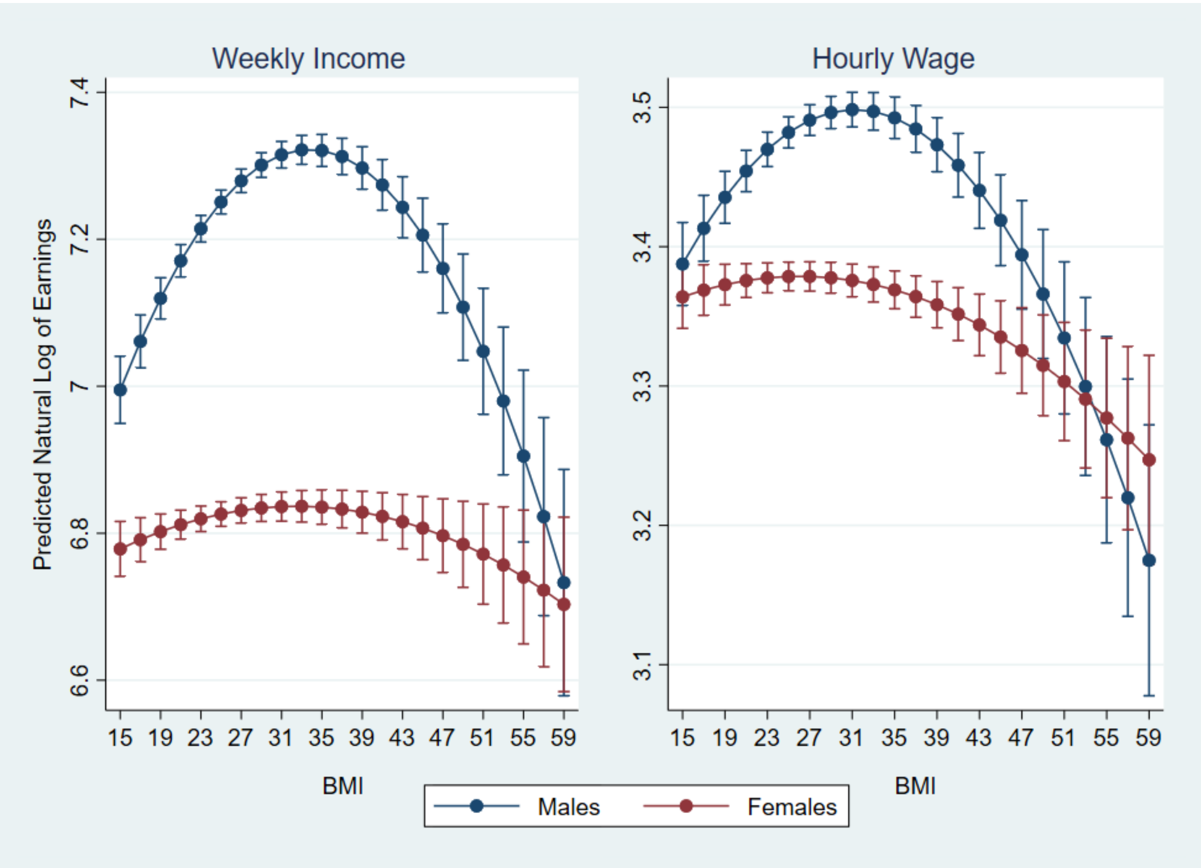


Figure 5.1 shows that in this specification men's earnings are more sensitive to BMI, than women's earnings are, due to the greater slopes. This model presents the penalty faced before accounting for any discrimination and acts as basis for comparison as we attempt to decompose the penalty and isolate the taste-based pay discrimination that our research focuses on.

Table 5.2: Results from decomposition models

	Income				Wage			
Equation:	4	5	6 (RE)	6 (FE)	4	5	6 (RE)	6 (FE)
BMI	0.0626*** (0.00553)	0.0341*** (0.00426)	0.0339*** (0.00427)	0.0278*** (0.00504)	0.0262*** (0.00351)	0.0303*** (0.00371)	0.0301*** (0.00371)	0.0228*** (0.00457)
BMI²	-0.000927*** (0.0000899)	-0.000543*** (0.0000698)	-0.000541*** (0.00007)	-0.000457*** (0.000080)	-0.000420*** (0.0000567)	-0.000475*** (0.0000599)	-0.000474*** (0.0000601)	-0.000366*** (0.000072)
Female	0.372*** (0.108)	0.192** (0.0818)	0.189** (0.0795)	-	0.208*** (0.0661)	0.224*** (0.0689)	0.218*** (0.0689)	-
BMI x Female	-0.0503*** (0.00708)	-0.0223*** (0.00533)	-0.0220*** (0.00533)	-0.0195*** (0.00628)	-0.0199*** (0.00439)	-0.0246*** (0.00461)	-0.0242*** (0.00461)	-0.0178*** (0.00564)
BMI² x Female	0.000737*** (0.000114)	0.000348*** (0.0000873)	0.000345*** (0.0000857)	0.000331*** (0.000099)	0.000299*** (0.0000711)	0.000363*** (0.0000750)	0.000359*** (0.0000751)	0.000283*** (0.0000886)
Dem Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Prod Controls	No	No	Yes	Yes	No	No	Yes	Yes
R^2	0.372	0.675	0.678	0.639	0.303	0.374	0.381	0.317
Observations	111,990	100,587	100,454	100,454	111,664	100,490	100,357	100,357

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Values rounded to three significant figures
RE = Random Effects / FE = Fixed Effects

Table 5.3: BMI values at which earnings are maximised

	Income				Wage			
Equation:	4	5	6 (RE)	6 (FE)	4	5	6 (RE)	6 (FE)
Males	33.8	31.4	31.3	30.4	31.2	31.9	31.8	31.1
Females	32.4	30.3	30.4	33.0	26.0	23.4	25.7	30.1

Our second model, Equation 5, further controls for job characteristics and allows us to estimate the penalty comparing workers in similar employment but allowing productivity to vary. This controls for discrimination at the hiring stage and represents the composite effect of justified and unjustified discrimination after employment is obtained. Comparing the coefficients of Equations 4 and 5, we see the inverted-U shape remains, as does the statistical evidence for gender differences, again women's earnings being less affected. Further, we see the coefficients have reduced in magnitude by approximately 50% for income, but for wages coefficients have slightly increased. This suggests some negative discrimination at the hiring stage affects incomes, and that around half of the previously established effect of BMI was due to this. For wages the story is more complex, it seems wages are penalised more due to BMI between workers in similar employment. Perhaps obese workers face greater wage penalties but work more hours to offset this. T-tests on working hours show obese workers work an average of two extra hours compared to healthy workers, and calculating how many more hours a person would like to work (actual hours – desired hours) we find obese workers desire 0.5 hours more than healthy workers do. Considering the turning points next, for income they have reduced by around two points, suggesting the penalty on income for workers in similar employment begins earlier but still in the obese group. For wages, women face the penalty in the healthy group, sooner than previously, while men face it slightly later than before. Again this suggests a complicated relation between discrimination at the hiring stage regarding wages rather than income.

Predicted earnings are again presented, in Figure 5.2 showing the disparity between men and women's incomes have reduced as the curve for men is low flatter. While for wages the predictions are similar to those in Equation 4.

Figure 5.4: Predicted Earnings (Equation 5)

Next we seek to control for productivity to decompose the penalty into justified (productivity-based) discrimination and unjustified (taste-based) discrimination. We do this in two stages, first by adding controls that aim to proxy the time varying determinants of productivity, and then by changing our estimation method from random-effects to fixed-effects to control for time-invariant determinants through the elimination of unobserved time-invariant heterogeneity.

Comparing the results of Equations 5 and 6 (RE), the coefficients are largely the same implying our proxies do not explain productivity-based discrimination against earnings. This has a number of potential explanations: productivity-based discrimination may not be based upon these specific determinants, these determinants may not proxy productivity well, or no productivity-based discrimination is occurring and all the remaining effect of BMI is due to taste-based discrimination. To address this last explanation, we can compare Equations 6 (RE) and 6 (FE).

The coefficients of BMI and the interaction with sex are now smaller, reducing by approximately 20-25%, when adopting the fixed-effects estimation methodology. This means around a quarter of the effect of BMI can be attributed to unobserved heterogeneity which is now being controlled for. We cannot attribute this reduction entirely to productivity, as we are now also controlling for other factors in u_i that determine earnings but not productivity. But assuming the determinants of productivity are within u_i we can conclude we have isolated taste-based discrimination.

We can therefore discuss the evidence our model presents on taste-based pay discrimination. Beginning with the turning points, for men their income and wages becomes penalised at the start of the obese group. While for women the penalty on their income begins later in the middle of the obese group, but on wages at the start of the obese category. For wages this marks a sudden delay of around 5 BMI points in the beginning of the penalty for women. To interpret the coefficients and measure the magnitude of discrimination we present the marginal effects of a one-point increase in BMI, at various levels, holding all the variables and other time-invariant heterogeneity constant, below in Table 5.4:

Table 5.4: Marginal effect of BMI due to discrimination (Equation 6 FE)

	Income		Wage	
Sex	Males	Females	Males	Females
BMI=30	+0.0380%	+0.0740%	+0.084%	+0.0020%
=32	-0.1448%	+0.0236%	-0.0624%	-0.0312%
=34	-0.3276%	-0.0268%	-0.2088%	-0.0644%
=36	-0.5104%	-0.0772%	-0.3552%	-0.0976%
=38	-0.6932%	-0.1276%	-0.5016%	-0.1308%

As the marginal effects for men are larger than for women, this implies men face greater discrimination due to BMI than women do. This goes against prior findings that suggest women face greater penalties due to greater stigmatisation or greater emphasis being placed on their appearance. The finding of an obesity penalty implies Australia is more similar in its penalty to America and Europe, than to Asia. Perhaps this can be explained by cultural similarities, for example both Australia and the United States began as British colonies, while this is not true of China or Korea – the nations mentioned in our literature review.

We can, as we did for the previous models, show the predicted earnings in Figure 5.3. We see men's earnings are again more sensitive to BMI than women's earnings are. The increased height of the confidence intervals can be attributed to our use of fixed-effects estimation which only uses the within variation of the data, compared to random-effects which uses both within and between variation, leading to a loss in efficiency.

Figure 5.5: Predicted Earnings (Equation 6 FE)

Our research question set out to investigate evidence of earning penalties from weight due to taste-based discrimination. We have found evidence that a higher BMI does reduce earnings after a BMI in the early 30s. Controlling for differences in employment and productivity explained some of this relationship but a penalty still exists, one that is stronger for males than for females, implying taste-based discrimination does occur in the Australian labour market.

Section 5.3: Robustness Checks

Having explored the findings of our model and producing an answer to our research question, we seek to investigate the sensitivity of our analysis by conducting two robustness checks as outlined in Section III: adjusting the threshold at which obesity is defined, and changing our key explanatory variable to a deviation from desired BMI. Full regression tables for this subsection available upon request.

First we shall adjust the obesity thresholds to account for measurement error, this requires altering our model from using a continuous BMI explanatory variable to a categorical variable with five groups, as defined in Section III. The standard threshold for obesity is a BMI of 30. As discussed in Section III, we shall test reducing this threshold by 0.5 points and 1 point. We use our final specification, for income only, to produce results under all three thresholds and compare the evidence for taste-based discrimination. We present a summary of the results below in table 5.5

Table 5.5: Results under varying obesity thresholds (Equation 6 FE)

Threshold:	$Obesity \geq 30$	$Obesity \geq 29.5$	$Obesity \geq 29$
Underweight	-0.0971*** (0.0279)	-0.0971*** (0.0279)	-0.0971*** (0.0279)
Healthy	Base group	.	.
Overweight	0.00557 (0.00600)	0.00570 (0.00600)	0.00551 (0.00603)
Obese	0.00400 (0.00838)	0.00366 (0.00819)	0.00309 (0.00795)
Severely obese	0.00800 (0.00771)	0.00772 (0.00769)	0.00856 (0.00765)
Under- x female	0.0636** (0.0323)	0.0637** (0.0323)	0.0638** (0.0323)
Healthy x female	Base group	.	.
Over- x female	-0.000447 (0.00862)	-0.000427 (0.00862)	-0.00149 (0.00866)
Obese x female	-0.0106 (0.0120)	-0.00976 (0.0118)	-0.00253 (0.0114)
Severely x female	-0.0138 (0.0107)	-0.0135 (0.0107)	-0.0129 (0.0106)

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Beginning with the results from the standard threshold, we have a significant penalty for being underweight, and premiums for all groups above a healthy weight, which are however insignificant. We also have no evidence of gender differences in this specification. Moving to the adjusted thresholds, coefficient become slightly smaller, implying smaller premiums but all remain insignificant. The most likely cause of this insignificance is the low rate of within variation in this variable. A fixed-effects estimator only uses the within variation in a variable, for a continuous BMI there was sufficient variation to produce precise results, but reducing this to a categorical variable lessens the variation that occurs among people over time. As such we are unable to draw any meaningful results from this test, as our regression specification requires more variation than our data provides for accurate testing of a dummy variable. Future research investigating the effect of measurement error on taste-based discrimination should investigate other ways of addressing the error that adjusts the individual BMIs reported to maintain a sufficient degree of within variation, or use an estimation method that is not dependent on this.

Next we remeasure our key explanatory variable to better reflect weight-related healthiness and/or adjust for gender or ethnic differences in healthy or preferred BMI. To do this we create a deviation variable. This is the difference between a person's actual BMI and their desired BMI, see Section III for more details. A negative value implies they would like to be heavier, while a positive value implies they would like to be lighter. For this analysis we restrict our data to the last five waves, around the 2019 wave where desired weight is measured. In table 5.6 we present results for equation three on the sub-sample, and this same model using deviation. We maintain the quadratic form as we assume high and low deviations represent underweight and overweight people who perhaps face discrimination, while small or zero values of deviation are those less likely to face a penalty due to being healthy.

Table 5.6: Deviation results on sub-sample (Equation 6 FE)

Measure (M):	BMI		Deviation	
	Income	Wage	Income	Wage
M	-0.0104	-0.00335	0.00307	0.00433**
	(0.00752)	(0.00622)	(0.00265)	(0.00212)
M^2	0.000182	0.0000529	0.000143	0.000238
	(0.000118)	(0.0000963)	(0.000189)	(0.000147)
M x female	0.00763	0.00133	-0.00617*	-0.00669**
	(0.00917)	(0.00782)	(0.00351)	(0.00296)
M^2 x female	-0.000131	-0.0000667	-0.0000866	-0.000169
	(0.000140)	(0.000118)	(0.000213)	(0.000170)

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We have some evidence of a wage effect of deviation, and some evidence of gender differences, but no evidence of a quadratic relationship. The wage model using deviation suggests men face a premium for having a BMI above their desired BMI (a positive deviation) and women face a penalty for this.

Our results are insignificant for both income models, and the wage model using BMI, which may have a number of explanations. Our prior results might have been driven by discrimination in the earlier part of our panel, and discrimination is no longer occurring after 2017 (the first year of our sub-sample). Running the model using BMI and restricting it to observations before 2017 produces significant results. As such this test may have revealed a new sensitivity, that of time; our findings may have discovered a feature of the Australian labour market that is no longer true. Alternatively, the restriction may be reducing the within variation available as discussed when we adjusted the obesity thresholds. However, restricting a model using BMI to a sample on the first five waves produces insignificant results, and on the middle five waves produces significant results. Future research should utilise modern data to examine which of these causes is true, whether discrimination has ended or whether we do not have enough data to precisely estimate the magnitude of discrimination.

It should be noted that using a random-effects model - which can utilise both between and within variation and thus avoid the losses in efficiency - on the 2017-21 subsample produces significant results. However random-effects does not control for time-invariant heterogeneity, so we are unable to establish if this significance is caused by improved efficiency or due to bias from these uncontrolled factors that likely correlate with BMI.

Before closing, we further attempted to adopt an instrumental variables approach to address any remaining endogeneity, using an instrument of average household BMI. However, upon testing we concluded our instrument was too weak, (with a Hausman test statistic of 6.32) and due large efficiency losses we decided not report these findings for reasons of length.

In conclusion to this section, we utilised a number of models to decompose the weight-wage penalty and found evidence in support of the existence of taste-based discrimination for both males and females, the latter of which face a smaller penalty. When analysing the robustness of our analysis we discovered a potential time sensitivity to our evidence for taste-based discrimination which requires follow up work to conclude if this is the result of efficiency losses or a changing labour market. Efficiency losses also plagued our attempts to correct for measurement error and remaining endogeneity. Future research should focus on data with enough variation to ensure precise results.

Section VI: Closing Remarks

In this paper we sought to assess the evidence for taste-based pay discrimination in the Australian labour market. To do this we utilised data from the HILDA panel survey and developed a wage equation model with BMI, a measure of obesity, as the key explanatory variable.

We first decomposed the penalty intuitively, that discrimination can occur at two stages: the hiring stage and after this during employment. At each point, discrimination can take two forms, justified discrimination that is based upon productivity, inferred or actual, and also unjustified discrimination based on employers' tastes. We then developed a model to isolate the unjustified discrimination after the hiring stage and estimated BMI to have a significant effect on earnings holding productivity, and other variables, constant, implying unjustified discrimination occurs, with a premium for healthy and overweight workers and a penalty for obese workers. Results varied by gender, both in the level of BMI at which the penalty begins and the magnitude of the penalty, with smaller penalties for women which goes against prior findings in other nations.

This paper was the first, to our knowledge, to study this phenomenon in Australia and our results suggest Australia shows greater similarity to western developed nations such the US and Europe, than it does to China and Korea where obesity premiums are more commonly found.

We attempted to correct for measurement error stemming from the self-reported nature of our BMI variable but a lack of within variation, prevented us producing significant results. We further analysed if discrimination was based on proximity to desired weight as a new measure. We found some evidence of this, however analysing the last five waves of data introduced a new sensitivity, that of time. The significance of our results varies depending on which 5-year subsample we examine. Whether this is due to lower precision from decreased sample sizes and within variation, or if discrimination has only occurred in certain years is for future work to analyse.

Future researchers might investigate why Australia shows a different pattern of gender differences than other countries with similar penalties. An investigation ethnic differences in the penalty may be warranted, which requires data on ethnicity which we lacked. They may further examine the time sensitivity of the evidence for unjustified discrimination. Improvements can also be made by adopting a medically assessed BMI to prevent measurement error, and collect improved measures of productivity to further ensure productivity is being controlled for and also to lessen the requirement of fixed-effects estimation so a more precise estimator, such as random-effects, can be used.

Regarding policy, as some of the penalty can be explained by differences in productivity, training programs focused on obese workers could be useful in addressing the penalty. The remaining penalty due to unjustified discrimination perhaps calls for regulation, to address conscious discrimination, or education, if this discrimination stems from an unconscious bias.

Section VII: Bibliography

Alauddin Majumder, M. (2013). Does obesity matter for wages? Evidence from the United States. *Economic Papers: A journal of applied economics and policy*, 32(2), 200-217.

Asirvatham, J., Thomsen, M. R., & Nayga Jr, R. M. (2019). Childhood obesity and academic performance among elementary public school children. *Educational Research*, 61(1), 1-21.

Arai, M. (1994). Compensating wage differentials versus efficiency wages: an empirical study of job autonomy and wages. *Industrial Relations: A Journal of Economy and Society*, 33(2), 249-262.

Australian Bureau of Statistics (2014) *'Average Weekly Earnings, Australia, Nov 2014'* ABS.gov. Available at: https://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/6302.0Main+Features1Nov%202014?OpenDocument= [Accessed 12 July 2023]

Australian Bureau of Statistics (2018) *'Overweight and obesity'* ABS.gov. Available at: https://www.abs.gov.au/statistics/health/health-conditions-and-risks/overweight-and-obesity/latest-release [Accessed 12 July 2023]

Australian Bureau of Statistics (2020) *'Insights into hours worked''* ABS.gov. Available at: https://www.abs.gov.au/articles/insights-hours-worked#where-to-find-hours-worked-data [Accessed 12 July 2023]

Australian Bureau of Statistics (2021) *'30% of Australia's population born overseas'* ABS.gov. Available at: https://www.abs.gov.au/media-centre/media-releases/30-australias-population-born-overseas [Accessed 12 July 2023]

Australian Bureau of Statistics. (2022). Population distribution in Australia in 2021, by state. Statista. Statista Inc.. Accessed: August 07, 2023. https://www.statista.com/statistics/608819/australia-population-distribution-by-state/

Averett, S. and Korenman, S. (1996). The Economic Reality of the Beauty Myth*, Journal of Human Resources*, 31, 304-330.

Averett, S. L. (2019). Obesity and labor market outcomes. *IZA World of Labor*.

Bagully, M. (2006). The impact of childhood obesity on academic performance (Doctoral dissertation).

Baum, C. L., & Ford, W. F. (2004). The wage effects of obesity: a longitudinal study. *Health economics*, 13(9), 885-899.

Bozoyan, C., & Wolbring, T. (2018). The weight wage penalty: a mechanism approach to discrimination. *European Sociological Review*, 34(3), 254-267.

Brunello, G., & d'Hombres, B. (2007). Does body weight affect wages?: Evidence from Europe. *Economics & Human Biology*, 5(1), 1-19.

Caliendo, M., & Lee, W. S. (2013). Fat chance! Obesity and the transition from unemployment to employment. *Economics & Human Biology*, 11(2), 121-133.

Campos-Vazquez, R. M., & Gonzalez, E. (2020). Obesity and hiring discrimination. *Economics & Human Biology*, 37, 100850.

Cawley, J. (2000). Body weight and women's labor market outcomes.

Cawley, J. (2003). What explains race and gender differences in the relationship between obesity and wages?. *Gender Issues*, 21(3), 30-49.

Cawley, J. (2004). The impact of obesity on wages. *Journal of Human resources*, 39(2), 451-474.

Charles, A., & Williams, D. R. (1990). Wage effects of obesity among young workers. *Social Science Quarterly,* 71(1), 130-41.

Dauphinot, V., Wolff, H., Naudin, F., Gueguen, R., Sermet, C., Gaspoz, J. M., & Kossovsky, M. P. (2009). New obesity body mass index threshold for self-reported data. *Journal of Epidemiology & Community Health*, 63(2), 128-132.

Davillas, A.(1) and Jones, A.M.(2,3) (2021) 'The implications of self-reported body weight and height for measurement error in BMI', *Economics Letters*, 209. doi:10.1016/j.econlet.2021.110101.

Hattori, A., & Sturm, R. (2013). The obesity epidemic and changes in self-report biases in BMI. *Obesity*, 21(4), 856-860.

DeBeaumont, R. (2009). Occupational differences in the wage penalty for obese women. *The Journal of Socio-Economics,* 38(2), 344-349.

Dou, J., Du, L., Wang, K., Sun, H., & Zhang, C. (2020). Wage Penalties or Wage Premiums? A Socioeconomic Analysis of Gender Disparity in Obesity in Urban China. I*nternational Journal of Environmental Research and Public Health*, 17(19), 7004.

Fidrmuc, J., & Paphawasit, B. (2018). Beautiful minds: Physical attractiveness and research productivity in economics. In 2nd *IZA/HSE Workshop*, Moscow.

Fletcher, J. M. (2014). The interplay between gender, race and weight status: Self perceptions and social consequences. *Economics & Human Biology*, *14*, 79-91.

Gates, D. M., Succop, P., Brehm, B. J., Gillespie, G. L., & Sommers, B. D. (2008). Obesity and presenteeism: the impact of body mass index on workplace productivity. *Journal of occupational and environmental medicine*, 39-45.

Goetzel, R. Z., Gibson, T. B., Short, M. E., Chu, B. C., Waddell, J., Bowen, J., ... & DeJoy, D. M. (2010). A multi-worksite analysis of the relationships among body mass index, medical utilization, and worker productivity. *Journal of occupational and environmental medicine*, S52-S58.

Gosse, M. A. (2014). How accurate is self-reported BMI?. *Nutrition bulletin*, 39(1), 105-114.

Gregory, C. A., & Ruhm, C. J. (2009). Where does the wage penalty bite? (No. w14984). *National Bureau of Economic Research.*

Greve, J. (2008). Obesity and labor market outcomes in Denmark. *Economics & Human Biology*, 6(3), 350-362.

Grimani, A., Aboagye, E., & Kwak, L. (2019). The effectiveness of workplace nutrition and physical activity interventions in improving productivity, work performance and workability: a systematic review. *BMC public health,* 19, 1-12.

Gvozdenodic, V. (2013). Beauty and wages: The effect of physical attractiveness on income using longitudinal data.

Hammer, C. (2017). A look into lookism: an evaluation of discrimination based on physical attractiveness.

Han, E., Norton, E. C., & Stearns, S. C. (2009). Weight and wages: fat versus lean paychecks. *Health economics,* 18(5), 535-548.

Härkönen, J., Räsänen, P., & Näsi, M. (2011). Obesity, unemployment, and earnings. Nordic Journal of working life studies, 1(2), 23-38.

Nault, K. A., Pitesa, M., & Thau, S. (2020). The attractiveness advantage at work: A cross-disciplinary integrative review. Academy of Management Annals, 14(2), 1103-1139.

Kaczorowski, J. (1998). Physical attractiveness and economic success.

Katz, L. F. (1986). Efficiency wage theories: A partial evaluation. NBER macroeconomics annual, 1, 235-276.

Kernper, K. A., Sargent, R. G., Drane, J. W., Valois, R. E., & Hussey, J. R. (1994). Black and white females' perceptions of ideal body size and social norms. Obesity research, 2(2), 117-126.

Kim, T. J., & von dem Knesebeck, O. (2018). Income and obesity: what is the direction of the relationship? A systematic review and meta-analysis. BMJ open, 8(1), e019862.

Komlos, J., Smith, P. K., & Bogin, B. (2004). Obesity and the rate of time preference: is there a connection?. Journal of biosocial science, 36(2), 209-219.

Lee, H., Ahn, R., Kim, T. H., & Han, E. (2019). Impact of obesity on employment and wages among young adults: observational study with panel data. *International journal of environmental research and public health,* 16(1), 139.

Liu, X., & Sierminska, E. (2014). Evaluating the Effect of Beauty on Labor Market Outcomes: A Review of the Literature. Luxembourg Institute of Socio-Economic Research (LISER) Working Paper Series, 11.

Love, P., Whelan, J., Bell, C., Grainger, F., Russell, C., Lewis, M., & Lee, A. (2018). Healthy diets in rural Victoria—cheaper than unhealthy alternatives, yet unaffordable. International journal of environmental research and public health, 15(11), 2469.

Lim, L. L., Seubsman, S. A., & Sleigh, A. (2009). Validity of self-reported weight, height, and body mass index among university students in Thailand: Implications for population studies of obesity in developing countries. Population Health Metrics, 7, 1-8.

Maralani, V., & McKee, D. (2017). Obesity is in the eye of the beholder: BMI and socioeconomic outcomes across cohorts. Sociological Science, 4, 288-317.

Maranto, C. L., & Stenoien, A. F. (2000). Weight discrimination: A multidisciplinary analysis. *Employee Responsibilities and Rights Journal*, 12, 9-24.

Mocan, N., & Tekin, E. (2011). Obesity, self-esteem and wages. *In Economic aspects of obesity* (pp. 349-380). University of Chicago Press.

Mobius, M. M., & Rosenblat, T. S. (2006). Why beauty matters. American Economic Review, 96(1), 222-235.

Pereira, M. J., Coombes, B. K., Comans, T. A., & Johnston, V. (2015). The impact of onsite workplace health-enhancing physical activity interventions on worker productivity: a systematic review. *Occupational and Environmental Medicine,* 72(6), 401-412.

Poran, M. A. (2002). Denying diversity: Perceptions of beauty and social comparison processes among Latina, Black, and White women. *Sex roles*, 47, 65-81.

Puhl, R. M., & Heuer, C. A. (2009). The stigma of obesity: a review and update. *Obesity*, 17(5), 941.

Ramaswamy, R., & Rowthorn, R. E. (1991). Efficiency wages and wage dispersion. *Economica,* 501-514.

Renzaho, A. M. (2023). The Lack of Race and Ethnicity Data in Australia—A Threat to Achieving Health Equity. *International Journal of Environmental Research and Public Health*, 20(8), 5530.

Reece, R. L. (2019). Coloring weight stigma: on race, colorism, weight stigma, and the failure of additive intersectionality. *Sociology of Race and Ethnicity*, 5(3), 388-400.

Rodbard, H. W., Fox, K. M., & Grandy, S. (2009). Impact of obesity on work productivity and role disability in individuals with and at risk for diabetes mellitus. *American Journal of Health Promotion*, 23(5), 353-360.

Roehling, M. V., Pilcher, S., Oswald, F., & Bruce, T. (2008). The effects of weight bias on job-related outcomes: a meta-analysis of experimental studies. *In Academy of Management Annual Meeting, Anahiem, CA*.

Rooth, D. O. (2009). Obesity, attractiveness, and differential treatment in hiring a field experiment. *Journal of human resources,* 44(3), 710-735.

Rust, R. T., Ambler, T., Carpenter, G. S., Kumar, V., & Srivastava, R. K. (2004). Measuring marketing productivity: Current knowledge and future directions. *Journal of marketing*, 68(4), 76-89.

Santana, C. C. A., Hill, J. O., Azevedo, L. B., Gunnarsdottir, T., & Prado, W. L. (2017). The association between obesity and academic performance in youth: a systematic review. *Obesity Reviews*, 18(10), 1191-1199.

Saporta, I., & Halpern, J. J. (2002). Being different can hurt: Effects of deviation from physical norms on lawyers' salaries. *Industrial Relations: A Journal of Economy and Society*, 41(3), 442-466.

Shinall, J. B. (2015). Occupational characteristics and the obesity wage penalty. *Vanderbilt Law and Economics Research Paper,* (16-12), 16-23.

Schainblatt, A. H. (1982). How companies measure the productivity of engineers and scientists. *Research Management,* 25(3), 10-18.

Slade, P. (2017). Body mass and wages: New evidence from quantile estimation. *Economics & Human Biology,* 27, 223-240.

Stinebrickner, R., Stinebrickner, T., & Sullivan, P. (2019). Beauty, job tasks, and wages: A new conclusion about employer taste-based discrimination. *Review of Economics and Statistics*, 101(4), 602-615.

Tangen, S. (2005). Demystifying productivity and performance. *International Journal of Productivity and performance management,* 54(1), 34-46.

Tsai, S. P., Ahmed, F. S., Wendt, J. K., Bhojani, F., & Donnelly, R. P. (2008). The impact of obesity on illness absence and productivity in an industrial population of petrochemical workers. *Annals of epidemiology*, 18(1), 8-14.

Teague, J., & Eilon, S. (1973). Productivity measurement: a brief survey. *Applied Economics*, 5(2), 133-145.

United Nations. (2022). Australia: Average age of the population from 1950 to 2100 (median age in years). Statista. Statista Inc.. Accessed: August 07, 2023. https://www.statista.com/statistics/260493/median-age-of-the-population-in-australia/

Ward, P. R., Verity, F., Carter, P., Tsourtos, G., Coveney, J., & Wong, K. C. (2013). Food stress in Adelaide: the relationship between low income and the affordability of healthy food. *Journal of environmental and public health*

Wu, N., Chen, Y., Yang, J., & Li, F. (2017). Childhood obesity and academic performance: the role of working memory. *Frontiers in psychology*, 8, 611.

Section VIII: Appendix

Appendix A: Industry & Occupation Summary Statistics

Table A1: Industry Summary Statistics

Industry:	Mean	Standard Deviation	Min	Max
Agriculture	.0236792	.1520482	0	1
Aquaculture	.0001979	.0140655	0	1
Forestry and Logging	.0006761	.0259928	0	1
Fishing, Hunting and Trapping	.0004452	.0210957	0	1
Agriculture, Forestry and Fishing Support Services	.0026136	.0510569	0	1
Coal Mining	.0063073	.079168	0	1
Oil and Gas Extraction	.0014346	.0378491	0	1
Metal Ore Mining	.0065959	.080947	0	1
Non-Metallic Mineral Mining and Quarrying	.0009482	.0307777	0	1
Exploration and Other Mining Support Services	.0018963	.0435055	0	1
Food Product Manufacturing	.0143213	.118812	0	1
Beverage and Tobacco Product Manufacturing	.003603	.059917	0	1
Textile, Leather, Clothing and Footwear Manufacturing	.0033804	.058043	0	1
Wood Product Manufacturing	.0039823	.0629796	0	1
Pulp, Paper and Converted Paper Product Manufacturing	.0017562	.0418698	0	1
Printing (including the Reproduction of Recorded Media)	.0030753	.0553705	0	1
Petroleum and Coal Product Manufacturing	.0008904	.0298271	0	1
Basic Chemical and Chemical Product Manufacturing	.004782	.0689868	0	1
Polymer Product and Rubber Product Manufacturing	.0026961	.0518538	0	1
Non-Metallic Mineral Product Manufacturing	.0032402	.0568309	0	1
Primary Metal and Metal Product Manufacturing	.0033474	.0577601	0	1
Fabricated Metal Product Manufacturing	.0080057	.0891163	0	1
Transport Equipment Manufacturing	.0070658	.0837613	0	1
Machinery and Equipment Manufacturing	.0093661	.0963249	0	1
Furniture and Other Manufacturing	.004848	.0694586	0	1
Electricity Supply	.0050541	.0709125	0	1
Gas Supply	.0003463	.0186055	0	1
Water Supply, Sewerage and Drainage Services	.0019293	.0438815	0	1
Waste Collection, Treatment and Disposal Services	.0030671	.0552965	0	1
Building Construction	.0137854	.1165995	0	1
Heavy and Civil Engineering Construction	.0120127	.1089427	0	1
Construction Services	.0544407	.2268861	0	1
Basic Material Wholesaling	.0067773	.082045	0	1
Machinery and Equipment Wholesaling	.0082778	.0906055	0	1
Motor Vehicle and Motor Vehicle Parts Wholesaling	.0022096	.0469548	0	1
Grocery, Liquor and Tobacco Product Wholesaling	.0049551	.0702185	0	1
Other Goods Wholesaling	.0057384	.0755349	0	1
Commission-Based Wholesaling	.0021931	.0467796	0	1
Motor Vehicle and Motor Vehicle Parts Retailing	.0065629	.0807457	0	1
Fuel Retailing	.0022921	.0478208	0	1
Food Retailing	.0274883	.163502	0	1
Other Store-Based Retailing	.053105	.2242438	0	1
Non-Store Retailing and Retail Commission-Based Buying and/or Selling	.0034216	.0583946	0	1
Accommodation	.0097124	.0980723	0	1
Food and Beverage Services	.0471193	.2118948	0	1
Road Transport	.0157889	.1246584	0	1
Rail Transport	.002457	.049507	0	1

Water Transport	.0012862	.0358406	0	1
Air and Space Transport	.0023745	.0486713	0	1
Other Transport	.0008327	.0288451	0	1
Postal and Courier Pick-up and Delivery Services	.0077089	.0874618	0	1
Transport Support Services	.0070906	.0839068	0	1
Warehousing and Storage Services	.0054746	.0737879	0	1
Publishing (except Internet and Music Publishing)	.0033804	.058043	0	1
Motion Picture and Sound Recording Activities	.0029187	.0539461	0	1
Broadcasting (except Internet)	.0016572	.0406753	0	1
Internet Publishing and Broadcasting	.0004947	.0222362	0	1
Telecommunications Services	.0051942	.071884	0	1
Internet Service Providers, Web Search Portals and Data Processing Services	.001583	.0397557	0	1
Library and Other Information Services	.0019705	.0443469	0	1
Finance	.0164402	.1271616	0	1
Insurance and Superannuation Funds	.0084345	.0914516	0	1
Auxiliary Finance and Insurance Services	.0097454	.098237	0	1
Rental and Hiring Services (except Real Estate)	.0030506	.0551481	0	1
Property Operators and Real Estate Services	.0112872	.1056403	0	1
Professional, Scientific and Technical Services (Except Computer System Design and Related	.06553	.2474597	0	1
Computer System Design and Related Services	.0156487	.1241126	0	1
Administrative Services	.0149644	.1214108	0	1
Building Cleaning, Pest Control and Other Support Services	.0157064	.1243377	0	1
Public Administration	.0417106	.199928	0	1
Defence	.007915	.0886141	0	1
Public Order, Safety and Regulatory Services	.0211645	.1439331	0	1
Preschool and School Education	.0716064	.2578362	0	1
Tertiary Education	.0247098	.1552398	0	1
Adult, Community and Other Education	.012425	.1107732	0	1
Hospitals	.0437059	.2044408	0	1
Medical and Other Health Care Services	.040746	.197702	0	1
Residential Care Services	.020777	.1426376	0	1
Social Assistance Services	.046402	.2103549	0	1
Heritage Activities	.0027455	.0523261	0	1
Creative and Performing Arts Activities	.0042708	.0652121	0	1
Sports and Recreation Activities	.0098856	.0989339	0	1
Gambling Activities	.0020035	.0447158	0	1
Repair and Maintenance	.0184849	.1346974	0	1
Personal and Other Services	.0197299	.1390712	0	1
Private Households Employing Staff and Undifferentiated Goods- and Service-Producing Activities	.0010553	.032469	0	1

Table A2: Occupation Summary Statistics

Occupation:	Mean	Standard Deviation	Min	Max
Managers	.0003867	.019662	0	1
Chief Executives, General Managers and Legislators	.0086533	.0926203	0	1
Farmers and Farm Managers	.0150104	.1215944	0	1
Specialist Managers	.0787341	.2693243	0	1
Hospitality, Retail and Service Managers	.0371272	.1890741	0	1
Professionals	.001555	.0394033	0	1
Arts and Media Professionals	.0089998	.0944397	0	1
Business, Human Resource and Marketing Professionals	.0574955	.2327879	0	1
Design, Engineering, Science and Transport Professionals	.0342266	.1818115	0	1
Education Professionals	.0618061	.240804	0	1
Health Professionals	.0490678	.2160105	0	1
ICT Professionals	.0188697	.1360655	0	1
Legal, Social and Welfare Professionals	.0260164	.1591847	0	1
Technicians and Trades Workers	.0007654	.0276558	0	1
Engineering, ICT and Science Technicians	.02314	.1503487	0	1
Automotive and Engineering Trades Workers	.0264273	.160403	0	1
Construction Trades Workers	.023978	.1529811	0	1
Electrotechnology and Telecommunications Trades Workers	.0185475	.1349207	0	1
Food Trades Workers	.0095316	.0971637	0	1
Skilled Animal and Horticultural Workers	.0107724	.1032298	0	1
Other Technicians and Trades Workers	.0148895	.1211113	0	1
Health and Welfare Support Workers	.0184991	.1347481	0	1
Carers and Aides	.0451923	.2077266	0	1
Hospitality Workers	.0198688	.1395501	0	1
Protective Service Workers	.0139307	.117204	0	1
Sports and Personal Service Workers	.0162431	.1264097	0	1
Clerical and Administrative Workers	.0002981	.0172634	0	1
Office Managers and Program Administrators	.022294	.1476387	0	1
Personal Assistants and Secretaries	.0092254	.0956052	0	1
General Clerical Workers	.019329	.1376791	0	1
Inquiry Clerks and Receptionists	.0231884	.150502	0	1
Numerical Clerks	.0296663	.1696656	0	1
Clerical and Office Support Workers	.0082424	.0904132	0	1
Other Clerical and Administrative Workers	.0279743	.1648998	0	1
Sales Workers	.0001611	.0126932	0	1
Sales Representatives and Agents	.0131411	.1138796	0	1
Sales Assistants and Salespersons	.0547561	.2275045	0	1
Sales Support Workers	.0131009	.1137072	0	1
Machinery Operators and Drivers	.0014664	.0382656	0	1
Machine and Stationary Plant Operators	.0124724	.1109817	0	1
Mobile Plant Operators	.0123354	.1103783	0	1
Road and Rail Drivers	.0238007	.1524284	0	1
Storepersons	.007622	.0869712	0	1
Labourers	.000564	.023742	0	1
Cleaners and Laundry Workers	.018201	.1336783	0	1
Construction and Mining Labourers	.0106273	.1025401	0	1
Factory Process Workers	.012553	.1113351	0	1
Farm, Forestry and Garden Workers	.0090804	.0948577	0	1
Food Preparation Assistants	.0108771	.103725	0	1
Other Labourers	.0192887	.1375384	0	1

Appendix B: Full Regression Outputs

Table B1: Regression output of Equations 4 & 5

Equation:	(4) the natural logarithm of weekly income	(5) natural logarithm of hourly wage	(4) the natural logarithm of weekly income	(5) natural logarithm of hourly wage
BMI_{t-1}	0.0626***	0.0262***	0.0341***	0.0303***
	(0.00553)	(0.00351)	(0.00426)	(0.00371)
BMI_{t-1}^2	-0.000927***	-0.000420***	-0.000543***	-0.000475***
	(0.0000899)	(0.0000567)	(0.0000698)	(0.0000599)
Female	0.372***	0.208***	0.192**	0.224***
	(0.108)	(0.0661)	(0.0795)	(0.0689)
Female x BMI_{t-1}	-0.0503***	-0.0199***	-0.0223***	-0.0246***
	(0.00708)	(0.00439)	(0.00533)	(0.00461)
Female x BMI_{t-1}^2	0.000737***	0.000299***	0.000348***	0.000363***
	(0.000114)	(0.0000711)	(0.0000873)	(0.0000750)
New South Wales	0	0	0	0
	(.)	(.)	(.)	(.)
Victoria	-0.0711***	-0.0341***	-0.0487***	-0.0435***
	(0.0130)	(0.00798)	(0.00869)	(0.00774)
Queensland	-0.0253*	-0.0410***	-0.0310***	-0.0409***
	(0.0141)	(0.00843)	(0.00906)	(0.00794)
Southern Australia	-0.0762***	-0.0428***	-0.0388***	-0.0459***
	(0.0207)	(0.0117)	(0.0124)	(0.0111)
Western Australia	0.0379*	0.0333***	0.0148	0.0245**
	(0.0207)	(0.0120)	(0.0124)	(0.0113)
Tasmania	-0.102***	-0.0800***	-0.0659***	-0.0820***
	(0.0284)	(0.0156)	(0.0176)	(0.0146)
Northern Territory	0.190***	0.0443*	0.0505*	0.0647**
	(0.0376)	(0.0259)	(0.0291)	(0.0256)
Australian Capital Territory	0.103***	0.0508***	0.0465**	0.0413***
	(0.0268)	(0.0169)	(0.0182)	(0.0159)
Legally married	0	0	0	0
	(.)	(.)	(.)	(.)
Living with Partner	0.122***	-0.0188***	0.0332***	0.00780
	(0.00859)	(0.00561)	(0.00614)	(0.00550)
Separated	0.0311**	-0.0264***	-0.00927	-0.0167*
	(0.0135)	(0.00915)	(0.0105)	(0.00933)
Divorced	0.0635***	-0.0440***	-0.0101	-0.0248**
	(0.0147)	(0.00997)	(0.0110)	(0.00997)

Widowed	-0.00366	-0.0583*	-0.0471	-0.0325
	(0.0470)	(0.0304)	(0.0319)	(0.0283)
Single	-0.0183	-0.0841***	-0.0572***	-0.0642***
	(0.0115)	(0.00695)	(0.00776)	(0.00684)
Age	0.122***	0.0465***	0.0658***	0.0522***
	(0.00204)	(0.00133)	(0.00148)	(0.00134)
Age^2	-0.00134***	-0.000477***	-0.000699***	-0.000546***
	(0.0000242)	(0.0000162)	(0.0000177)	(0.0000161)
Postgrad - masters or doctorate	0	0	0	0
	(.)	(.)	(.)	(.)
Grad diploma, grad certificate	-0.159***	-0.0503***	-0.0777***	-0.0562***
	(0.0237)	(0.0154)	(0.0159)	(0.0143)
Bachelor or honours	-0.122***	-0.0987***	-0.0981***	-0.106***
	(0.0215)	(0.0123)	(0.0130)	(0.0115)
Adv diploma, diploma	-0.459***	-0.216***	-0.244***	-0.216***
	(0.0249)	(0.0142)	(0.0152)	(0.0136)
Cert III or IV	-0.572***	-0.290***	-0.311***	-0.275***
	(0.0231)	(0.0129)	(0.0145)	(0.0126)
Year 12	-0.556***	-0.268***	-0.260***	-0.260***
	(0.0232)	(0.0129)	(0.0144)	(0.0126)
Year 11 and below	-1.108***	-0.451***	-0.599***	-0.454***
	(0.0250)	(0.0136)	(0.0164)	(0.0137)
Undetermined	-2.648***	-1.536**	-1.870***	-1.643***
	(0.236)	(0.686)	(0.296)	(0.553)
Australia	0	0	0	0
	(.)	(.)	(.)	(.)
United Kingdom	-0.0386	0.0231	0.00712	0.00797
	(0.0250)	(0.0170)	(0.0169)	(0.0162)
New Zealand	0.118***	0.0477***	0.0539***	0.0458***
	(0.0274)	(0.0184)	(0.0185)	(0.0170)
Oceania	-0.0463	-0.0410	-0.0221	-0.0300
	(0.0453)	(0.0285)	(0.0300)	(0.0273)
Europe	-0.0718**	-0.00770	-0.0247	-0.0183
	(0.0321)	(0.0220)	(0.0231)	(0.0210)
Asia	-0.228***	-0.108***	-0.0985***	-0.106***
	(0.0201)	(0.0136)	(0.0142)	(0.0131)
Africa	-0.0701*	-0.0149	-0.0372	-0.0306
	(0.0396)	(0.0269)	(0.0285)	(0.0274)
The Americas	-0.191***	-0.00307	-0.0782***	-0.0507*

	(0.0391)	(0.0287)	(0.0292)	(0.0282)
Socio-economic background	0.00460***	0.00798***	0.00480***	0.00661***
	(0.00126)	(0.000824)	(0.000919)	(0.000813)
Wave 2	0	0	0	0
	(.)	(.)	(.)	(.)
Wave 3	0.0482***	0.0497***	0.0471***	0.0445***
	(0.00678)	(0.00581)	(0.00600)	(0.00565)
Wave 4	0.0719***	0.0947***	0.0872***	0.0885***
	(0.00747)	(0.00604)	(0.00650)	(0.00601)
Wave 5	0.115***	0.140***	0.125***	0.127***
	(0.00785)	(0.00628)	(0.00674)	(0.00620)
Wave 6	0.152***	0.180***	0.165***	0.164***
	(0.00800)	(0.00643)	(0.00682)	(0.00635)
Wave 7	0.183***	0.214***	0.200***	0.199***
	(0.00813)	(0.00633)	(0.00671)	(0.00620)
Wave 8	0.195***	0.235***	0.222***	0.223***
	(0.00828)	(0.00637)	(0.00678)	(0.00625)
Wave 9	0.208***	0.257***	0.238***	0.239***
	(0.00848)	(0.00635)	(0.00692)	(0.00627)
Wave 10	0.236***	0.279***	0.268***	0.265***
	(0.00871)	(0.00649)	(0.00704)	(0.00640)
Wave 11	0.266***	0.310***	0.301***	0.295***
	(0.00877)	(0.00657)	(0.00698)	(0.00639)
Wave 12	0.299***	0.335***	0.327***	0.320***
	(0.00896)	(0.00664)	(0.00708)	(0.00648)
Wave 13	0.340***	0.367***	0.361***	0.351***
	(0.00908)	(0.00680)	(0.00726)	(0.00668)
Wave 14	0.380***	0.408***	0.399***	0.388***
	(0.00926)	(0.00682)	(0.00723)	(0.00662)
Wave 15	0.411***	0.458***	0.462***	0.435***
	(0.00940)	(0.00703)	(0.00745)	(0.00687)
Wave 16	0.462***	0.483***	0.485***	0.465***
	(0.00966)	(0.00701)	(0.00749)	(0.00686)
Occupation			-0.00203***	-0.00207***
			(0.000119)	(0.000106)
Agriculture			0	0
			(.)	(.)
Aquaculture			0.103	0.0556
			(0.169)	(0.173)

Forestry and Logging	0.173***	0.141***
	(0.0557)	(0.0424)
Fishing, Hunting and Trapping	-0.110	0.0744
	(0.171)	(0.124)
Agriculture, Forestry and Fishing Support Services	0.159***	0.114***
	(0.0446)	(0.0437)
Coal Mining	0.473***	0.486***
	(0.0385)	(0.0334)
Oil and Gas Extraction	0.401***	0.481***
	(0.0495)	(0.0456)
Metal Ore Mining	0.339***	0.457***
	(0.0378)	(0.0326)
Non-Metallic Mineral Mining and Quarrying	0.239***	0.251***
	(0.0466)	(0.0488)
Exploration and Other Mining Support Services	0.380***	0.447***
	(0.0420)	(0.0388)
Food Product Manufacturing	0.163***	0.144***
	(0.0293)	(0.0264)
Beverage and Tobacco Product Manufacturing	0.111**	0.0950**
	(0.0505)	(0.0463)
Textile, Leather, Clothing and Footwear Manufacturing	0.0842	0.0389
	(0.0582)	(0.0552)
Wood Product Manufacturing	0.136***	0.0818**
	(0.0355)	(0.0337)
Pulp, Paper and Converted Paper Product Manufacturing	0.278***	0.222***
	(0.0539)	(0.0503)
Printing (including the Reproduction of Recorded Media)	0.185***	0.160***
	(0.0392)	(0.0356)
Petroleum and Coal Product Manufacturing	0.392***	0.395***
	(0.0552)	(0.0494)

Basic Chemical and Chemical Product Manufacturing	0.276***	0.231***
	(0.0365)	(0.0334)
Polymer Product and Rubber Product Manufacturing	0.186***	0.175***
	(0.0397)	(0.0329)
Non-Metallic Mineral Product Manufacturing	0.189***	0.152***
	(0.0405)	(0.0363)
Primary Metal and Metal Product Manufacturing	0.274***	0.261***
	(0.0351)	(0.0325)
Fabricated Metal Product Manufacturing	0.192***	0.147***
	(0.0296)	(0.0284)
Transport Equipment Manufacturing	0.213***	0.175***
	(0.0308)	(0.0284)
Machinery and Equipment Manufacturing	0.214***	0.180***
	(0.0274)	(0.0250)
Furniture and Other Manufacturing	0.0467	0.00733
	(0.0380)	(0.0363)
Electricity Supply	0.405***	0.378***
	(0.0396)	(0.0368)
Gas Supply	0.283***	0.255***
	(0.0935)	(0.0893)
Water Supply, Sewerage and Drainage Services	0.399***	0.348***
	(0.0410)	(0.0389)
Waste Collection, Treatment and Disposal Services	0.186***	0.175***
	(0.0414)	(0.0355)
Building Construction	0.203***	0.181***
	(0.0289)	(0.0262)
Heavy and Civil Engineering Construction	0.301***	0.314***
	(0.0285)	(0.0265)

Construction Services	0.186***	0.142***
	(0.0262)	(0.0238)
Basic Material Wholesaling	0.144***	0.127***
	(0.0286)	(0.0254)
Machinery and Equipment Wholesaling	0.198***	0.166***
	(0.0300)	(0.0275)
Motor Vehicle and Motor Vehicle Parts Wholesaling	0.167***	0.128***
	(0.0328)	(0.0293)
Grocery, Liquor and Tobacco Product Wholesaling	0.177***	0.137***
	(0.0342)	(0.0304)
Other Goods Wholesaling	0.161***	0.132***
	(0.0289)	(0.0264)
Commission-Based Wholesaling	0.136***	0.116**
	(0.0467)	(0.0464)
Motor Vehicle and Motor Vehicle Parts Retailing	0.130***	0.103***
	(0.0344)	(0.0310)
Fuel Retailing	0.0393	0.0249
	(0.0459)	(0.0384)
[Food Retailing	0.0328	0.0406*
	(0.0276)	(0.0243)
Other Store-Based Retailing	0.0313	0.0264
	(0.0261)	(0.0233)
Non-Store Retailing and Retail Commission-Based Buying and/or Selling	-0.000628	0.00538
	(0.0496)	(0.0436)
Accommodation	-0.0203	-0.0111
	(0.0353)	(0.0314)
Food and Beverage Services	-0.0752***	-0.0554**
	(0.0264)	(0.0234)
Road Transport	0.129***	0.154***

	(0.0296)	(0.0269)
Rail Transport	0.364^{***}	0.340^{***}
	(0.0371)	(0.0363)
Water Transport	0.313^{***}	0.371^{***}
	(0.0807)	(0.0692)
Air and Space Transport	0.313^{***}	0.296^{***}
	(0.0562)	(0.0513)
Other Transport	0.160^{**}	0.155^{***}
	(0.0667)	(0.0591)
Postal and Courier Pick-up and Delivery Services	0.0546	0.0862^{***}
	(0.0395)	(0.0334)
Transport Support Services	0.256^{***}	0.250^{***}
	(0.0303)	(0.0280)
Warehousing and Storage Services	0.214^{***}	0.157^{***}
	(0.0305)	(0.0279)
Publishing (except Internet and Music Publishing)	0.174^{***}	0.167^{***}
	(0.0514)	(0.0417)
Motion Picture and Sound Recording Activities	0.0352	0.0689^{*}
	(0.0499)	(0.0411)
Broadcasting (except Internet)	0.171^{***}	0.166^{***}
	(0.0567)	(0.0494)
Internet Publishing and Broadcasting	0.155^{**}	0.152^{***}
	(0.0638)	(0.0590)
Telecommunications Services	0.274^{***}	0.231^{***}
	(0.0350)	(0.0320)
Internet Service Providers, Web Search Portals and Data Processing Services	0.204^{***}	0.177^{***}
	(0.0399)	(0.0408)
Library and Other Information Services	0.170^{***}	0.181^{***}
	(0.0455)	(0.0358)

Finance	0.307***	0.282***
	(0.0293)	(0.0271)
Insurance and Superannuation Funds	0.313***	0.251***
	(0.0317)	(0.0293)
Auxiliary Finance and Insurance Services	0.257***	0.224***
	(0.0300)	(0.0278)
Rental and Hiring Services (except Real Estate)	0.0704**	0.0852***
	(0.0344)	(0.0305)
Property Operators and Real Estate Services	0.121***	0.123***
	(0.0336)	(0.0301)
Professional, Scientific and Technical Services (Except Computer System Design and Related	0.182***	0.155***
	(0.0258)	(0.0233)
Computer System Design and Related Services	0.219***	0.194***
	(0.0287)	(0.0265)
Administrative Services	0.183***	0.145***
	(0.0276)	(0.0248)
Building Cleaning, Pest Control and Other Support Services	0.0222	0.0445
	(0.0309)	(0.0285)
Public Administration	0.268***	0.225***
	(0.0260)	(0.0234)
Defense	0.279***	0.247***
	(0.0343)	(0.0304)
Public Order, Safety and Regulatory Services	0.250***	0.226***
	(0.0287)	(0.0254)
Preschool and School Education	0.125***	0.106***
	(0.0273)	(0.0245)
Tertiary Education	0.182***	0.207***
	(0.0291)	(0.0267)
Adult, Community and Other Education	-0.0546	0.0569**

	(0.0337)	(0.0290)
Hospitals	0.290***	0.220***
	(0.0271)	(0.0242)
Medical and Other Health Care Services	0.202***	0.152***
	(0.0271)	(0.0244)
Residential Care Services	0.158***	0.112***
	(0.0285)	(0.0251)
Social Assistance Services	0.119***	0.0881***
	(0.0267)	(0.0239)
Heritage Activities	0.124***	0.0779**
	(0.0410)	(0.0367)
Creative and Performing Arts Activities	0.0469	0.0825*
	(0.0469)	(0.0473)
Sports and Recreation Activities	-0.0686**	0.00503
	(0.0340)	(0.0292)
Gambling Activities	0.169***	0.166***
	(0.0501)	(0.0498)
Repair and Maintenance	0.145***	0.109***
	(0.0285)	(0.0261)
Personal and Other Services	-0.0304	-0.0277
	(0.0312)	(0.0277)
Private Households Employing Staff and Undifferentiated Goods- and Service-Producing Activities	0.0931	0.0840
	(0.0875)	(0.0775)
Hours per week	0.0261***	-0.00986***
	(0.000282)	(0.000206)
I have a lot of choice in deciding what I do at work	0.00190*	0.00435***
	(0.00101)	(0.000910)
My job requires me to take initiative	0.00975***	0.00876***
	(0.00126)	(0.00113)
I have to work fast in	0.00319***	0.00187*

my job				
			(0.00121)	(0.00108)
Currently have more than one job			-0.103***	-0.0922***
			(0.00704)	(0.00641)
Constant	3.785***	1.955***	4.009***	2.149***
	(0.0943)	(0.0591)	(0.0756)	(0.0672)
Observations	111990	111664	100587	100490

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B2: Regression Output for Equation 6

Equation:	(6) RE the natural logarithm of weekly income	(6) FE the natural logarithm of weekly income	(6) RE natural logarithm of hourly wage	(6) FE natural logarithm of hourly wage
BMI_{t-1}	0.0339***	0.0278***	0.0301***	0.0228***
	(0.00427)	(0.00504)	(0.00371)	(0.00457)
BMI_{t-1}^2	-0.000541***	-0.000457***	-0.000474***	-0.000366***
	(0.0000700)	(0.0000804)	(0.0000601)	(0.0000722)
Female	0.189**	0	0.218***	0
	(0.0795)	(.)	(0.0689)	(.)
Female x BMI_{t-1}	-0.0220***	-0.0195***	-0.0242***	-0.0178***
	(0.00533)	(0.00628)	(0.00461)	(0.00564)
Female x BMI_{t-1}^2	0.000344***	0.000331***	0.000359***	0.000283***
	(0.0000875)	(0.0000992)	(0.0000751)	(0.0000886)
New South Wales	0	0	0	0
	(.)	(.)	(.)	(.)
Victoria	-0.0462***	-0.0669***	-0.0410***	-0.0599***
	(0.00862)	(0.0225)	(0.00768)	(0.0198)
Queensland	-0.0272***	-0.0455**	-0.0369***	-0.0551***
	(0.00898)	(0.0203)	(0.00787)	(0.0175)
Southern Australia	-0.0387***	-0.0459	-0.0457***	-0.0223
	(0.0124)	(0.0349)	(0.0110)	(0.0301)
Western Australia	0.0174	-0.0141	0.0272**	0.00995
	(0.0123)	(0.0314)	(0.0112)	(0.0268)
Tasmania	-0.0681***	-0.140***	-0.0836***	-0.127***
	(0.0173)	(0.0422)	(0.0145)	(0.0342)
Northern Territory	0.0525*	0.0647	0.0669***	0.0804**
	(0.0288)	(0.0428)	(0.0254)	(0.0373)
Australian Capital Territory	0.0500***	0.0351	0.0445***	0.0324
	(0.0179)	(0.0276)	(0.0157)	(0.0233)
Legally married	0	0	0	0
	(.)	(.)	(.)	(.)
Living with Partner	0.0356***	0.0374***	0.0102*	0.0199***
	(0.00611)	(0.00770)	(0.00548)	(0.00682)
Separated	-0.00622	0.00247	-0.0139	-0.00492
	(0.0104)	(0.0115)	(0.00924)	(0.0103)
Divorced	-0.00663	0.0117	-0.0214**	-0.00664
	(0.0109)	(0.0136)	(0.00992)	(0.0122)

Widowed	-0.0439	-0.0579	-0.0294	-0.0306
	(0.0312)	(0.0381)	(0.0278)	(0.0351)
Single	-0.0557***	-0.0315***	-0.0628***	-0.0380***
	(0.00774)	(0.0104)	(0.00683)	(0.00906)
Age	0.0650***	0.0629***	0.0515***	0.0520***
	(0.00147)	(0.00690)	(0.00133)	(0.00629)
Age^2	-0.000709***	-0.000702***	-0.000556***	-0.000597***
	(0.0000177)	(0.0000233)	(0.0000161)	(0.0000209)
Postgrad - masters or doctorate	0	0	0	0
	(.)	(.)	(.)	(.)
Grad diploma, grad certificate	-0.0813***	-0.0976***	-0.0601***	-0.0546***
	(0.0158)	(0.0243)	(0.0142)	(0.0203)
Bachelor or honours	-0.0998***	-0.0984***	-0.107***	-0.0845***
	(0.0130)	(0.0203)	(0.0115)	(0.0161)
Adv diploma, diploma	-0.245***	-0.270***	-0.216***	-0.158***
	(0.0152)	(0.0271)	(0.0135)	(0.0216)
Cert III or IV	-0.310***	-0.362***	-0.274***	-0.207***
	(0.0145)	(0.0275)	(0.0126)	(0.0211)
Year 12	-0.262***	-0.319***	-0.262***	-0.232***
	(0.0144)	(0.0241)	(0.0126)	(0.0190)
Year 11 and below	-0.599***	-0.812***	-0.455***	-0.471***
	(0.0164)	(0.0307)	(0.0137)	(0.0229)
Undetermined	-1.903***	0	-1.672***	0
	(0.369)	(.)	(0.624)	(.)
Australia	0	0	0	0
	(.)	(.)	(.)	(.)
United Kingdom	0.0126	0	0.0129	0
	(0.0167)	(.)	(0.0160)	(.)
New Zealand	0.0583***	0	0.0497***	0
	(0.0183)	(.)	(0.0168)	(.)
Oceania	-0.0173	0	-0.0248	0
	(0.0301)	(.)	(0.0272)	(.)
Europe	-0.0217	0	-0.0152	0
	(0.0231)	(.)	(0.0210)	(.)
Asia	-0.0899***	0	-0.0976***	0
	(0.0140)	(.)	(0.0130)	(.)
Africa	-0.0339	0	-0.0277	0
	(0.0286)	(.)	(0.0274)	(.)
The Americas	-0.0704**	0	-0.0433	0

	(0.0292)	(.)	(0.0281)	(.)
Socio-economic background	0.00437***	0.00108	0.00619***	0.000429
	(0.000914)	(0.00115)	(0.000810)	(0.00102)
Wave 2	0	0	0	0
	(.)	(.)	(.)	(.)
Wave 3	0.0468***	0.0487***	0.0442***	0.0476***
	(0.00601)	(0.00875)	(0.00565)	(0.00808)
Wave 4	0.0854***	0.0878***	0.0868***	0.0929***
	(0.00649)	(0.0146)	(0.00600)	(0.0133)
Wave 5	0.125***	0.129***	0.126***	0.136***
	(0.00674)	(0.0207)	(0.00620)	(0.0189)
Wave 6	0.163***	0.170***	0.163***	0.178***
	(0.00683)	(0.0269)	(0.00635)	(0.0245)
Wave 7	0.198***	0.205***	0.197***	0.216***
	(0.00671)	(0.0332)	(0.00620)	(0.0303)
Wave 8	0.220***	0.230***	0.220***	0.244***
	(0.00678)	(0.0397)	(0.00625)	(0.0362)
Wave 9	0.236***	0.246***	0.237***	0.265***
	(0.00693)	(0.0462)	(0.00628)	(0.0422)
Wave 10	0.266***	0.277***	0.263***	0.294***
	(0.00704)	(0.0527)	(0.00641)	(0.0481)
Wave 11	0.298***	0.310***	0.292***	0.328***
	(0.00699)	(0.0593)	(0.00640)	(0.0542)
Wave 12	0.324***	0.340***	0.317***	0.358***
	(0.00709)	(0.0658)	(0.00649)	(0.0601)
Wave 13	0.358***	0.377***	0.347***	0.394***
	(0.00728)	(0.0725)	(0.00670)	(0.0663)
Wave 14	0.396***	0.418***	0.385***	0.437***
	(0.00725)	(0.0790)	(0.00664)	(0.0722)
Wave 15	0.458***	0.481***	0.431***	0.486***
	(0.00748)	(0.0856)	(0.00690)	(0.0782)
Wave 16	0.481***	0.507***	0.461***	0.522***
	(0.00752)	(0.0922)	(0.00689)	(0.0842)
Occupation	-0.00207***	-0.00174***	-0.00200***	-0.00154***
	(0.000128)	(0.000144)	(0.000115)	(0.000127)
Agriculture	0	0	0	0
	(.)	(.)	(.)	(.)
Aquaculture	0.106	0.0567	0.0563	0.0210
	(0.175)	(0.167)	(0.179)	(0.163)

Forestry and Logging	0.165***	0.0861	0.132***	0.0662
	(0.0574)	(0.0683)	(0.0437)	(0.0515)
Fishing, Hunting and Trapping	-0.127	-0.142	0.0546	0.0271
	(0.168)	(0.156)	(0.122)	(0.126)
Agriculture, Forestry and Fishing Support Services	0.162***	0.0942**	0.116***	0.0470
	(0.0434)	(0.0474)	(0.0426)	(0.0468)
Coal Mining	0.477***	0.334***	0.485***	0.350***
	(0.0381)	(0.0447)	(0.0333)	(0.0388)
Oil and Gas Extraction	0.401***	0.273***	0.480***	0.343***
	(0.0499)	(0.0541)	(0.0462)	(0.0520)
Metal Ore Mining	0.337***	0.224***	0.453***	0.330***
	(0.0375)	(0.0426)	(0.0326)	(0.0377)
Non-Metallic Mineral Mining and Quarrying	0.243***	0.147***	0.253***	0.158***
	(0.0454)	(0.0508)	(0.0475)	(0.0522)
Exploration and Other Mining Support Services	0.383***	0.256***	0.445***	0.320***
	(0.0422)	(0.0464)	(0.0388)	(0.0445)
Food Product Manufacturing	0.166***	0.0993***	0.141***	0.0898***
	(0.0292)	(0.0334)	(0.0263)	(0.0301)
Beverage and Tobacco Product Manufacturing	0.111**	0.0444	0.0919**	0.0421
	(0.0508)	(0.0557)	(0.0466)	(0.0509)
Textile, Leather, Clothing and Footwear Manufacturing	0.0823	0.0495	0.0335	0.0111
	(0.0584)	(0.0642)	(0.0554)	(0.0611)
Wood Product Manufacturing	0.131***	0.0722*	0.0755**	0.0468
	(0.0353)	(0.0386)	(0.0335)	(0.0359)
Pulp, Paper and Converted Paper Product Manufacturing	0.263***	0.155**	0.205***	0.0980
	(0.0528)	(0.0666)	(0.0487)	(0.0621)
Printing (including the Reproduction of Recorded Media)	0.180***	0.106**	0.153***	0.0957**
	(0.0386)	(0.0450)	(0.0351)	(0.0399)
Petroleum and Coal Product Manufacturing	0.390***	0.242***	0.392***	0.261***
	(0.0559)	(0.0607)	(0.0500)	(0.0540)

Basic Chemical and Chemical Product Manufacturing	0.277***	0.185***	0.229***	0.148***
	(0.0365)	(0.0413)	(0.0335)	(0.0371)
Polymer Product and Rubber Product Manufacturing	0.179***	0.0845**	0.167***	0.0929***
	(0.0393)	(0.0428)	(0.0325)	(0.0343)
Non-Metallic Mineral Product Manufacturing	0.191***	0.105**	0.152***	0.0755*
	(0.0404)	(0.0452)	(0.0362)	(0.0405)
Primary Metal and Metal Product Manufacturing	0.264***	0.162***	0.250***	0.163***
	(0.0351)	(0.0405)	(0.0326)	(0.0370)
Fabricated Metal Product Manufacturing	0.188***	0.109***	0.142***	0.0810**
	(0.0296)	(0.0333)	(0.0284)	(0.0315)
Transport Equipment Manufacturing	0.208***	0.114***	0.170***	0.0916***
	(0.0308)	(0.0352)	(0.0283)	(0.0322)
Machinery and Equipment Manufacturing	0.210***	0.129***	0.173***	0.104***
	(0.0276)	(0.0306)	(0.0252)	(0.0277)
Furniture and Other Manufacturing	0.0409	0.000310	-0.000450	-0.0230
	(0.0382)	(0.0414)	(0.0366)	(0.0386)
Electricity Supply	0.397***	0.271***	0.368***	0.254***
	(0.0396)	(0.0464)	(0.0369)	(0.0435)
Gas Supply	0.283***	0.174*	0.252***	0.164*
	(0.0926)	(0.0995)	(0.0886)	(0.0928)
Water Supply, Sewerage and Drainage Services	0.391***	0.279***	0.339***	0.245***
	(0.0417)	(0.0498)	(0.0397)	(0.0472)
Waste Collection, Treatment and Disposal Services	0.190***	0.0810*	0.176***	0.0873**
	(0.0414)	(0.0473)	(0.0359)	(0.0404)
Building Construction	0.201***	0.114***	0.176***	0.0932***
	(0.0290)	(0.0329)	(0.0263)	(0.0295)
Heavy and Civil Engineering Construction	0.298***	0.194***	0.310***	0.213***
	(0.0287)	(0.0324)	(0.0266)	(0.0297)

Construction Services	0.182***	0.0927***	0.137***	0.0669**
	(0.0263)	(0.0300)	(0.0239)	(0.0271)
Basic Material Wholesaling	0.141***	0.0579*	0.119***	0.0521*
	(0.0287)	(0.0315)	(0.0254)	(0.0275)
Machinery and Equipment Wholesaling	0.196***	0.118***	0.161***	0.0970***
	(0.0300)	(0.0333)	(0.0274)	(0.0300)
Motor Vehicle and Motor Vehicle Parts Wholesaling	0.157***	0.0733**	0.113***	0.0588*
	(0.0330)	(0.0363)	(0.0294)	(0.0319)
Grocery, Liquor and Tobacco Product Wholesaling	0.178***	0.113***	0.132***	0.0804**
	(0.0347)	(0.0380)	(0.0309)	(0.0334)
Other Goods Wholesaling	0.159***	0.0834***	0.125***	0.0681**
	(0.0292)	(0.0315)	(0.0266)	(0.0284)
Commission-Based Wholesaling	0.133***	0.0407	0.108**	0.0266
	(0.0465)	(0.0478)	(0.0464)	(0.0475)
Motor Vehicle and Motor Vehicle Parts Retailing	0.128***	0.0734*	0.0965***	0.0655*
	(0.0342)	(0.0402)	(0.0308)	(0.0361)
Fuel Retailing	0.0457	-0.0417	0.0224	-0.0312
	(0.0458)	(0.0506)	(0.0382)	(0.0429)
Food Retailing	0.0317	-0.0164	0.0317	-0.0103
	(0.0279)	(0.0319)	(0.0244)	(0.0278)
Other Store-Based Retailing	0.0311	-0.0249	0.0181	-0.0228
	(0.0264)	(0.0302)	(0.0235)	(0.0266)
Non-Store Retailing and Retail Commission-Based Buying and/or Selling	0.00250	-0.0143	0.00173	-0.00612
	(0.0496)	(0.0501)	(0.0436)	(0.0437)
Accommodation	-0.00515	-0.0648	-0.00119	-0.0571
	(0.0352)	(0.0396)	(0.0314)	(0.0355)
Food and Beverage Services	-0.0657**	-0.116***	-0.0520**	-0.0960***
	(0.0265)	(0.0304)	(0.0235)	(0.0267)
Road Transport	0.126***	0.0571*	0.149***	0.0821***

	(0.0297)	(0.0336)	(0.0269)	(0.0303)
Rail Transport	0.361***	0.201***	0.335***	0.195***
	(0.0365)	(0.0425)	(0.0358)	(0.0409)
Water Transport	0.308***	0.216**	0.364***	0.256***
	(0.0793)	(0.0847)	(0.0685)	(0.0724)
Air and Space Transport	0.309***	0.150**	0.290***	0.142**
	(0.0555)	(0.0652)	(0.0507)	(0.0586)
Other Transport	0.165**	0.140*	0.156***	0.123*
	(0.0660)	(0.0781)	(0.0593)	(0.0687)
Postal and Courier Pick-up and Delivery Services	0.0513	-0.00249	0.0805**	0.0433
	(0.0391)	(0.0449)	(0.0331)	(0.0386)
Transport Support Services	0.255***	0.132***	0.245***	0.134***
	(0.0304)	(0.0338)	(0.0280)	(0.0309)
Warehousing and Storage Services	0.220***	0.136***	0.158***	0.0938***
	(0.0307)	(0.0338)	(0.0280)	(0.0307)
Publishing (except Internet and Music Publishing)	0.160***	0.118**	0.152***	0.119**
	(0.0512)	(0.0581)	(0.0415)	(0.0477)
Motion Picture and Sound Recording Activities	0.0246	-0.0153	0.0562	0.0152
	(0.0503)	(0.0560)	(0.0415)	(0.0456)
Broadcasting (except Internet)	0.162***	0.0626	0.155***	0.0599
	(0.0573)	(0.0650)	(0.0496)	(0.0553)
Internet Publishing and Broadcasting	0.146**	0.0805	0.141**	0.0828
	(0.0633)	(0.0619)	(0.0588)	(0.0560)
Telecommunications Services	0.266***	0.154***	0.220***	0.124***
	(0.0351)	(0.0401)	(0.0320)	(0.0363)
Internet Service Providers, Web Search Portals and Data Processing Services	0.202***	0.103**	0.173***	0.0890**
	(0.0400)	(0.0425)	(0.0410)	(0.0440)
Library and Other Information Services	0.162***	0.131***	0.173***	0.153***
	(0.0447)	(0.0491)	(0.0356)	(0.0401)

Finance	0.298***	0.189***	0.271***	0.173***
	(0.0296)	(0.0347)	(0.0272)	(0.0315)
Insurance and Superannuation Funds	0.310***	0.205***	0.245***	0.149***
	(0.0318)	(0.0367)	(0.0295)	(0.0334)
Auxiliary Finance and Insurance Services	0.254***	0.151***	0.217***	0.120***
	(0.0301)	(0.0345)	(0.0279)	(0.0313)
Rental and Hiring Services (except Real Estate)	0.0707**	0.0182	0.0813***	0.0384
	(0.0344)	(0.0372)	(0.0305)	(0.0326)
Property Operators and Real Estate Services	0.126***	0.0361	0.121***	0.0409
	(0.0333)	(0.0384)	(0.0298)	(0.0340)
Professional, Scientific and Technical Services (Except Computer System Design and Related	0.177***	0.104***	0.148***	0.0811***
	(0.0260)	(0.0295)	(0.0234)	(0.0263)
Computer System Design and Related Services	0.212***	0.0993***	0.186***	0.0813***
	(0.0288)	(0.0327)	(0.0266)	(0.0298)
Administrative Services	0.188***	0.119***	0.146***	0.0890***
	(0.0277)	(0.0312)	(0.0249)	(0.0278)
Building Cleaning, Pest Control and Other Support Services	0.0325	-0.0128	0.0525*	0.0150
	(0.0308)	(0.0348)	(0.0285)	(0.0321)
Public Administration	0.267***	0.169***	0.222***	0.138***
	(0.0261)	(0.0300)	(0.0235)	(0.0267)
Defense	0.267***	0.157***	0.234***	0.140***
	(0.0343)	(0.0410)	(0.0304)	(0.0368)
Public Order, Safety and Regulatory Services	0.260***	0.157***	0.230***	0.140***
	(0.0285)	(0.0332)	(0.0252)	(0.0291)
Preschool and School Education	0.126***	0.0961***	0.100***	0.0676**
	(0.0274)	(0.0329)	(0.0244)	(0.0292)
Tertiary Education	0.184***	0.116***	0.204***	0.146***
	(0.0291)	(0.0340)	(0.0267)	(0.0311)
Adult, Community and Other Education	-0.0497	-0.0767**	0.0562*	0.0225

	(0.0337)	(0.0367)	(0.0291)	(0.0320)
Hospitals	0.300***	0.211***	0.225***	0.145***
	(0.0272)	(0.0321)	(0.0243)	(0.0282)
Medical and Other Health Care Services	0.211***	0.136***	0.156***	0.0866***
	(0.0271)	(0.0314)	(0.0244)	(0.0280)
Residential Care Services	0.178***	0.109***	0.126***	0.0758***
	(0.0285)	(0.0332)	(0.0251)	(0.0290)
Social Assistance Services	0.134***	0.0891***	0.0975***	0.0652**
	(0.0267)	(0.0307)	(0.0239)	(0.0272)
Heritage Activities	0.121***	0.0658	0.0738**	0.0270
	(0.0411)	(0.0433)	(0.0369)	(0.0392)
Creative and Performing Arts Activities	0.0391	-0.00227	0.0738	0.0436
	(0.0469)	(0.0505)	(0.0475)	(0.0511)
Sports and Recreation Activities	-0.0573*	-0.107***	0.0105	-0.0384
	(0.0340)	(0.0382)	(0.0291)	(0.0328)
Gambling Activities	0.169***	0.0719	0.161***	0.0844
	(0.0497)	(0.0568)	(0.0491)	(0.0575)
[Repair and Maintenance	0.141***	0.0844***	0.104***	0.0652**
	(0.0287)	(0.0320)	(0.0263)	(0.0291)
Personal and Other Services	-0.0211	-0.0577	-0.0225	-0.0447
	(0.0312)	(0.0355)	(0.0277)	(0.0311)
Private Households Employing Staff and Undifferentiated Goods- and Service-Producing Activities	0.114	0.108	0.103	0.0916
	(0.0874)	(0.0916)	(0.0772)	(0.0822)
Hours per week	0.0260***	0.0240***	-0.00990***	-0.0113***
	(0.000281)	(0.000309)	(0.000205)	(0.000231)
I have a lot of choice in deciding what I do at work	0.00135	0.00151	0.00388***	0.00282***
	(0.00100)	(0.00107)	(0.000906)	(0.000964)
My job requires me to take initiative	0.00992***	0.00884***	0.00883***	0.00747***
	(0.00125)	(0.00134)	(0.00112)	(0.00120)
I have to work fast in	0.00310**	0.00223*	0.00176	0.000966

my job				
	(0.00121)	(0.00129)	(0.00107)	(0.00115)
Currently have more than one job	-0.107***	-0.123***	-0.0956***	-0.106***
	(0.00704)	(0.00748)	(0.00640)	(0.00676)
Tenure with current employer (years)	0.00269***	0.00239***	0.00257***	0.00230***
	(0.000372)	(0.000443)	(0.000344)	(0.000400)
Tenure in current occupation (years)	0.00188***	0.00116***	0.00186***	0.00106***
	(0.000238)	(0.000258)	(0.000221)	(0.000240)
Days absent	0.000397**	0.000340**	0.000468**	0.000387*
	(0.000168)	(0.000171)	(0.000198)	(0.000209)
Social Job	-0.0178***	-0.0234***	-0.00554	-0.0151***
	(0.00476)	(0.00537)	(0.00425)	(0.00475)
Active Job	-0.0292***	-0.0200***	-0.0294***	-0.0153***
	(0.00518)	(0.00602)	(0.00444)	(0.00514)
Constant	4.056***	4.560***	2.189***	2.529***
	(0.0758)	(0.229)	(0.0674)	(0.209)
Observations	100454	100454	100357	100357

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$