Compensating Wage Differentials for Risky Jobs: Evidence from Australia

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Statement of Originality

This work has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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Abstract

The theory of compensating wage differentials (CWDs) postulates that workers need to be compensated with higher earnings for job disamenities. The risk of death and injury at work are examples of such disamenities. Combining recent fatality and injury data from Safe Work Australia with data from the Household, Income and Labour Dynamics in Australia (HILDA) survey, this research updates the earlier work of Kniesner and Leeth (1991) and Miller, Mulvey and Norris (1997) who found evidence that Australian workers that are exposed to fatal risk are compensated with higher earnings. Constructing a risk rate that varies according to the worker's industry and occupation, and using panel techniques to control for unobserved heterogeneity, CWDs for job risk are estimated. It is found that only female workers who belong to a union receive CWDs for fatal risk. The study finds no evidence that Australian workers receive CWDs for non-fatal risk. The estimated CWDs are used to infer the value of statistical life (VSL) for Australian female union members.

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Abbreviations

ABS	Australian Bureau of Statistics
CPI	Consumer Price Index
CWD	compensating wage differential
HILDA	Household, Income and Labour Dynamics in Australia
VSI	value of statistical injury
VSL	value of statistical life

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Introduction

Compensating wage differentials (CWDs) are a realisation of the theory of equalising differences which dates to Book 1 of Adam Smith's *The Wealth of Nations* (1776). The theory of CWDs postulates that in a competitive market, firms need to compensate workers for undesirable job characteristics in order to equalise the total monetary and nonmonetary benefits across all jobs (Rosen, 1986). If compensation is not offered, workers will choose a job which better match their risk/earnings preferences. That is, the role of compensating wages is to equalise the net attractiveness of jobs and entice workers into markets which would otherwise receive no labour supply. When considering undesirable job characteristics, one might think of an inconvenient geographical location, a high level of job-related stress or the state of the physical working environment. While undoubtedly these characteristics are unattractive to most, some workers may enjoy the travel distance or the stress of a fast-paced work environment. If this is the case, firms will have little reason to compensate workers for these conditions. Thus, using such measures as proxies for undesirable job characteristics may lead to empirical results that are difficult to interpret as the extent to which individual workers are (dis)satisfied with these characteristics could vary greatly. It could also be the case that individual preferences, and thus compensation required for undesirable work conditions, change constantly (over the course of the week, month, or over the course of the worker's life). In other words, worker preferences for job characteristics are dynamic. Empirically determining the extent to which compensating payments are paid for dynamic and unobservable preferences is neither feasible nor possible.

It is for this reason that researchers use work induced injuries (non-fatal risk) and fatalities (fatal risk) as job disamenities in the estimation of CWDs as it is assumed that the average, risk-averse agent will find the risk of injury or death to always be an unappealing characteristic of any job. Consequently, a continuously positive relationship between risk and wages is expected. In this sense, estimated CWDs should reflect the marginal worker's willingness to accept a riskier work environment[1]. Hedonic wage regressions have served as the main econometric tool used by labour economists to gauge the size and significance of CWD payments for work disamenities.

Studies that find evidence of CWDs are also able to compute value of statistical life (VSL) and value of statistical injury (VSI) estimates. Most studies use the revealed preference (or willingness to pay) method to calculate VSL and VSI estimates as they can be directly inferred from hedonic wage regressions. A significant CWD implies that the firm must compensate each worker by the size of the CWD for taking on an additional unit of risk. For example, if there are

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[1] The marginal worker is the worker who, in equilibrium, is indifferent between a 'safe' job and a 'risky' job at the CWD being offered for the 'risky' job.

100,000 workers and the risk of death increases by 1/100,000 then statistically, one life will be lost. If the CWD for a unit increase in fatal risk indicates workers require an additional $5 in wages continue working, the value of the life lost will be the sum of all worker's additional earnings ($500,000). The same process is used for VSI estimates. Such estimates have been used to inform policymakers of the relative costs and benefits associated with workplace risk reduction (Kenkel, 2003).

The enrichening of datasets over time and the econometric development of panel data approaches have made it possible to correct for much of the coefficient bias suspected in earlier cross-sectional studies. These advancements allow hedonic estimates to more closely reflect the true extent to which CWDs are paid to workers in risky jobs and consequently narrow the range of VSL and VSI estimates. If biases are not accounted for, the VSL and VSI estimates inferred directly from the hedonic regressions will be misleading to public policymakers who use such estimates to evaluate the cost and benefit of workplace safety investments. Consequently, much taxpayer and/or private funding may be misallocated to risk-reduction reforms in occupations and industries which are improperly determined to require action.

Using the recent Safe Work Australia reports on job injury and fatality rates, and panel data from recent waves of the Household Income Labour Dynamics in Australia (HILDA) survey, this study updates the earlier research by Kniesner and Leeth (1991) and Miller, Mulvey and Norris (1997) who, using cross-sectional data, found evidence of CWDs for fatal risk in Australia. During the period covered by their studies, Australia's wage-setting process was highly centralised, which may have made it difficult for employers to readily (and perhaps appropriately) alter the wages paid to employees for job risks. Given that Australia has moved towards a more decentralised system of wage setting since that period, the size and significance of any CWDs (if found) is expected to be greater. The aim of this study is to provide a contemporary measure of the extent to which CWDs are paid for risky jobs in Australia by reducing many of the biases which are suspected in the older studies. The study makes the following three contributions to the CWD literature for Australia. Firstly, this research is, to the author's knowledge, the first which attempts to merge fatality and injury risk data from Safe Work Australia with worker and workplace data from the HILDA panel. Secondly, and perhaps most importantly, this is the first study in an Australian context which attempts to assign workers a single risk rate, for fatal and non-fatal risk, that reflects their industry/occupation combination. Using a more refined risk measure will produce estimates that more accurately reflect CWDs for risk. Thirdly, this research is, to the author's knowledge, the first to make use of the HILDA dataset, along with carefully specified fixed-effect models, to determine CWD for job risk[2]. In this study, VSL and VSI estimates are computed for Australian workers where possible.

This study has the following structure. The Review of Literature section gives a broad review of both older and more recent literature relevant to CWDs as well as some discussion of the theoretical assumptions crucial to the estimation of CWDs. Reasons why previously estimated CWDs may be bias and thus misleading is also discussed. The Data section provides an extensive outline of the data and procedure used to calculate the joint industry/occupation risk rates for fatal and non-fatal risk. The Method section specifies the econometric models employed to estimate CWDs and provides clear definitions of the dependent and independent variables. The Results and Discussion section provides the relevant empirical outputs with appropriate interpretations and discussion on how the estimates computed in this study compare to what has previously been found for Australia as well as in other studies.

[2] The general term 'risk' from here on refers to both fatal and non-fatal risk.

Review of Literature

Previous Australian Studies

There is very little research on CWDs for job risk in Australia, with only two studies – Kniesner and Leeth (1991) and Miller, Mulvey and Norris (1997) – having been undertaken in the last 30 years. Both studies were limited because only cross-sectional data was available; consequently, the studies could not easily control for biases associated with unobservable worker heterogeneity. There have been two significant data developments since these studies were conducted. One was the launch of the HILDA survey in 2001, which has provided access to panel data on Australian workers. The other is the availability of a more comprehensive measure of fatality and injury rates integral to the estimation of CWDs for Australian workers, which is published yearly by Safe Work Australia. These developments have provided researchers with an opportunity to re-examine CWDs for job risk in Australia. This review will firstly discuss the extent to which Kniesner and Leeth (1991) and Miller et al. (1997) found CWDs to exist in Australia. Then, the review will focus on why the cross-sectional estimates found in the above studies may be biased and which other sources of bias are likely to remain. Lastly, the review will look at some of the underlying assumptions of the CWD framework and some recent theoretical extensions to their estimation.

Kniesner and Leeth (1991) made use of workplace fatality data for manufacturing workers in 1984 and 1985 to provide a cross-sectional estimate of the extent to which male manufacturing workers are compensated for job risks. The researchers used Australian Bureau of Statistics (ABS) data on industrial accidents and manufacturing establishments pertaining only to blue-collar workers. Blue-collar workers have often been used in older studies for two reasons: capital-intensive industries and occupations often exhibit the highest death and injury risks; and general workplace disamenities owing to the use of capital equipment which is integral to the job. For example, undesirable job characteristics such as inflexible pace of work, inflexible work hours, and hazardous work environments are associated with the heavy machinery used by blue-collar workers. While not a limitation, it is worth noting that the authors only used data from New South Wales, Victoria, Queensland and South Australia, as most manufacturing workers (90%) were employed in these States. Miller et al. (1997) used industry-based fatality risk data collected by Safe Work Australia and worker demographic information taken from the 1991 Australian Census of Population and Housing (1994). Unlike Kniesner and Leeth, Miller et al. did not restrict their sample to manufacturing workers and included eight occupational categories in which workers were classified[3]. Where both occupational and industry fatality rates are available, using

[3] Agricultural workers, however, were excluded due to concerns over the validity of income reporting.

industry risk measures have often resulted in larger CWD estimates for risk in hedonic regressions, compared to occupational measures of risk (see Smith, 1979; Dillingham, 1985; Meng, 1991). When the choice is available, an industry measure of risk may be preferable, as workers have been found to be more accurate in identifying their industry of employment compared to their occupation of employment (Bound, Brown & Mathiowetz, 2001). It might be that workers cannot as easily define the difference between two occupations as they can industries (the distinction between mining and agricultural industries is clearer than the distinction between the occupations of professional and manager). Consequently, studies that have used an occupational based measure of risk have likely introduced measurement error into the regressions which has biased estimates toward zero (Miller et al., 1997). Given that much of the data used in CWD studies is self-reported by the worker, using the more accurate industry measure of risk should more closely reflect any compensating wages paid for workplace risk.

When using an industry fatality risk measure, Kniesner and Leeth (1991) found that manufacturing workers that were exposed to the mean fatality rate earned an average risk premium of approximately 2.5% when compared to workers in a risk-free job. By contrast, Miller et al. (1997) found that workers who were exposed to the mean industry fatality risk received, on average, a risk premium of 4.8%, compared to workers who were in a completely safe job. The estimated premium for fatal risk was reduced to 2.8% when occupational controls were removed from the model[4]. In Miller et al. (1997), the fatal risk rate was measured per 1,000 workers and therefore the coefficient of the fatal risk variable could be interpreted as the increase in earnings required to compensate workers for a 1/1,000 increase in fatal risk. This corresponded to a CWD of 70.4% per unit increase in fatal risk[5]. Kniesner and Leeth (1991) estimated a coefficient on the fatal risk variable which implied a CWD as high at 106% when fatal risk was measured per 1,000. Using the estimated CWD, Miller et al. (1997) computed a VSL of $19.43 million for their sample of Australian workers in 1991. When CWDs were estimated using a model which had no worker occupation or occupational status controls, the CWD fell to 42% per unit increase in fatal risk. Consequently, the estimated VSL fell to $11.45 million. Despite finding a significant CWD for fatal risk, a VSL estimate was not computed by Kniesner and Leeth.

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[4] The risk premium for both Australian studies were calculated as the risk coefficient multiplied by the average risk rate. It is the average return to risk for workers who face the mean fatality rate compared to a worker who is exposed to zero fatality risk.

[5] CWDs refers to the coefficient on estimated risk coefficients. The estimated coefficients can be interpreted as the compensation that would be required if the risk variable were to increase by one unit, and thus the estimate varies depending on how risk is measured. For example, if the risk rate used by Miller et al. (1997) was expressed per 100,000 workers, the corresponding CWD would be equal to 0.7% for a 1/100,000 increase in fatal risk. Most recent studies express fatal risk per 100,000 workers.

The Australian CWD estimates in both studies were considerably larger than previous estimates found by similar cross-sectional studies in other countries. Martinello and Meng (1992) used Canadian data from 1986 to test for CWDs for fatal and non-fatal risk and found that the CWD for a unit increase in fatal risk ranged from 9% to 32% per 1,000 workers, depending on the specification used. (Both estimates are significantly smaller than 70.4% which was found by Miller et al., 1997.) Martinello and Meng's results were highly significant and implied a VSL as high as $6 million (in 1986 US dollars). Also using Canadian data, Cousineau, Lacroix and Girard (1992) found a significant CWD of 19% per 1/1,000 increase in fatal risk, which implied a VSL of $3.9 million (also in 1986 US dollars). For the United Kingdom, Marin and Psacharopoulos (1982) found a significant CWD of approximately 23% per 1/1,000 increase in fatal risk for their sample of workers from the United Kingdom 1978. The corresponding VSL from their study was €681,000.

CWDs and the Risk Variable

Virtually all studies on CWDs for job risk have used either an industry risk rate or an occupational risk rate as their variable of interest. There exist very few studies that have utilised both. If only an industry risk variable is used, a worker in a relatively riskless occupation for a given industry is assigned a risk rate which is identical to a worker in the same industry whose occupation is more dangerous. The same argument can be made when only the occupational risk of the worker is considered. As fatality and injury risks would undoubtedly depend on both the worker's industry and occupation, failure to incorporate both in the risk variable will lead to CWD estimates which do not accurately reflect the compensation for risk received by workers (Purse, 2004). Although, given data limitations, constructing a more refined measure of risk is not always possible.

This form of risk misrepresentation was first addressed by Martinello and Meng (1992) who used Canadian data to construct a risk variable which was an average of the fatal risk faced by the worker, and which varied according to the worker's industry/occupation combination. They estimated an average CWD of approximately 16% per unit (1/1,000) increase in fatal risk, an estimate which was not unlike what was computed by Cousineau et al. (1992) who also used Canadian data but using a simple occupational measure of risk, estimated a CWD of approximately 16% to 19% per unit (1/1,000) increase in fatal risk. Viscusi (2004) combined worker data from the United States and fatal risk from the Census of Fatal Occupational Injuries (CFOI)[6]. A combined fatal risk rate was calculated as the ratio of fatalities to employed persons

[6] The introduction of the CFOI in 1992 has allowed for the occupation and the industry categories of the worker to be paired for US data.

for each industry/occupational cell, as permitted by the data. When the combined risk measure was used, a CWD of 0.15% for a unit (1/100,000) increase in fatal risk was found for the full sample. When risk varied only by industry, the CWD for a unit increase in fatal risk for the same sample increased to 0.35%. Consequently, the VSLs more than doubled from $4.7 million to $10 million when occupational variation in risk was ignored. Such results highlight the importance of using a more refined measure of risk. Viscusi did however find that using the combined risk measure resulted in insignificant fatality risk coefficients of mixed signs for females, and the CWDs for males were higher for blue-collar workers than for the entire male sample, the opposite of what was expected.

Similar CWD estimates were found by Scotton (2013) who used the same CFOI risk data to construct six risk variable which varied by the worker's industry/occupation pair[7]. Using the constructed risk variables, it was found that CWDs of 0.14% to 0.22% of the worker's gross weekly wage was paid for a unit (1/100,000) increase in fatal risk. The larger estimate was produced using a sample consisting only of wage and salary workers, the greatest amount of industry controls, and an industry/occupation risk rate which was calculated using employment figures from the Occupational Employment Survey (OES). Hence, variation in CWD and VSL estimates could also be attributed to the data and method used to construct the risk variable, for which there is no accepted correct approach. Despite sensitivity to construction, the current study will utilise a risk variable which varies by both industry and occupation. As noted earlier, such a risk rate will more accurately capture the risk to earnings trade-off in hedonic wage regressions when compared to models that used only an industry or occupational risk, such as the two previous Australian studies.

CWD Controls and Estimation Bias

The results from both Australian studies have provided strong evidence for the existence of CWDs for job risk in Australia. However, an undesirable feature of previous cross-sectional estimates is the ease with which they are biased when statistically relevant variables are omitted. If not properly accounted for, the omission of statistically relevant variables will result in biased estimates which misrepresent the true compensation paid to workers for risk. Consequently, inferred VSL and VSI estimates which are evaluated directly from CWDs are inaccurate. Bias arising from the omission of relevant variables is a persistent problem among researchers who use earnings functions, as many variables that could be important determinants of a worker's

[7] The risk rates were calculated as the average number of fatalities per industry/occupation pairing, divided by the average number of workers in the same industry/occupation pair. The risk rates differed by how the average number of workers in each industry/occupation pair were estimated, and which workers were included in the fatality sample (all classes of workers or only wage and salary earners).

wage are both unobservable and challenging to proxy. (Examples of unobservable heterogeneity include innate ability, task repetition and worker motivation.). If panel data is available, the use of fixed effects can alleviate the bias that arises from unobservable heterogeneity. Such an approach can be traced back to Brown (1980) who used panel data and individual fixed effects to estimate CWDs for job risk. Interestingly, Brown (1980) found that many of the coefficients for variables that were expected to produce equalizing differences in wages were insignificant or wrongly signed. Like Brown (1980), Duncan and Holmlund (1983) used panel data and individual fixed effects, but unlike Brown (1980), concluded that the estimated CWDs for risk using the panel approach was an improvement over the cross-sectional estimates as their panel coefficients were of the expected sign and significance to be consistent with CWD theory. As the introduction of the HILDA survey allows for panel estimation techniques, the use of a fixed effects model in this study should reduce many of the estimate biases that may arise from the unobservable heterogeneity of workers – an option that was not available to Kniesner and Leeth (1991) or Miller et al. (1997).

Directly relevant to the topic of omitted variables is the omission of appropriate controls for worker industry and occupation. When using wage equations, consistent estimation requires that all worker and job characteristics which have an impact on earnings be included as covariates. If a full set of job characteristics are not included in the wage equation, any CWD estimates may become bias (through omission of relevant variables) and inconsistent (if the ignored covariates are correlated with fatality or injury risk). Hence, the inclusion of industry and occupational fixed effects are crucial when estimating CWDs as they control for all unobservable job characteristics which are tied to the worker's industry and occupation. Studies which do not use the appropriate controls would have inevitably introduced bias into their results or produced estimates which are statistically inconsistent.

The importance of including industry and occupational controls is furthered when considering that there may be some systematic difference in the remuneration structure between industries and occupations which are independent of the risk level faced by the worker. For example, even when worker characteristics and occupation are controlled, there is some consistent wage premium found common to all workers in one industry when compared to another (termed inter-industry differentials). If the industry of the worker is not properly controlled, the CWDs which are computed using an industry-varying risk rate, may in part reflect inter-industry differentials rather than compensation for risk. If inter-industry differentials are correlated with industry risk differentials, not including the appropriate controls for worker industry results in a misspecification of the model (Mrozek & Taylor, 2002). When industry dummies are included to control for inter-industry differentials, some authors have found the risk variable to be an insignificant determinant of a worker's wage (Leigh, 1995; Dorman & Hagstrom, 1998). This could imply that inter-industry differentials were responsible for the significant CWDs found in previous studies which did not use industry controls. It is also plausible that adding occupational controls to a model which uses an industry measure of risk may remove any systematic difference in wages across occupations within industries. In the Australian study by Miller et al. (1997) the estimated CWD fell from 70.4% to 67.5% when occupational control dummies were added in place of the occupational status control[8]. When instead an occupational risk measure was used with industry control dummy variables, no significant CWDs were found for the Australian data.

As the risk rate in the current study varies by both industry and occupation, the most relevant research highlighting the important of adequate controls is Scotton (2013) who demonstrated that when using a combined risk rate, if neither industry or occupation controls are used, CWDs were much larger in magnitude compared to when industry or both industry and occupation controls are used[9]. When only industry controls were used with an industry/occupation risk rate, the corresponding CWDs became negative and insignificant. Interestingly, when only occupational controls were used, the CWD remained positive and significant although larger in magnitude compared to when both controls were employed. Evidently, CWDs are sensitive to the combination of industry and occupational controls used when estimated using a measure of risk that varies by both industry and occupation. Considering this, controls for both industry and occupation should be used when possible to reduce any systematic industry and occupational effects on CWD estimates.

The sheer difficulty of obtaining unbiased CWDs has implications for the corresponding VSL estimates. Specifically, it gives rise to a consideration range in VSL estimates. Viscusi and Aldy (2003) provided a comprehensive summary of many of the CWD studies and corresponding VSL estimates. They reported that published VSL estimates computed from CWDs fell anywhere between approximately zero and $22 million. More recent studies which have made use of richer datasets and contemporary econometric techniques have found VSL estimates that fall between a narrower range of $4 million to $14 million (DeLeire, Khan & Timmins, 2013; Robinson & Hammitt, 2016; Guardado & Ziebarth, 2019). Furthermore, it is thought that publication bias may have been responsible for the large variation in VSL and VSI estimates (Ashenfelter & Greenstone, 2004; Doucouliagos, Stanley & Giles, 2012) arising from the failure of researchers

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[8] The occupational status control was a socioeconomic status scale which measured occupational prestige, occupational requirements, and occupational rewards associated with employment. It is expected that occupational control dummies were more specific than the occupational status control, and thus were able to better control for any inter-occupational differentials.

[9] Scotton (2013) found that using no industry or occupational controls resulted in CWDs of 5.5% for a 1/10,000 increase in fatal risk. The CWD fell in size to approximately 4.5% when both industry and occupational controls were used. When only occupational controls were used, the corresponding CWD for fatal risk was approximately 8%.

to report on estimates that do not conform well to theory, or the unwillingness of peer-reviewed journals to publish unconventional results (Viscusi, 2015). This may be a reason as to why only a handful of published studies (Leigh, 1991; Leigh, 1995; Dorman and Hagstrom, 1998) find insignificant evidence that CWDs are paid for job risk. Doucouliagos, Stanley and Giles (2012) have explored the impact of publication selectivity bias on VSL estimates computed from hedonic wage equations. The authors found that VSL estimates fell by 70% to 80% when accounting for publication bias. When meta-regression approximations were used to reduce publication biases, VSL estimates were found to fall by as much as 82% (Stanley and Doucouliagos, 2014). The considerable range of VSL estimates also has policy implications because the estimates are often used by governments as reference points when assessing the potential benefits of risk-reducing investments (Viscusi & Aldy, 2003).

The Effects of Bargaining Power

Perhaps the most widely researched area of CWDs for job risk is the effects of bargaining power in wage negotiations for risk. If workers are unhappy about the level of compensation they receive when workplace risk changes, and if individual bargaining power with the firm is low, it is unlikely that individual employee-employer negotiations will provide better wage outcomes. Situations where worker bargaining power is strong may pressure the firm into reviewing the compensation paid for workplace hazards. This, among other reasons, explains the interest in the role of unions in CWDs for workplace risk. Prior to 1981, the consensus was that workers who belong to a union received larger CWDs for job risk when compared to their non-union counterparts. (For examples, see Thaler and Rosen (1975); Viscusi (1980); Olson (1981); Dorsey and Walzer (1983), and Siebert and Wei (1994).) This is possibly because union membership allows greater information transparency between members about the true risks faced on the job than is available to non-union workers (Kosters, 1975). Consequently, CWD payments are higher to union members as they are more informed about the risks faced and can use union power to push for higher wages. Siebert and Wei (1994) proposed that UK studies found higher CWDs for union members because workers employed at firms which recognised unions could demand a safety representative who had the power to investigate safety in the workplace. Consequently, workers at such firms became more knowledgeable about the risks faced and demanded appropriate compensation. Siebert and Wei (1994) also reported that smaller firms were less likely to acknowledge unions (thus no safety representative was demanded) and as a result faced less pressure to pay CWDs to workers.

In contrast to earlier studies, Marin and Psacharopoulos (1982) found that worker bargaining power weakened CWD payments for fatal risk in the United Kingdom[10]. It is suggested by the authors that the weakening effect may be explained by unions pushing for a safer work environment, rather than pushing for compensation for workers in the form of higher wages. Sandy, Elliott, Siebert, and Wei (2001) also concluded there was evidence that non-union workers in the United Kingdom received higher CWDs for job risk, although the inability to deal with measurement errors in the risk data used for CWD estimation made understanding the true relationship between unions and CWDs difficult. The same weakening effects were found for manufacturing workers in the United Kingdom by Herzog and Schlottmann (1990) and have also been found in studies for the United States (Dickens, 1984; Dillingham & Smith, 1984). Siebert and Wei (1994), and Arabsheibani and Marin (2000) found no significant difference between the CWDs for unionised and non-unionised male workers in the United Kingdom during the 1980s. Despite the mixed findings, union status and its interaction with job risk can provide some important insights into how compensating wages for risk are generated. Kniesner and Leeth (1991) included union status in their wage model but did not provide any empirical analysis of its role in the earnings function or CWD payments. Miller et al (1997) did not incorporate union status or its interaction with risk into their hedonic wage model, leading to potentially biased CWD and VSL estimates for Australian workers.

Endogeneity Concerns

Along with the omission of statistically relevant variables, bias in CWD estimates occur whenever explanatory variables in the hedonic wage equation are incorrectly modelled as exogenous. Many earlier studies have treated the risk variable as exogenous in the worker's earning function (e.g., Rosen, 1974; Thaler & Rosen, 1975; Kniesner & Leeth, 1991; Miller et al, 1997). However, if safety is a normal good, then it is plausible that as individuals acquire higher levels of wealth, their willingness to trade off risk for lower wages increases (Viscusi, 1978). Thus, workers with higher income potential (dictated by human-capital attributes) may experience an income effect and self-sort into less risky jobs and consequently introduce downward bias into CWD estimates for risk (Garen, 1988). However, if workers are not fully aware of the risks they face, or perhaps do not care about the risks they face, any income effects could be weakened, perhaps to the point of insignificance. Such a perspective is supported by Shilling and Brackbill (1987) who estimated that only 5% of US workers were fully informed about the risks of their work. However, it is

[10] The authors represented bargaining power though the variable 'Union' which was calculated as the portion of workers covered by a collective agreement. The authors do not attribute their findings to their specification of the Union variable.

possible that the asymmetry of risk information declines as workers spend more time on the job (Viscusi & O'Connor, 1984). Lingard (2002) found no evidence that explicitly making workers aware (through first-aid training) of the specific injuries that can arise in the workplace impacts on the perception of risk faced by workers. Some authors have addressed this form of risk endogeneity by using two-stage least-squares (2SLS) estimation and found that CWDs for job risk were larger in magnitude (Garen, 1988 and Sandy & Elliot, 1996). Endogeneity in the choice of risk also arises when there are attributes of workers that cannot be observed, and that are significant in determining a worker's productivity in different risk environments. Some workers may find themselves more productive in riskier jobs (perhaps owing to the effects of adrenaline or cool headedness). If higher productivity is rewarded with higher wages, there exists a positive correlation between earnings and the level of job risk chosen by the worker. This means that wages and risk must be modelled as interdependent as failure to do will result in estimates that are biased. The use of panel techniques (if possible) could be used to alleviate the endogeneity bias caused in this instance. There is also the possibility that some workers choose riskier jobs because they prefer risk. Such workers would thus require a lower level of compensation to face job risk. Ignoring endogeneity of risk in this case would introduce downward bias in CWD estimates for job risk (Day, 1999). If risk is truly endogenous, previous studies which have modelled risk as exogenous would have underestimated the true returns to job risk (Purse, 2004).

Another possible source of endogeneity bias has been explored by Siebert and Wei (1994) and Arabsheibani and Marin (2000) who recognised that union membership may depend on the level of workplace risk faced by the worker. Both studies endogenised the union variable to account for the possible interdependence of risk and union membership. Siebert and Wei concluded that not allowing for the endogeneity of the union variable caused CWD estimates to be biased downward. However, the bias was sensitive to the instrumental variables used to deal with the endogeneity. Arabsheibani and Marin (2000) used two-stage estimates to account for endogenous variables and found that doing so had little effect on the estimates for fatal risk. Consequently, Arabsheibani and Marin (2000) concluded that the possible endogeneity of the union variable is relatively unimportant when calculating CWDs for fatal risk. More recently, Lavetti and Schmutte (2018) considered the effects of endogenous job mobility on CWD estimates using administrative matched data for male workers from Brazil. Under imperfect labour market conditions where search frictions exist, workers over time may choose to switch between firms that offer different levels of compensation. In other words, workers will seek out jobs in firms that simultaneously increase their wage and decrease the level of risk they are exposed to. Consequently, bias in panel estimates of CWDs for job risk may be amplified in the presence of endogenous job mobility. When controls for establishment-specific effects were added to allow for endogenous job mobility, Lavetti and Schmutte (2018) found the estimated CWD for fatal risk increased from 3.7% to 17%. Unfortunately, comprehensive workplace specific data is not available for Australia, meaning such instances of bias cannot be controlled for, and is thus noted as a limitation of the CWD estimates computed in this study. Recent studies on CWD for job risk, such as Scotton (2013) and Guardado and Ziebarth (2019) did not consider risk endogeneity either.

Recent Contributions to the CWD Literature

The CWD theory proposes that, all else equal, workers need to be appropriately compensated to accept jobs with undesirable characteristics. If firms do not offer compensation for disamenities, the worker will switch to a job which better matches their risk/earnings preferences. Hence, an underlying assumption of CWD theory is perfect mobility of workers. It is however unreasonable to believe that workers can switch between jobs whenever they feel the need to do so (Purse, 2004). One cannot ignore the possible mobility hindering effects of institutional agreements such as employer-provided pensions and health insurance which incentivise the worker to remain with their current employer. Employer provided health insurance has been found to reduce labour mobility in the United States by as much as 25% (Madrian, 1994)[11]. Further to this point, the high degree of labour mobility required for CWD theory is necessarily hampered by inefficient labour markets. Loose (inefficient) labour markets, characterised by high levels of unemployment, hinders the mobility of workers through fear of inability to find more suitable employment elsewhere. That is, the expected utility of workers decreases as the prospect of involuntary unemployment increase and consequently workers may choose to remain working for their current employer even if they are not receiving adequate compensation for job risk. Such an idea is evident in the work of Robinson (1991) and Viscusi (1979). The work of Viscusi (1979) demonstrated that job turnover rates are higher for hazardous jobs in the presence of relatively tight labour markets, and Robinson (1991) was able to show that the rate of job turnover in hazardous jobs declines in the context of weaker labour markets. Thus, relatively loose labour market conditions may shield employers from worker's expectations of receiving appropriate CWD payments for job risk.

To demonstrate the effects of labour market conditions on CWDs, Bender and Mridha (2011) used local unemployment rates as a proxy for labour market tightness and found that when allowing for the interaction between unemployment and non-fatal risk, the estimated CWDs for job injury fell by 0.1% for every percentage point increase in the unemployment rate. This finding was reinforced by Mridha and Khan (2013) who estimated CWDs for fatal risk. Specifically, they

[11] Labour immobility should be less of a concern in Australia given that pensions tend to be defined contribution (rather than defined benefit), and the extensive health care system (Medicare) obviates the need for employer-provided health insurance.

found that local unemployment rates weakened the CWDs paid for fatal risk by 0.05% for union members and 0.02% non-union members. It is thus possible that estimated CWDs from hedonic wage regressions exhibit significant biases when controls for labour market tightness are absent. The current study will include unemployment rates for each Australian State and Territory in the sample to control for this potential source of bias; as such, it is an improvement on the estimates of CWDs produced by Kniesner and Leeth (1991) and Miller et. al (1997) who did not control for labour market tightness in their Australian studies.

Much of the literature assumes that increasing the level of safety expenditure by the firm is the only way to decrease the likeliness of a workplace accident. Presumably, the firm can lower worker wages to enable expenditure to produce a safer work environment. Safety expenditure could be in the form of investments in the state of the physical work environment or upgrades of the capital equipment used by workers. The latter is appropriate provided that the risk imposed on the worker is at least in part exogenously determined by the capital equipment. It may also be possible that the firm can reduce wages in order to provide workplace safety training to workers. Such a sentiment is evident in Dobbie, Nahm and MacMillan (2017) who found that worker engagement in workplace training (although not specifically for work risks) resulted in a small trade-off in future wage growth for union members. Recently, the assumption that the firm is the vehicle through which workplace safety risks are reduced has been relaxed by Guardado and Ziebarth (2019) who argue that workplace risk can be reduced by the workers themselves through worker-provided safety investments. If workplace accidents are costly to the profit of the firm, then it follows that firms will be willing to pay some premium for any worker-provided safety as it reduces the likeliness of a workplace accident. This in turn predicts a negative relationship between worker risk and wages. The negative relationship may offset some of the positive relationship which is generally expected between risk and wages. Although the idea of worker-provided safety was suggested by Chelius (1974) and Oi (1974), the research produced by Guardado and Ziebarth (2019) was the first study which explicitly allowed for workers to supply their own safety that firms are willing to pay for. Guardado and Ziebarth (2019) used separate fixed-effects models for fatal and non-fatal risk, and proxied worker safety investments with changes in the worker's body mass, and found that allowing for worker-provided safety and its interaction with fatal job alters the CWD and consequently the VSL estimates, although not in a statistically significant sense. The lack of statistical significance may be owing to the indirect and perhaps weak proxy of worker-provided safety. The current study furthers the worker-safety investment hypothesis put forward by Guardado and Ziebarth (2019) by using worker participation in training programs as a more direct proxy for worker-provided safety investments.

Purpose of the Current Study

Evidently, many improvements to the previous Australian studies on CWDs for job risk can be made. The most notable improvements are due to the introduction of the HILDA panel which allows the current study to control for unobserved heterogeneity which could have biased estimates in both previous Australian cross-sectional studies. The more detailed worker information contained in the HILDA surveys allows for the construction of a risk variable which varies by both industry and occupation. When combined with controls for worker industry and occupation, the impacts of inter-industry and inter-occupational differentials on CWDs for risk will be minimised. Consequently, the model will produce CWD estimates that better reflect the risk/earnings trade-off faced by Australian workers. The recent developments in the CWD literature are also considered in this study. Specifically, the effects of labour market tightness and unionisation on CWDs are considered for Australia. Although a union dummy was used in Kniesner and Leeth (1991), the interaction between union and risk was not included. The possible effects of labour market tightness were also not considered in either Australian study. Lastly, the current study will analyse the impact of worker-provided safety investments on CWD payments for job risk in a style similar to Guardado and Ziebarth (2019).

Data

The Sample and Data Sources

The worker and workplace data used in the current study has been extracted from waves of the Household, Income and Labour Dynamics in Australia (HILDA) survey. Introduced in 2001, the HILDA survey is answered by more than 17,000 Australians each year and collects a broad range of self-reported worker information such as income, health, education, and family dynamics as well as information regarding respondents' working lives, such as union status, industry and occupation of employment, and number of years employed. The surveys are longitudinal as respondents who complete one wave of the survey are followed up in subsequent periods. There are 17 waves of data available as of 2019.

In the current study, only data from Wave 10 to Wave 17 inclusive (2010–2017) is used. Prior to Wave 9, there was no differentiation between respondents who belong to a trade union as opposed to an employee association. As firms have no legal obligation to engage in collective bargaining with employee associations, it is less likely that CWD payments for risk will emerge for such workers. If the two groups of workers are not distinguishable, the effect of bargaining power between employees and employers, designed to be measured by the union variable, may be diluted. The question was changed from Wave 9 onward to allow for identification of trade union members separately.

Local unemployment rates were sourced from the ABS. The ABS collect an extensive range of macroeconomic data for Australia. Unemployment rates are available for each Australian State and Territory for each quarter[12]. It would be ideal to have unemployment rates that reflect the conditions of local areas within each State or Territory to better reflect the tightness of labour markets throughout Australia. This level of disaggregation is not available via the ABS, or the HILDA survey, as respondents are separated into States and Territories, and capital cities only. The unemployment rates were calculated as the average rate over the four quarters for each year from 2010 to 2017 inclusive.

The Consumer Price Index (CPI) data used for the calculation of respondents' real wages has also been obtained from the ABS for the years 2010 to 2017. The CPI data is available by State and Territory and is available for each quarter[13]. While it is possible to calculate State and Territory-specific CPIs, the current study does not do so. The CPI data indicates how much prices have changed across locations over a given period but does not allow for comparison of prices between areas. For example, in New South Wales and Western Australia, the CPI may have

[12] Unemployment data sourced from ABS survey number 6202.0.

[13] CPI data sourced from ABS survey number 6401.0.

increased from 100 to 100.4 between quarters, but this does not mean that the price levels across the States are equal. As the CPI only indicates the change in the price level, there is no reason to use area-specific CPI values. For this reason, an Australia-wide value for the CPI has been used and was calculated as the average CPI value for Australia over the four quarters of each year.

Fatal and non-fatal risk rates were sourced from Safe Work Australia. This statutory body publishes workplace health and safety, and workers compensation data each year. The fatal risk rates (risk of death) were taken from Safe Work's *Fatality Statistics* reports, which give the rates of death each year from workplace accidents. The rates are given per 100,000 workers. Fatality data from the 2007 to 2017 (inclusive) reports was used. The reports draw on compensation claims and coroners' reports to determine legitimate worker fatalities. To be deemed a fatality, the worker must have died in Australia or Australian waters as the result of work activity or work exposure. There are two unique features of the Safe Work Australia fatality data which are important to note. Firstly, the calculation of the published fatality rates includes bystander deaths which occur as a direct consequence of work actions. That is, the rates reported are the fatality risks to the worker and to immediate persons who may or may not be involved in the workplace. Because the theory of CWD assumes that workers have perfect information about job risks, workers must also be aware that the given risk is also risk of death to others. Informing workers that their actions at the workplace pose danger to others should not alter their behaviours in any way as this information is assumed to be known by the worker. Secondly, for some years, the fatality data included 'commuter deaths' in the calculation of the fatality rates. Commuter deaths are worker fatalities that occur as they travel to or from their workplace. The more recent Safe Work Australia publications (2012 onward) exclude commuter deaths as they have been challenging to distinguish from other road fatalities, and rely on workers compensation data (specifically for commuting), which has not been as readily available in recent years (Safe Work Australia, 2019). Unfortunately, commuter deaths and bystander deaths cannot be separated from the yearly workplace risks.

Non-fatal (injury) data was taken from Safe Work Australia's *Compensation Statistics* reports. Like the fatality reports, they are released annually, but unlike the fatality reports, cover the financial year period. Data from reports which cover the beginning of the year in question were used; so, for the year 2010, the financial year starting July 2009 and ending June 2010 was used. To be considered a non-fatal injury, the worker must have an accepted workers compensation claim which has resulted in an absence from work of at least one working week. Also, unlike the earlier fatality data, injuries sustained travelling to or from the workplace are excluded. Non-fatal risk rates are expressed per 1,000 workers.

The fatal and non-fatal risk rates are classified by industry and occupation separately. The industry categorisations follow the 2006 Australia and New Zealand Standard Industrial

Classification (ANZSIC) system and are given by major industry (at the one-digit level). There are 19 industry classifications in total. This classification system is available in the HILDA data at the same level, which removes the need for individual sorting of workers into industries. Similarly, occupational categories are given by Safe Work Australia and by HILDA as per the one-digit, 2006 Australia and New Zealand Standard Occupational Classification (ANZSCO) system. There are eight occupational categories used.

Construction of the Risk Variables

A longstanding challenge faced by researchers when estimating CWDs for job risk has been accounting appropriately for both the industry risk and occupation risk of workers. Failure to account for both leads to biased CWD estimates (Scotton, 2013). Safe Work Australia publishes risk rates for each occupation and each industry separately. The approach that was taken in the current study was to use the total risk rates for each industry and occupation to calculate the appropriate risk for each industry/occupation combination, of which there are 152 (8 occupations across 19 industries).

A simple illustration of the approach for fatal risk is given below[14]. The risk rate for each industry/occupation combination cell needs to be calculated using the rates on the margins which are taken from the Safe Work fatality reports. The requirements for the risk rates are: each cell must represent the risk rate per 100,000 workers; and, the sum over all industries in a given occupation, or the sum over all occupations in a given industry, must match the risk rate for the corresponding occupation or industry on the margins.

To make the relevant calculations, it is assumed that the relative risks between different occupations are the same across industries. For example, the ratio of risk rates between clerical workers and labourers is assumed to be fixed for all industries. Thus, the risk rate for occupation k in industry j is estimated as:

$$r_{kj} = K \times I_j \times \frac{O_k}{\sum_{k=1}^{K} O_k} \qquad for\ k = 1,\ldots,K\ (8);\ and\ j = 1,\ldots,J\ (19)$$

where r_{kj} is the risk rate per 100,000 workers of occupation k in industry j, I_j is the marginal risk rate per 100,000 workers in industry j, and O_k is the marginal risk rate per 100,000 workers for occupation k. The reason for multiplying by 8 (K) is to express the risk rate per 100,000 workers.

[14] The same procedure is used to calculate non-fatal rates that vary by the industry/occupation combination of the worker. The only difference is that each cell represents the injury risk per 1,000 workers.

Without this step, the risk rate in each occupation cell would represent the risk rate per 12,500 workers (as each of the eight occupational cells would contain 12,500 workers).

Due to statistical rounding and the omission of minor occupational categories the risk rates calculated using the above method will require an adjustment. In other words, the total accidents across all 19 industries will not equal the total accident count over all 8 occupations. This is problematic as all fatalities recorded in the industry need to be accounted for in the appropriate occupations. To overcome this issue, occupational risks rates have been scaled upward or downward depending on the relative difference between occupation and industry risk totals. That is, each occupational risk rate has been multiplied by the following scalar factor:

$$\lambda = \frac{\sum_{j=1}^{J} I_j \times K}{\sum_{k=1}^{K} O_k \times J}$$

As an illustration, suppose there are two industries and three occupations and their marginal risk rates in 2017 are given as:

2017	Occupation 1 (2 per 100,000)	Occupation 2 (1 per 100,000)	Occupation 3 (3 per 100,000)
Industry 1 (3 per 100,000)			
Industry 2 (2 per 100,000)			

Notice that the sum of accidents implied by the marginal risk rates for both industries (5) does not equal the sum implied by the marginal risk rates for all occupations (6). To see this, assume that each industry/occupation combination cell contains 100,000 workers, which means that, reading across the rows, each industry has a total of 300,000 workers, and, reading down the columns, each occupation has a total of 200,000 workers. The sum of all accidents (out of the total 600,000 workers) implied by the marginal risk rates for occupations is 12 (=2×2 + 1×2 + 3×2), while the sum of all accidents implied by the marginal risk rates for industries is 15 (=3×3 + 2×3). To make the sum of accidents across occupations equal to the sum of accidents across industries, the risk rate for each occupation is multiplied by the scale factor, λ = 1.25 (=15÷12), which results in the marginal risk rates in the table below[15]:

[15] Each marginal risk rate for occupation, for example, is computed as the existing marginal rate $\times$ 2 (accounting for the two industries) and then multiplied by the scalar. Hence, the marginal risk rate for occupation 1 in the above table is calculated as $2 \times 2 \times 1.25 = 5$. The size of the scalar each year ranged from 0.926 to 1.434.

Industry (j) / Occupation (k)	Occupation 1 (5 per 200,000)	Occupation 2 (2.5 per 200,000)	Occupation 3 (7.5 per 200,000)
Industry 1 (9 per 300,000)	3	1.5	4.5
Industry 2 (6 per 300,000)	2	1	3

Note that the risk rate for each occupation is multiplied by the scalar factor (1.25). The risk rate for each industry/occupation combination cell is then computed as explained above. For example, the risk rate for occupation 1 in industry 1 is computed as (3×3×2.5)÷7.5 = 3 (per 100,000 workers).

By keeping constant the relative risk between occupations across all industries or keeping constant the relative risk between industries across all occupations (the same outcome is achieved either way), unique risk rates for all industry/occupation combinations can be computed. Note that in the table above, the risk of fatality in occupation 1 is always twice as high as that for occupation 2 for all industries. Occupation 3 is always three times riskier than occupation 2, and one-and-a-half times riskier than occupation 1. Total accidents across all industries are equal to the total accidents across all occupations by construction.

The need for the constant relative risk assumption may be viewed as a necessary limitation of the current study, although, the assumption sounds reasonable. It is likely that fatal (and non-fatal) risk is determined by the working environment and capital equipment used by workers. It seems plausible that all managers will experience less risk than that of labourers, regardless of which industry they work in. Although it is unlikely that the relative risk will be fixed in proportion across all industries, the assumption still allows for risk to vary, to a large degree, between industries and occupations. This is a significant improvement to the risk variables used in older CWD studies, which varied by either occupation or industry. Using such risk variables assumes that all workers in each industry (occupation) face the same level of risk regardless of their occupation (industry), which is known to give rise to inter-industry bias in CWD estimates (Scotton, 2013).

Virtually all CWD studies model risk and wages in the same period. However, it may be possible that individuals and unions engage in bargaining with employers once the overall risk rate (accident count) for the year is known by agents other than the workers (who, by assumption, are already aware of the risk they face). If this is the case, wages in the current period would have been affected by workplace risk from past periods. The current study will also use a three-year moving average of risk to capture this possibility. The three-year moving averages have been calculated as the average of the relevant risk three years prior to the current wave (for example, the 2010 three-year industry/occupation risk rates are calculated as an average of the industry/occupational rates from 2007 to 2009). This should be useful in reducing the impact of

Safe Work Australia's exclusion of 'commuter deaths' as noted earlier. Such an approach would also remove the impact of any random fluctuations in fatalities and injuries (Kniesner, Viscusi, Woock and Ziliak, 2012). One drawback of this approach is that any impact of significant workplace fatalities would be reduced by averaging. That is, any wage effects that arise from a particularly dangerous year for a given industry/occupation combination would be minimised. Unfortunately, the 2006 ANZSIC and ANZSCO classifications were not applied in the Safe Work Australia risk reports for 2006. Consequently, Wave 9 from HILDA has been dropped from the sample as risk data for 2009 requires data from 2006 for the calculation of the moving average. This would not be problematic when using a single-year risk rate, but Wave 9 has been excluded from the sample for consistency.

Descriptive Statistics

To be included in the sample, respondents must be working for pay and have income data available for each wave. Respondents must also have both an occupational and industry classification for each year and must not be studying full time or be self-employed. Excluding the self-employed is a common practice when estimating CWDs for risk as the fatal and non-fatal risk faced by those that are self-employed is higher compared to their counterparts who are not self-employed (Pegula, 2004). Further, self-employed workers are excluded from Safe Work Australia's calculation of industry and occupation risk rates. The HILDA survey asks employed respondents to nominate a labour force status of either full time or part time. If the nature of part-time work is such that the worker is less exposed to risky environments or capital, it may be possible that they receive little to no compensation for risk when compared to their full-time counterparts. To be consistent with older studies, only workers with a labour force status of full-time are included in the final sample (Viscusi & Aldy, 2003). The more recent study by Scotton (2013) included only full-time workers in the sample. It is also worth noting that many of the risk rates used in previous studies pertained to full-time workers only (for example, fatal risk per 100,000 full-time workers), while the fatality rates given by Safe Work Australia which are used in this study are expressed more generally (as per 100,000 workers). The Australian workers who contribute to the fatality statistics may have a labour force status of full time, part time, or not employed (in the case of a bystander death). Consequently, caution should be exercised when interpreting the CWD results (if found here) paid to workers with a full-time status. Workers who report a nominal hourly wage lower than the minimum wage for each period or who report a real hourly wage greater than $400 are dropped[16]. The final dataset contains 45,353 observations on full-time workers across eight waves (years).

[16] There were 1,758 observations which reported a nominal hourly wage less than the minimum wage, and one instance of a worker reporting a real hourly wage in excess of $400. Workers who report a nominal hourly wage less than the minimum wage may have few skills desirable in the market, and thus may except payment irrespective of the risk level faced. In other words, these workers may not require compensation for higher risk on the job and thus have been excluded from the sample.

Table 1: Breakdown of the sample by major worker categories

Male									
Wave	10	11	12	13	14	15	16	17	Total
FT respondents	2,768	3,601	3,556	3,496	3,505	3,537	3,516	3,518	27,497
%	*0.61*	*0.61*	*0.61*	*0.61*	*0.61*	*0.61*	*0.60*	*0.59*	*0.61*
Wage bargaining power									
EA	886	1,182	1,198	1,240	1,197	1,193	1,091	1,128	9,115
%	*0.32*	*0.33*	*0.34*	*0.35*	*0.34*	*0.34*	*0.31*	*0.32*	*0.33*
Union member	676	852	826	808	766	781	729	725	6,163
%	*0.24*	*0.24*	*0.23*	*0.23*	*0.22*	*0.22*	*0.21*	*0.21*	*0.22*
Employment contract [a]									
Permanent	2,259	2,979	2,928	2,892	2,873	2,908	2,878	2,862	22,579
%	*0.82*	*0.83*	*0.82*	*0.83*	*0.82*	*0.82*	*0.82*	*0.81*	*0.82*
Fixed	281	348	347	313	328	322	318	323	2,580
%	*0.10*	*0.10*	*0.10*	*0.09*	*0.09*	*0.09*	*0.09*	*0.09*	*0.09*
Casual	221	269	277	283	300	296	311	325	2,282
%	*0.08*	*0.07*	*0.08*	*0.08*	*0.09*	*0.08*	*0.09*	*0.09*	*0.08*
Female									
Wave	10	11	12	13	14	15	16	17	Total
FT respondents	1,758	2,280	2,307	2,282	2,230	2,290	2,309	2,400	17,856
%	*0.39*	*0.39*	*0.39*	*0.39*	*0.39*	*0.39*	*0.40*	*0.41*	*0.39*
Wage bargaining power									
EA	572	805	825	880	855	855	843	875	6,510
%	*0.3*	*0.4*	*0.4*	*0.4*	*0.4*	*0.4*	*0.4*	*0.4*	*0.4*
Union member	487	590	594	566	545	551	545	568	4,446
%	*0.28*	*0.26*	*0.26*	*0.25*	*0.24*	*0.24*	*0.24*	*0.24*	*0.25*
Employment contract [a]									
Permanent	1,413	1,862	1,860	1,827	1,782	1,853	1,847	1,891	14,335
%	*0.80*	*0.82*	*0.81*	*0.80*	*0.80*	*0.81*	*0.80*	*0.79*	*0.80*
Fixed	231	254	291	312	276	290	314	333	2,301
%	*0.13*	*0.11*	*0.13*	*0.14*	*0.12*	*0.13*	*0.14*	*0.14*	*0.13*
Casual	113	162	152	142	166	146	148	175	1,204

Note. FT = full time; EA = enterprise agreement.
[a] Employment contract for full-time workers only.

Table 1 shows the number of respondents for each wave as well as the breakdown of male and female respondents across each wave. The sample contains more male respondents than female (60% to 40% respectively) but this is not seen as problematic. The employment contract groupings of the full-time respondents are near identical between the male and female groups over all waves.

The variable *EA* represents respondents who indicated that their wage is determined through collective enterprise agreements (a wage-setting process where minimum pay and employment conditions are negotiated through collective bargaining at the enterprise level). From Table 1, it is evident that the percentage of workers in the sample who have their pay determined through enterprise agreements is greater than the percentage of workers who identify as union members for both male and female groups. It is also evident that the percentage of workers, both male and female, whose pay is determined through enterprise agreements has been increasing over time while density of union membership declines. In other words, the percentage of union members across groups has been decreasing, but the percentage of workers who may benefit from the strength of union power has been increasing. As employers cannot discriminate against non-union members, those who are not union members still benefit from the efforts of the union's negotiations. As a result, the wage effects of the union may also be reflected by workers whose pay is set through enterprise agreements, rather than just those who belong to a union. Only 56% of respondents whose pay is determined through enterprise agreements are also union members. A drawback of using the *EA* variable in place of the union variable is that it must be assumed enterprise agreements are union negotiated and thus can serve as appropriate measure of the union influence in commanding higher wages for workplace risk. Dobbie, Nahm and MacMillan (2017) found that as of 2015, approximately 38% of all registered collective agreements were non-union negotiated in Australia. Thus, using *EA* as a measure of union influence (or bargaining power) would introduce some doubt as to the true extent to which bargaining power between employees and employer determines compensation for risk. Most previous studies have captured the effects of wage bargaining power using a union membership dummy variable[17], where union membership is self-reported by the worker. As the HILDA data is also self-reported, and to be consistent with previous studies, the current study has used the worker's union status as a proxy for wage bargaining power.

Table 2 provides the breakdown of industry and occupation of work for males and females across all waves of the sample. The education and training industry, and the health care and social assistance industry are dominated by females, while the manufacturing industry, mining industry, and transport, postal and warehousing industry are dominated by males.

[17] For example, Thaler and Rosen (1976); Viscusi (1980); Kniesner and Leeth (1991); Leigh (1995); Arabsheibani and Marin (2000); Viscusi (2004); Kniesner et al. (2012).

Table 2: Industry and occupation categories with male and female numbers reported separately

Industry	Male	%	Female	%	Total
Agriculture, forestry and fishing [1]	504	*85.9%*	83	*14.1%*	587
Mining [2]	1181	*84.8%*	211	*15.2%*	1392
Manufacturing [3]	3842	*82.4%*	823	*17.6%*	4665
Electricity, gas, water and waste services [4]	599	*82.4%*	128	*17.6%*	727
Construction [5]	3523	*92.0%*	308	*8.0%*	3831
Wholesale trade [6]	1387	*73.0%*	512	*27.0%*	1899
Retail trade [7]	1571	*53.0%*	1394	*47.0%*	2965
Accommodation and food services [8]	697	*51.6%*	655	*48.4%*	1352
Transport, postal and warehousing [9]	2104	*83.3%*	421	*16.7%*	2525
Information media, telecommunications [10]	592	*59.6%*	402	*40.4%*	994
Financial and insurance services [11]	1128	*52.1%*	1038	*47.9%*	2166
Rental, hiring and real estate services [12]	315	*44.7%*	390	*55.3%*	705
Professional, scientific, technical services [13]	2197	*60.6%*	1427	*39.4%*	3624
Administrative and support services [14]	588	*51.6%*	552	*48.4%*	1140
Public administration and safety [15]	2759	*61.9%*	1695	*38.1%*	4454
Education and training [16]	1596	*34.0%*	3098	*66.0%*	4694
Health care and social assistance [17]	1494	*26.7%*	4097	*73.3%*	5591
Arts and recreation services [18]	392	*62.8%*	232	*37.2%*	624
Other services [19]	1028	*72.5%*	390	*27.5%*	1418
Occupation	**Male**	**%**	**Female**	**%**	**Total**
Managers [1]	4645	*65.4%*	2459	*34.6%*	7104
Professionals [2]	6150	*49.7%*	6228	*50.3%*	12378
Technicians and trades workers [3]	5960	*90.2%*	650	*9.8%*	6610
Community and personal service workers [4]	1602	*44.8%*	1975	*55.2%*	3577
Clerical and administrative workers [5]	2278	*33.8%*	4469	*66.2%*	6747
Sales workers [6]	1098	*49.0%*	1143	*51.0%*	2241
Machinery operators and drivers [7]	3392	*93.2%*	248	*6.8%*	3640
Labourers [8]	2372	*77.6%*	684	*22.4%*	3056

For occupations, females dominate in clerical and administrative services roles, while males dominate in machinery operator and driver roles, and technician and trade worker roles. In 2017, Safe Work Australia identified that out of the 190 fatalities for the year, 119 were related to vehicles. Further, 15% of fatalities were caused by falls from a height and 18% by being hit by moving objects. Given that male workers appear to have a much higher risk of death (owing to working in the riskier industries and occupations) it is unsurprisingly that 179 of the 190 fatalities for the year were male.

Lastly, Table 3 provides a breakdown of the average fatal and non-fatal risk rates calculated for each industry/occupation combination. For fatal risk, each cell represents the average fatality rate per 100,000 workers over the years 2010 to 2017 inclusive, according to their industry/occupation combination. Given that most workplace fatalities were related to vehicles, it is no surprise that the highest average fatality rate of 63 per 100,000 workers belongs to machinery operators and drivers in the agriculture, forestry and fishing industry. The machinery operator and driver occupation does exhibit the highest rate of fatality across industries that are characterised by machinery usage (for example, transport, postal and warehousing). Workers in the financial and insurance services industry and workers in the clerical and administrative occupation routinely experience the lowest fatality risk. Specifically, workers who have the exact industry/occupation combination (clerical and administrative worker / financial and insurance services industry) experience the lowest average fatality risk of 0.03 workers per 100,000 workers.

For non-fatal (injury) risk, each cell represents the average rate of non-fatal risk per 1,000 workers. It is evident that workers in the financial and insurance services industry and workers in the clerical and administrative occupation face the lowest incidence of workplace injury risk. Workers with this exact industry/occupation combination experience the lowest incidence of workplace injury of 0.6 incidents of injury for every 1,000 workers. Labourers are most injury-prone occupation, followed closely by the machinery operator and driver occupation. This is expected given the intensely physical nature of these occupations. When looking at industry alone, the highest prevalence of injury occurs in the agriculture, forestry and fishing industry. Labourers in this industry on average experience 41.2 injuries per 1,000 workers. This is equivalent to 4.1% of workers on average sustaining an injury over the course of the year. There is also a very high prevalence of injury for labourers, and for machinery operators and drivers in industries that require significant physical labour (such as construction, manufacturing, and transport, and postal and warehousing).

Table 3: Average fatal and non-fatal risk rates for each industry/occupation combination

Fatal risk (per 100,000 workers)								
Industry/Occupation	Managers [1]	Professionals [2]	Technicians, trades [3]	Community, pers. serv. [4]	Clerical and admin. [5]	Sales workers [6]	Machine ops, drivers [7]	Labourers [8]
Agriculture, forestry and fishing [1]	15.52	4.71	13.66	5.34	1.06	2.25	63.44	27.22
Mining [2]	2.84	0.84	2.54	1.07	0.20	0.41	11.95	5.14
Manufacturing [3]	1.49	0.47	1.33	0.55	0.11	0.20	5.96	2.59
Electricity, gas, water and waste services [4]	2.22	0.65	1.99	0.75	0.16	0.35	9.94	4.24
Construction [5]	2.97	0.94	2.70	1.01	0.21	0.42	12.32	5.33
Wholesale trade [6]	1.23	0.40	1.08	0.47	0.09	0.21	5.08	2.25
Retail trade [7]	0.34	0.10	0.28	0.12	0.02	0.06	1.32	0.57
Accommodation and food services [8]	0.28	0.08	0.27	0.11	0.02	0.05	1.31	0.58
Transport, postal and warehousing [9]	7.52	2.34	6.63	2.56	0.54	1.09	31.34	13.48
Information media, telecommunications [10]	0.59	0.21	0.53	0.18	0.04	0.07	2.20	0.97
Financial and Insurance services [11]	0.05	0.02	0.05	0.01	0.00	0.01	0.26	0.11
Rental, hiring and real estate services [12]	0.98	0.33	0.86	0.34	0.07	0.17	3.92	1.74
Professional, scientific, technical services [13]	0.27	0.09	0.22	0.09	0.02	0.04	1.04	0.44
Administrative and support services [14]	1.57	0.50	1.42	0.54	0.10	0.23	6.31	2.73
Public administration and safety [15]	0.96	0.29	0.83	0.35	0.07	0.14	3.74	1.63
Education and training [16]	0.18	0.06	0.15	0.05	0.01	0.02	0.72	0.30
Health care and social assistance [17]	0.20	0.06	0.18	0.07	0.01	0.03	0.81	0.35
Arts and recreation services [18]	2.78	0.85	2.54	1.03	0.20	0.42	11.96	5.22
Other services [19]	0.87	0.24	0.75	0.32	0.06	0.13	3.54	1.49

Non-fatal risk (per 1,000 workers)								
Industry/Occupation	Managers [1]	Professionals [2]	Technicians, trades [3]	Community, pers. serv. [4]	Clerical and admin. [5]	Sales workers [6]	Machine ops, drivers [7]	Labourers [8]
Agriculture, forestry and fishing [1]	6.39	7.36	23.43	26.35	5.98	9.23	38.15	41.21
Mining [2]	3.66	4.23	13.41	15.12	3.44	5.28	21.85	23.52
Manufacturing [3]	5.79	6.66	21.17	23.84	5.42	8.34	34.48	37.21
Electricity, gas, water and waste services [4]	2.97	3.43	10.90	12.25	2.78	4.29	17.74	19.14
Construction [5]	5.46	6.28	20.04	22.52	5.11	7.89	32.62	35.28
Wholesale trade [6]	4.20	4.83	15.40	17.30	3.92	6.06	25.06	27.13
Retail trade [7]	2.65	3.05	9.70	10.92	2.48	3.82	15.80	17.08
Accommodation and food services [8]	2.69	3.09	9.85	11.09	2.52	3.88	16.04	17.34
Transport, postal and warehousing [9]	6.23	7.19	22.76	25.69	5.86	8.97	37.10	39.90
Information media, telecommunications [10]	1.01	1.17	3.70	4.17	0.95	1.46	6.03	6.51
Financial and insurance services [11]	0.68	0.78	2.47	2.79	0.64	0.97	4.03	4.33
Rental, hiring and real estate services [12]	1.91	2.21	7.00	7.89	1.80	2.75	11.40	12.25
Professional, scientific, technical services [13]	0.80	0.93	2.93	3.31	0.76	1.15	4.78	5.13
Administrative and support services [14]	3.77	4.35	13.76	15.51	3.54	5.41	22.39	24.08
Public administration and safety [15]	4.20	4.86	15.36	17.34	3.96	6.04	25.04	26.89
Education and training [16]	2.48	2.86	9.08	10.22	2.32	3.58	14.79	15.97
Health care and social assistance [17]	4.35	5.01	15.89	17.93	4.08	6.26	25.89	27.89
Arts and recreation services [18]	3.67	4.23	13.44	15.13	3.43	5.29	21.89	23.61
Other services [19]	2.92	3.35	10.67	12.03	2.73	4.21	17.38	18.80

Method

The following wage equations are estimated to determine the existence of CWDs for fatal and non-fatal risk[18]:

$$w_{it} = \beta_1 FRisk_{it} + X_{it}'\beta_2 + \beta_3 Union_{it} + \beta_4(Union_{it} \times FRisk_{it}) + \beta_5 Unemp_{it} + \beta_6(Unemp_{it} \times FRisk_{it}) + \delta_t + \alpha_i + \varphi_k + \psi_j + \varepsilon_{it} \quad (1)$$

$$w_{it} = \beta_1 NFRisk_{it} + X_{it}'\beta_2 + \beta_3 Union_{it} + \beta_4(Union_{it} \times NFRisk_{it}) + \beta_5 Unemp_{it} + \beta_6(Unemp_{it} \times NFRisk_{it}) + \delta_t + \alpha_i + \varepsilon_{it} \quad (2)$$

where w_{it} is the natural logarithm of real hourly wages of worker i at time t. Industry and occupation subscripts have been dropped as the individual and time subscripts implicitly include the industry/occupation combination of the worker. The model includes individual fixed effects (α_i) to capture any unobservable and time-invariant individual characteristics in wage determination, such as work ethic and motivation. Industry and occupational fixed effects (ψ_j and φ_k respectively) are included for the fatal model to capture the impacts that any exogenous shocks may have on an individual's earnings and remove any inter-industry and inter-occupational differentials. Industry and occupation fixed effects are excluded from the non-fatal model as industry and occupational dummies are highly collinear with the injury risk variable used, a problem not uncommon to research of this nature. The yearly fixed effects (δ_t) capture any time trends not explained by other explanatory variables. The yearly fixed effects should also alleviate the impact of Safe Work Australia's exclusion of commuter deaths from the fatality reports from 2012 onwards. The variable $Union$ is a dummy variable which is equal to 1 if the respondent reports belong to a union in year t, and $Unemp$ is a variable which represents the unemployment level depending on the year and the worker's location. To make the interpretation of the marginal effect of risk simple, the unemployment variable is defined as the difference from the variable's sample mean value. All individual worker and workplace information known to be important determinants in earnings functions (such as age, experience, geographical region and firm size) are contained in the vector X_{it}. It is likely that some of the unobservable individual heterogeneity is correlated with important explanatory variables contained in X_{it}. In such a case, random effects estimation will lead to biased and inconsistent estimates. It is for this reason that a fixed effects

[18] Although the models are different (and thus the explanatory variables should be specified with different coefficients and the random error terms should be denoted differently), both are specified using the same coefficients to allow for a streamlined explanation of the variables and interpretation of results.

model is employed. (The Hausman test strongly rejects the use of a random effects model.) Idiosyncratic errors are given by ε_{it} for both models.

The size of the CWD for fatal and non-fatal risk for non-union workers at the sample mean of unemployment is given by the coefficient β_1 in models (1) and (2) respectively. This coefficient represents the CWD paid to non-union workers as the risk of death increases by 1 in 100,000 under model (1) or when the risk of injury increases by 1 in 1,000 under model (2). If the worker belongs to a union the CWDs for workplace risk for both models will instead be given by $\beta_1 + \beta_4$, evaluated at the sample mean of unemployment. In the case where union status plays no significant role in the determination of CWDs, β_4 will not be statistically different from zero, and both union and non-union members will receive CWDs equal to β_1. The extent to which union status and local unemployment rates influence the size of CWDs is captured by the coefficients of the interaction terms β_4 and β_6 respectively. The expected sign of the union interaction coefficient (β_4) is positive for both models if it is the case that unions can command compensation for the risk of death and injury for their members. The interaction between unemployment and risk is included to test for the effects of labour market tightness on CWDs (Bender & Mridha, 2011). The interaction term between the centred value of unemployment and risk (β_6) is expected to be negative for both models implying that relatively looser labour markets weaken the CWDs for risk.

To capture the possibility that compensation for risk in the current period is determined by an average of the risk in past periods, the risk variables for the fatal and non-fatal model are replaced with three-year moving averages of the appropriate risk. The coefficient β_1 will instead reflect the CWDs paid to non-union workers for fatal and non-fatal risk realised in past periods, evaluated at the mean unemployment rate. As it could be the case that wage bargaining between employers and unions takes place with knowledge of previous years' accident rates (*ex post* rather than *ex ante*), the interaction between unions and the moving average risks are also expected to be positive if unions are able to command higher compensation for their members. Using a moving average reduces the noise that may arise from one-off catastrophic accidents which may over-represent the typical risk faced by workers in each industry/occupation combination.

Extension

A further contribution of the current study is to add to the worker safety investment hypothesis put forward by Guardado and Ziebarth (2019). The goals of this extension are to test their hypothesis using a more direct proxy for worker safety investments. The usual assumption is that workers can accept lower wages to have safety training or a safer working environment provided to them by the firm. This assumption is now relaxed such that workers can provide safety to the firm (worker-provided safety) at no additional cost and in return receive higher wages. Firms will demand (and thus pay for) worker-provided safety because it is cheaper than incurring an accident cost with probability, in part, determined by the worker (otherwise exogenously determined through working capital employed).

Using the profit function of the firm (Guardado and Ziebarth, 2019):

$$\Pi = Q - W - S - p(e)A$$

Labour and prices are normalised to 1.

Where:

$Q = firm's\ output$

$W = worker's\ wage$

$S = firm's\ exogenous\ safety\ expenses$

$e = safety\ inputs\ by\ workers\ which\ lower\ probability\ of$

$\quad a\ workplace\ injury\ or\ fatality\ (p)$ where $0 \leq p \leq 1$

$A = fixed\ accident\ cost$

The standard argument is that firms can create a safer work environment by increasing safety expenses (S) but doing so results in a decrease worker wages (W) such that profit remains constant. Now suppose that workers can influence the firm's profit through their own investments in safety (e) which decrease the likelihood of accidents occurring (p). A function of $p(e)$ is specified such that the marginal effects of safety investments decrease at a diminishing rate (that is, $p' < 0$ and $p'' > 0$). Also suppose that output of workers can increase if they are able to 'cut corners' by not adhering to proper workplace practices. By doing so, they increase the probability of a workplace accident. That is, Q and p are positively related. Now a situation exists in which the firm may have some incentive to limit the amount of safety investment (which results in lower p) that workers can provide.

The profit function for the firm under the new framework is defined as:

$$\Pi = Q\big(p^{NF}(e)\big) - W - S - [A^{NF} * p^{NF}(e) + A^{F} * p^{F}] \quad (3)$$

The probability of a workplace accident (p) is divided into fatal accident probability (p^F) and non-fatal accident probability (p^{NF}). In the case of an accident, the firm incurs accident costs A^F and A^{NF} respectively. The safety investment variable (e) can be interpreted as a measure of the risk aversion of the worker. Given the choice, only workers who are relatively risk-averse will invest in safety (that is, the firm does not require workers to participate in training programs). Consequently, workers who participate (invest) in safety training are less likely (due to their risk preferences) to engage in risky work practices, and the likeliness of an accident decreases. The worker safety investment variable (e) is proxied by Australian workers in the HILDA panel who indicated they have participated in training programs for reasons of health and safety. It is assumed that the firm provides the highest level of safety training possible (S) such that the risk of death is at its lowest. This is to say, the work environment and the capital equipment used in the workplace pose an exogenous (minimum) level of fatal risk to workers and thus cannot be reduced through worker safety investments.

It would, however, not be implausible to believe that workplace injuries that arise from cutting corners (such as rushing through physical tasks which puts undue strain on the body or getting jobs completed quicker by not taking the time to properly equip safety equipment) are within the worker's control. As they are worker-induced injuries, no amount of safety investment from the firm can reduce the likelihood of such occurrences, and even though the accident is produced by the worker, the firm is still liable to pay the accident costs (A^{NF}). The worker can decrease the likelihood of a non-fatal accident by providing their own safety to the firm[19]. From the firm's perspective, decreases in injury risk are ideal as it decreases the expected accident costs (by lowering p^{NF}) to the firm and consequently increase profit. The firm is then able to distribute the profit back to workers in the form of higher wages. However, encouraging workers to provide safety at the workplace comes with a cost to the firm. It is likely output will fall as workers begin to, for example, ease the strain of physical labour by working at a slower pace. This implies a positive relationship between non-fatal risk and the firm's output level. Overall, worker-provided safety has both a positive and negative impact on the firm's profit level. Whether or not workers are rewarded for such investments would thus depend on the magnitude of each effect.

In a competitive context where profits are equal to zero, the equation for wages can be expressed as:

$$W = Q(p^{NF}(e)) - S - [A^{NF} * p^{NF}(e) + A^{F} * p^{F}] \tag{4}$$

Output, Q, is defined as a positive function of non-fatal risks (which is in turn a negative function of safety inputs) and fatal risk has zero marginal effect on output.

Taking partial derivatives of the wage function (4) with respect to risk gives:

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[19] It may be unrealistic to view adherence to the safety standards expected by the firm as an investment in safety, but the safety investment variable (e) is viewed as a measure of risk-aversion of the worker. Workers who have engaged in training programs (invested in e) are viewed as relatively more risk-averse and are less likely to be the workers who are increasing output by not following proper safety procedures (cutting corners) compared to a worker who has not invested in e.

$$\frac{dW}{dp^F} = -A^F < 0 \tag{5}$$

$$\frac{dW}{dp^{NF}} = Q' - A^{NF} \tag{6}$$

The partial derivative in (5) implies that decreases in fatal-risk result in higher wages to workers. This is because the firm faces no trade-off between fatal risk and output. Only exogenous decreases in fatal risk will result in higher wages to workers.

The result of (6) could be positive or negative depending on the rate of change in output that result from changes in non-fatal risk. The result would be positive if increases in p^{NF} lead to increases in output at a faster rate than the corresponding increase in non-fatal accident costs. This would suggest that worker investments in e which decrease p^{NF} will have negative impact on the worker's wage.

Taking the total derivative with respect to worker safety inputs yields:

$$\frac{dW}{de} = \overset{(-)}{\frac{\partial p^{NF}(e)}{\partial e}} Q' - \overset{(+)}{\frac{\partial p^{NF}(e)}{\partial e}} A^{NF} \tag{7}$$

The overall result of worker investments in safety (7) can be either positive or negative depending on the relative rate of change in non-fatal accident costs, compared to the rate of change in output which result from engaging in riskier (in a non-fatal sense) work actions.

If $\frac{dW}{de} > 0$, workers are rewarded for providing safety to the firm as the reduction in expected accident costs outweigh the reduction in output resulting from fewer shortcuts being taken on the job. That is:

$$\left|\frac{\partial p^{NF}(e)}{\partial e} Q'\right| < -\frac{\partial p^{NF}(e)}{\partial e} A^{NF}$$

Or if $\frac{dW}{de} \leq 0$, workers are not rewarded for providing safety to the firm. The reduction in costs of expected accidents due to lower accident probabilities does not outweigh the reduction in output resulting from safer work practices on the job. That is:

$$\left|\frac{\partial p^{NF}(e)}{\partial e}Q'\right| \geq -\frac{\partial p^{NF}(e)}{\partial e}A^{NF}$$

The HILDA survey asks respondents if they have attended any training courses during the year. If they had, the survey follows up by asking how many days of training they have had and what was the reason they engaged in training. Respondents who reported that they had participated in training for health and safety reasons have been used in each wave to proxy the safety input variable, e. The variable e is a continuous variable which reflects the intensity of participation in worker training programs. It has been calculated as the number of training days the worker has attended during the year, divided by the number of training courses attended during the same year, provided the training was for health and safety purposes. A limitation of this approach is that a total of only 5,130 respondents over the eight-year period indicated that they had engaged in training for safety. This number is made up of 3,099 male respondents and 2,031 female respondents. Interestingly, workers with an occupation of 'professional' engaged the most in training programs (approximately 30% of the 5,130 respondents), while workers with an occupation of 'labourer' or 'machine operator' made up only 7.3% and 8.4% of the total number of safety training respondents, respectively.

The following models are used to estimate the effects of worker training on wages[20]:

$$w_{it} = \beta_1 FRisk_{it} + X_{it}'\beta_2 + \beta_3 Union_{it} + \beta_4(Union_{it} \times FRisk_{it}) + \beta_5 Unemp_{it} + \beta_6(Unemp_{it} \times FRisk_{it}) + \beta_7 WT_{it} + \beta_8(WT_{it} \times FRisk_{it}) + \delta_t + \alpha_i + \varphi_k + \psi_j + \varepsilon_{it} \quad (8)$$

$$w_{it} = \beta_1 NFRisk_{it} + X_{it}'\beta_2 + \beta_3 Union_{it} + \beta_4(Union_{it} \times NFRisk_{it}) + \beta_5 Unemp_{it} + \beta_6(Unemp_{it} \times NFRisk_{it}) + \beta_7 WT_{it} + \beta_8(WT_{it} \times NFRisk_{it}) + \delta_t + \alpha_i + \varepsilon_{it} \quad (9)$$

where WT is the variable for worker training as a proxy for worker safety inputs (e). Models (8) and (9) are estimated with single-year risk rates as well as three-year moving averages for risk. The coefficient β_7 indicates the effect of worker training on wages for both models when there is no risk of death or injury. It reflects the premium paid to workers who provide safety to the firm compared to workers who do not, provided risks are zero. The coefficient for the interaction terms (β_8) will indicate the effect of worker safety investments on CWDs for a given

[20] Although the models are different (and thus the explanatory variables should be specified with different coefficients and the random error terms should be denoted differently), both are specified using the same coefficients to allow for a streamlined explanation of the variables and interpretation of results.

level of risk. The overall return to worker-provided safety investments for jobs with some positive level of risk will be given by $\beta_7 + \beta_8 FRisk_{it}$ for the fatal model, and $\beta_7 + \beta_8 NFRisk_{it}$ for the non-fatal model. All else being equal, the total CWD received by union workers in risky jobs who face the mean unemployment rate and who have provided some level of safety inputs, will be given by $\beta_1 + \beta_4 + \beta_8 WT_{it}$ for a one unit increase in the level of job risk. If the worker is not a union member, the CWD is instead given by $\beta_1 + \beta_8 WT_{it}$.

Results and Discussion

Sample Means

The mean real hourly wage for the sample of Australian workers between 2010 to 2017 inclusive is reported for major categories in Table 4. Across all categories in Table 4, the average hourly wage of males exceeds that of females and the difference in means between the two groups is highly significant. Of note, union workers on average receive a higher real hourly wage compared to non-union workers. The average union premium is close to two dollars for male workers and three dollars for females. It is also evident that the average wage paid to public sector workers exceeds that paid to private sector workers for both groups by approximately four to seven dollars per hour.

When analysing the average wages for educational attainment, the difference between male and female average real wages increases with each increase in qualification. The disparity between average male and female wages is largest for tertiary qualifications where males on average earn approximately ten dollars per hour more than females. When analysing the variables indicating how wage is set, unsurprisingly, the difference in real hourly wages for employees paid exactly the award rate is insignificant between male and female workers. Although not reported in Table 4 (to save space), the data indicates that the average hourly wage paid to males across all industries and occupations is larger than the average hourly wage paid to females. Although interestingly, the difference in wages is not statistically different between the two groups in arts and recreational services, and other services (industries 18 and 19, respectively). The difference is significant across all occupational groups. Sample means of real hourly wages for all categories are reported in full in the appendix.

Table 4: Sample means of real hourly wage for male and female Australian workers for the period 2010–2017 (inclusive)

Category	Male	Female		Category	Male	Female	
All workers	35.48	30.36	**	Highest education			
				Tertiary[a]	45.32	35.74	**
Union	36.92	32.59	**	Diploma[b]	41.49	32.87	**
Non-union	35.06	29.62	**	Certificate[c]	31.99	24.87	**
Public sector	38.83	34.72	**	Year 12	29.77	25.79	**
Not public	34.53	28.02	**	≤ Year 11	27.34	24.93	**
Full-time contract				Firm size			
Fixed term	39.75	32.54	**	< 20	30.41	25.71	**
Casual	27.50	24.80	**	20–99	33.19	28.08	**
Permanent	35.79	30.47	**	100–499	37.48	30.05	**
				500–999	38.63	31.67	**
Wage setting				1000–4999	40.59	33.12	**
Collective	36.10	31.97	**	5000–19,900	40.52	33.27	**
Individual	38.12	31.26	**	≥ 20,000	38.11	32.17	**
Combination[d]	35.20	30.68	**				
Award only	27.54	26.96					

Note. Full results available in Table 9.
[a] Includes bachelor's, honours, master's and doctoral degrees. [b] Includes diplomas, graduate/advanced diplomas and graduate certificates. [c] Includes certificates III and IV.
[d] Combination of collective/enterprise agreement and individual agreement.
* and ** indicate a significant difference in mean real hourly wage between the two groups at 5% and 1% respectively.

Results for Model (1) and Model (2)

To determine the extent to which Australian workers are compensated for job risk, models (1) and (2) are estimated, with key results reported in Table 5. (See the appendix for full estimation results for both models.)

For both groups, worker experience and its square have the typical signs and significance consistent with human capital theory. Tenure with current employer, measured in years, is not significant for male workers when years of experience and occupational tenure are controlled for, consistent with other research for Australia (Dobbie, MacMillan & Watson, 2014), but is significant for female workers. By contrast, tenure in current occupation, also measured in years, is not significant for females but is significant for males. As the models have been estimated with individual fixed effects, the coefficients on the education variable indicate the return to education only for those that change their reported education level across waves. The insignificant coefficients for both male and females imply that there is little return to completing formal education when already full-time employed[21].

There is also a consistent wage premium received by public sector workers. Under the fatal risk model, the premium is 1.8% of a private-sector worker's wage for males and 3.4% of a private-sector worker's wage for females. The premium for male workers decreases to 1.6% but increases for females to 4.3% when the non-fatal model is used. The results are highly significant in both models for female workers only. The negative coefficients for *Permanent* indicate that both male and female permanent contract workers experience a significant wage penalty of approximately 4% when compared to a casual contract worker. The negative relationship may be reflective of the non-wage benefits available only to workers who are employed on a permanent basis. That is, permanent contract workers pay for the non-wage benefits they receive by taking a wage cut (of approximately 4%) compared to the base group of casual contract workers. It may also be reflective of the 20% casual loading paid to casual workers under award agreements. Average wages for firms of all sizes, except firms that have between 20 and 99 employees, are significantly higher than the average wage for firms of the smallest size. The effect of firm size on wages appears to be monotonically positive (increasing). The coefficients for *Union* give the wage premium received by workers who are union members. Interestingly, when modelled using fatal risk rates, a significant wage premium is found for male union members in Australia. The premium is equal to 2.2% of a non-union worker's wage and is highly significant. The same is not found for females under the same model or for either group when injury risk is used.

The coefficients for the variable *Risk* give the CWDs paid to non-unionised workers who face the mean unemployment rate for fatal risk (model 1) and non-fatal risk (model 2). For both male and female workers, the negative coefficient for fatal risk implies both groups suffer a decrease in earnings as fatal job risk increases; however, the coefficient lacks statistical significance. The coefficient for injury risk for male workers is also negative implying the same punishment of lower earnings when non-fatal job risk increases but again, the coefficient lacks statistical significance. The non-fatal risk coefficient has the expected positive sign for female workers but is not significant. These results would indicate that risk of death and injury at the workplace are insignificant determinants of a non-unionised worker's wage in Australia. This conclusion is inconsistent with the earlier Australian studies by Miller et al. (1997) and Kniesner and Leeth (1991) who found significant CWDs for fatal risk (for male workers).

[21] The significant negative coefficient for males who have completed year 12 indicates a penalty to full-time male workers who have graduated high school for the first time. This change in education levels occurred noticeably only for waves 10 and 11. Dropping waves 10 and 11 from the sample yield insignificant coefficients on the Year 12 variable.

Table 5: Key estimation results from models (1) and (2) for male and female workers

	Model (1) for fatal risk				Model (2) for non-fatal risk			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	SE	Coefficient	*SE*	Coefficient	*SE*
	Human capital covariates							
Worker experience	0.072***	*0.010*	0.052***	*0.010*	0.074***	*0.011*	0.052***	*0.010*
Worker experience squared	-0.0005***	*0.000*	-0.0005***	*0.000*	-0.0005***	*0.000*	-0.0005***	*0.000*
Tenure (employment)[a]	0.001	*0.001*	0.001**	*0.001*	0.001	*0.001*	0.001**	*0.001*
Tenure (occupation)[a]	0.001**	*0.000*	0.000	*0.000*	0.001**	*0.000*	0.000	*0.000*
Age[a]	-0.011	*0.010*	0.008	*0.009*	-0.012	*0.010*	0.008	*0.009*
Public sector	0.018	*0.012*	0.034***	*0.011*	0.016	*0.013*	0.043***	*0.011*
	Education (Base Year 11)							
Tertiary	0.005	*0.039*	0.011	*0.035*	0.009	*0.039*	0.017	*0.035*
Diploma	0.042	*0.031*	0.025	*0.030*	0.041	*0.031*	0.034	*0.031*
Certificate	-0.003	*0.024*	-0.016	*0.026*	-0.008	*0.024*	-0.015	*0.027*
Year 12	-0.060*	*0.032*	-0.005	*0.034*	-0.064**	*0.032*	-0.003	*0.034*
	Contract (Base casual)[b]							
Permanent worker	-0.042***	*0.010*	-0.043***	*0.013*	-0.039***	*0.010*	-0.041***	*0.013*
Fixed term	-0.013	*0.012*	-0.026*	*0.014*	-0.010	*0.012*	-0.023	*0.014*

	Model (1) for fatal risk				Model (2) for non-fatal risk			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
	Firm size (base < 20 employees)							
20–99	0.005	*0.008*	0.000	*0.009*	0.004	*0.008*	0.001	*0.009*
100–499	0.026***	*0.008*	0.019**	*0.008*	0.024***	*0.008*	0.020**	*0.008*
500–999	0.041***	*0.009*	0.019**	*0.009*	0.041***	*0.009*	0.021**	*0.010*
1,000–4,999	0.048***	*0.008*	0.030***	*0.008*	0.051***	*0.008*	0.033***	*0.008*
5,000–19,999	0.055***	*0.008*	0.028***	*0.008*	0.057***	*0.008*	0.030***	*0.008*
≥ 20,000	0.054***	*0.009*	0.026***	*0.008*	0.058***	*0.010*	0.029***	*0.008*
	Risk = Fatal				Risk = Non-fatal			
Risk	-0.000	0.002	-0.000	0.002	-0.000	0.000	0.000	0.001
Unemp	-0.004	0.005	-0.003	0.005	-0.004	0.006	0.001	0.006
Unemp × Risk	0.000	0.000	-0.001	0.001	0.000	0.000	-0.001	0.000
Union	0.022**	0.009	-0.000	0.008	0.015	0.012	-0.002	0.011
Risk × Union	0.001	0.001	0.007**	0.003	0.001	0.001	0.001	0.001

Note. SE = standard error. Unemp = centred unemployment rate. Full results available in Table 10.
[a] Measured in years. [b] Employment contract for full-time workers only.
* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$. Clustered standard errors are used and reported.

Also relevant to the study of CWDs is the interaction between risk and union status, and the interaction between risk and unemployment rates. The coefficients for the interaction between unemployment and risk determine the extent to which CWDs are strengthened (or weakened) by tight labour markets. The negative coefficient on the interaction between unemployment and risk for female workers in both models indicates that any CWDs paid to females for job risk are reduced by 0.1% as the unemployment rate increase by one percentage point from the sample mean value. Unfortunately, the terms lack statistical significance. The coefficient for the interaction between risk and unemployment for male workers is positive, but also lacks significance. The Australian data shows a lack of support for the work of Mridha and Khan (2013), and Bender and Mridha (2011) who found significant negative-signed coefficients for the interaction between unemployment and both fatal and non-fatal risks.

The interaction term between fatal risk and union status is not statistically different from zero for the male group but is significant at the 5% level for females. The positive coefficient indicates that, all else being equal, female union members who face the mean unemployment rate and fatality risk receive a CWD of 0.7% more of their current wage level for a unit increase in the risk of death at the workplace, compared to non-union female workers. From this, the value of statistical life (VSL) can be calculated as $\frac{\partial(\ln w)}{\partial FRisk} \times 100{,}000 \times h \ \times w$, where w is the real hourly wage, h is the number of hours worked over the course of the year and 100,000 represents the fact that fatal risk is expressed per 100,000 workers. For union members, the partial derivative for calculating the VSL is equal to $\beta_1 + \beta_4$ from equations (1) and (2)[22]. While only β_4 is individually significant, it may be that the sum of the coefficients is significant and thus useful for VSL estimation (that is, $\beta_1 + \beta_4 \neq 0$). This is found to be the case for female workers only under the fatal risk model. The sum of the coefficients yields 0.00683 which implies a total CWD of 0.68% for each additional unit increase in fatal risk. The linear sum of coefficients is not significant under the non-fatal model. For this reason, a VSL is inferred for female's union workers only under the fatal risk model. For non-union workers, the risk variables are not statistically different to zero and consequently a VSL is not calculated for either male or female group.

As HILDA only collects usual hours worked per week, h is multiplied by 52 to reflect the fact that only full-time workers make up the sample. This results in a total of 2,153 hours on average worked by female union members over a one-year period. This figure is between the values used by other studies that calculate a VSL in this way. (Kniesner et al., 2010 and Guardado & Ziebarth, 2019 use $h = 2{,}000$, and Kniesner et al., 2012 use a sample mean of $\bar{h} = 2{,}287$ hours

[22] The partial derivative of the wage equation with respect to risk is equal to $\beta_1 + \beta_4 Union + \beta_6 Unemp_{it}$. When evaluated at the sample mean of unemployment, the expression reduces to $\beta_1 + \beta_4 Union$ as unemployment is defined as the difference from its sample mean value.

when they infer a VSL estimate for CWDs paid to males.) When evaluating at sample means of $\bar{w} = \$32.59$ and $\bar{h} = 2{,}153$ and holding unemployment constant at the mean value of $\bar{U} = 5.6$ percent, the corresponding VSL for female union members is approximately $47.9 million. This VSL result is noticeably large when considering Miller et al.'s (1997) estimate of between $11 million to $19 million for male blue-collar workers, although the magnitude of the CWD estimate is almost identical between the two studies. The CWD found in Miller et al. (1997) was 70.4% for an increase in fatal risk of 1/1,000. This would equate to 0.7% for a 1/100,000 increase in fatal risk, which is essentially found in the current study. Caution should however be exercised when comparing the results between the two studies. Miller et al.'s (1997) estimate is calculated from a sample of male non-agricultural workers whereas the estimate in this study is calculated for females who may work in the agricultural sector and belong to a union. Further, the estimates calculated in this study considers the joint significance of the coefficient of fatal risk and the interaction terms, rather than an estimate based off only a single risk coefficient. The large variation in the VSL estimate found between the two studies (the VSL was between $11 million to $19 million in Miller et al (1997) and was estimated to be $47.9 million in this study) can be attributed to the increase in workers' average annual incomes over time. That is to say, the term $\bar{w} \times \bar{h}$ in the calculation of VSL is much larger in this study than what was used in Miller et al (1997).

Models (1) and (2) are re-estimated using three-year moving averages of fatal and non-fatal risk. Estimation output relevant to CWDs is reported in Table 6 (see appendix for the estimates in full).

Table 6: Key estimation results for models (1) and (2) for male and female workers with three-year moving averages of risk

	Model (1) for fatal risk MA				Model (2) for non-fatal risk MA			
	Male		Female		Male		Female	
Variable	C	*SE*	C	*SE*	C	*SE*	C	*SE*
	Risk = Fatal MA				Risk = Non-fatal MA			
RiskMA	-0.001	0.001	-0.001	0.001	-0.000	0.000	0.000	0.001
Unemp	-0.004	0.005	-0.003	0.005	-0.004	0.006	0.001	0.006
Unemp × RiskMA	0.000	0.000	-0.001	0.001	0.000	0.000	-0.001	0.000
Union	0.023***	0.009	-0.001	0.008	0.015	0.012	-0.002	0.011
Union × RiskMA	0.000	0.001	0.006**	0.003	0.001	0.001	0.001	0.001

Note. MA = moving average. C = coefficient. *SE* = standard error. Unemp = centred unemployment rate. Full results available in Table 11.
* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$. Clustered standard errors are used and reported.

Table 6 shows that there is little statistical difference between using current period risk rates and three-year moving averages of risk. The coefficients for fatal and non-fatal risk remain insignificant across both groups, as do the effects of unemployment rates. The union wage premium received by males under the fatal moving-average model has increased slightly to 2.3% (from 2.2%) while remaining insignificant in the non-fatal specification. The total CWD for female union members who face the mean fatality risk also decreases from 0.68% to 0.51% when evaluated at the mean unemployment rate. The result is significant just outside the 5% level. Applying the sample mean values for wage and hours worked results in a reduced VSL estimate of approximately $35.4 million for female union workers. Overall, using a three-year moving average had a small effect on the rate at which Australian female workers appear to be compensated for workplace risks. The moving-average approach has had no significant effect on the rate at which Australian non-union female workers are compensated, or the extent to which Australian male workers are compensated.

Results for Model (8) and Model (9)

To determine if workers are rewarded for their self-provided safety (safety investments), models (8) and (9) are estimated with single period risk rates. Relevant output to CWDs is provided in Table 7 (with full estimation results in the appendix).

Table 7: Key estimation results for models (8) and (9) for male and female workers which includes worker safety investments and interaction with risk

	Model (8) for fatal risk				Model (9) for non-fatal risk			
	Male		Female		Male		Female	
Variable	C	*SE*	C	*SE*	C	*SE*	C	*SE*
	Risk = fatal risk				Risk = non-fatal risk			
Risk	-0.000	0.001	0.000	0.001	-0.000	0.000	-0.000	0.000
Unemp	-0.004	0.005	-0.003	0.005	-0.004	0.006	0.001	0.006
Unemp × Risk	0.000	0.000	-0.001	0.001	0.000	0.000	-0.001	0.000
Union	0.023***	0.009	-0.001	0.008	0.015	0.012	-0.002	0.011
Union×Risk	0.001	0.001	0.007**	0.003	0.001	0.001	0.001	0.001
WT	-0.001*	0.001	-0.001	0.001	-0.001**	0.001	-0.002	0.002
WT × Risk	0.000	0.000	-0.001	0.001	0.000	0.000	0.000	0.000

Note. C = coefficient. SE = standard error. Unemp = centred unemployment rate. WT = worker training. Full results available in Table 12.
* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$. Clustered standard errors are used and reported.

The variable WT indicates the effect on earnings for workers who have participated in training programs, specifically for the reasons of health and safety. It is the proxy for the safety input variable (e) under the theoretical framework. The sign of the safety input variable is negative for both groups and significant only for males. The appropriate interpretation would be that all else equal, male workers who face no risk at work suffer a wage penalty of 0.1% for providing safety to the firm. The interaction term between risk and worker safety investments can be used to interpret the impact of worker safety investments on the size of CWDs when there is a non-zero risk of death or injury at the workplace. The coefficient for the interaction between fatal risk and worker training (β_8 in model 8) is positive for male workers but not statistically different from zero. The interaction between injury risk and worker training (β_8 in model (9)) is also positive but insignificant. The fact that β_8 is greater than zero in both models indicates that the marginal effect of WT on wages is a positive function of risk. That is, the higher the current level of risk, the larger the effect of an increase in WT on wages. This in turn implies that the expression given in (7) is a positive function of risk.

The total CWD that union members receive for workplace risk is now given by $\beta_1 + \beta_4 + \beta_8 WT$. While only β_4 is individually significant for females under the fatal model, the sum of the coefficients is significant[23]. The estimates imply a total CWD of 0.73% for each additional unit of fatal risk. The corresponding VSL estimate is $50.2 million when evaluated at sample means ($\bar{h} = 2{,}148,\ \bar{w} = \$32.11,\ \bar{U} = 5.6,$ and $\overline{WT}$ of 0.31). This result is almost identical to the results from model (2) when worker safety training was not included. The inclusion of worker safety investments in the model has increased the estimated CWD to female union members by 0.04% (compared to model 2 which uses the same single-period risk rate).

Finally, models (8) and (9) are re-estimated with three-year moving averages of risk. Relevant output to CWDs is provided in Table 8 (with full estimation results available in the appendix). Again, only the fatal risk model for female union workers has a sum of partial derivative coefficients which is significant. When using the three-year moving average of fatal risk, the total CWD paid to female union members who face the mean fatality risk reduces from 0.73% to 0.55%. This implies a VSL estimate of $37.6 million. Including worker safety investments has, however, increased the estimated CWD by 0.04% (when compared to model (2) when estimated with the same moving average of risk). The conclusions drawn by Guardado and Ziebarth (2019), that worker provided safety investments increase CWD estimates for risk are only found in the current study when the overall significance of the sum of risk coefficients is considered. Unlike Guardado and Ziebarth (2019), the coefficient for risk, and the coefficient for

[23] The sum of coefficients remains insignificant for unionised female workers under the non-fatal model. The same is true for both union and non-union male workers under both models.

the interaction between worker safety investment and risk, is never found to be individually significant for male or female workers.

Table 8: Key estimation results for models (8) and (9) for male and female workers when a three-year moving average of risk is used

	Model (8) for fatal risk				Model (9) for non-fatal risk			
	Male		Female		Male		Female	
Variable	C	*SE*	C	*SE*	C	*SE*	C	*SE*
	Risk = fatal MA				Risk = non-fatal MA			
RiskMA	-0.001	0.001	-0.001	0.001	-0.000	0.000	0.000	0.001
Unemp	-0.004	0.005	-0.003	0.005	-0.004	0.006	0.001	0.006
Unemp × RiskMA	0.000	0.000	-0.001	0.001	0.000	0.000	-0.001	0.000
Union	0.024***	0.009	-0.001	0.008	0.015	0.012	-0.003	0.011
Union × RiskMA	0.000	0.001	0.006**	0.003	0.001	0.001	0.001	0.001
WT	-0.001*	0.001	0.000	0.001	-0.001**	0.001	-0.002	0.002
WT × Risk	0.000	0.000	-0.001	0.001	0.000	0.000	0.000	0.000

Note. MA = moving average. C = coefficient. SE = standard error. Unemp = centred unemployment rate. WT = worker training. Full results available in Table 13.
* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$. Clustered standard errors are used and reported.

Discussion

Overall, this study finds limited evidence for the existence of CWDs for fatal and non-fatal job risk in Australia. Under the standard wage models (models 1 and 2), the risk of death is not found to be a significant determinant of an Australian worker's wage. This is in direct contrast to what was found in the two previous Australian studies by Kniesner and Leeth (1991) and Miller et al. (1997). It is possible that the lack of both industry and occupational controls in the previous studies led to overestimates of the return to fatal risk as the risk coefficients may have been reflecting inter-industry and/or inter-occupational differentials. Using industry and occupational controls in the current study would alleviate such an upward bias in the fatal risk coefficient which may help to explain the insignificance of the risk variable in the current study. This study also includes non-fatal risk but finds no evidence that CWDs are paid for the risk of injury for any group of workers. This could be a signal that Australia's compulsory workers compensation scheme provides the appropriate ex-post compensation for workplace injuries, removing the need for ex-ante compensation in the form of CWDs for injury.

The results also show that male workers who belong to a union receive a wage premium of approximately 2.2% when the fatal model is used. Interestingly, no union premium is found for female workers in Australia. However, the interaction between union status and risk is positive and significant for female workers under the fatal risk model. The positive sign implies that, all else equal, unionised female workers receive greater compensation for fatal risk when compared to their non-unionised counterparts. The positive interaction term is consistent with what is often found in the literature. It is surprising that unionised male workers were not found to receive higher CWDs for fatal risk, especially as most workers in risker industries and occupations are male (as evident in Table 2). In sum, there is evidence that union membership increases earnings to both male and female workers, although in different ways. Males receive higher earnings by belonging to a union, but do not receive additional earnings as (fatal) risk increases. Females on the other hand do not receive a premium for belonging to a union, but those that are union members receive higher earnings as fatal risk increases.

Individually, unemployment rates are found to have no significant effect on an Australian worker's wage in any model specification. The interaction term between workplace risk and unemployment rates is positive for male workers but negative for female workers. The positive coefficient implies that, all else equal, male workers are compensated with higher earnings for risk as labour markets become relatively looser. The negative coefficient for females suggests that female workers suffer a wage penalty for workplace risk (both fatal and non-fatal) as labour markets become relatively looser. The negative effect for females is consistent with what was found by Bender and Mridha (2011), and Mridha and Khan (2013), although individually, the results in the current study are not statistically significant. Following the work of Guardado and Ziebarth (2019), models (8) and (9) allow for worker safety investments to influence CWDs for risk. The results show that for fatal risk and non-fatal risk, male workers suffer a wage penalty of 0.1% of their current wage rate for each additional unit increase in safety-investment, provided the risk faced by the worker is zero. There however is no significant impact on wages for female workers when they participate in safety training when exposed to zero workplace risk. Individually, the interaction terms between risk and worker safety investments are insignificant which is in stark contrast to the findings of Guardado and Ziebarth (2019) who found significant negatively signed coefficients on their interaction terms.

Unlike Bender and Mridha (2011), Mridha and Khan (2013), and Guardado and Ziebarth (2019), the significance of unemployment rates and worker-provided safety are only apparent when considering the joint sum of risk coefficients. Without the inclusion of safety training, the CWD for unionised female workers of average fatality risk when evaluated at sample means is 0.68%. The negative sign found on the interaction term between unemployment and fatal risk implies that looser labour markets reduce CWD payments for job risk. The reduction in CWDs is approximately 0.14% per percentage point increase in unemployment but pertains only for unionised female workers. In this sense, there is some evidence for the conclusions drawn by Mridha and Khan (2013) that looser labour markets weaken CWDs for fatal risk. When the interaction between fatal risk and safety training is included, the CWD for fatal risk increases from 0.68% to 0.73%. The provision of worker safety results in higher CWD estimates for fatal risk for unionised female workers. The conclusion that worker safety investments increase CWD payments is consistent with the findings of Guardado and Ziebarth (2019), although the positive association between worker-provided safety and higher CWD payments for fatal risk is not found for unionised male workers, or for non-unionised workers of either sex.

The significant CWD results found in this Australian study are similar in magnitude to the results found in Kniesner and Leeth (1991) and Miller et al. (1997), although comparisons between this study and earlier studies should be made with caution for two reasons. Firstly, the risk variables between the previous studies and this study are constructed differently. The previous Australian studies are limited to using a risk variable which reflects only the industry of the worker whilst the current study constructs a risk variable which considers both the worker's industry and occupational risk. All else equal, the risk variable used in the current study for the estimation of CWDs should better reflect the true risk faced by each worker in the sample and consequently improve the accuracy of CWD and VSL estimates risk. Secondly, the current study makes use of the HILDA panel and a fixed effects model to better control for unobservable heterogeneity and reduce estimation bias. The HILDA survey allows for the inclusion of a richer set of covariates than was previously available (covariates such as firm size, employment contract, and occupation and employer tenure are now able to be included) which reduces the possibility that omitted variable bias distorts the estimated CWDs for risk. Having a panel dataset also allows for fixed effects to be used which reduces the extent to which worker and workplace heterogeneity can affect the estimates. Further, the use of both industry and occupational dummies in the current study should have reduced the likelihood that the estimated risk coefficient reflected any inter-industry or inter-occupational differentials, which may have been the case for both Kniesner and Leeth (1991) and Miller et al. (1997). However, it may also be the case that the industry and occupation fixed effects are absorbing the significant effects of risk on wages. Because it was assumed that occupation and industry risk are independent when the risk variable was constructed, it is possible that there is little variation in the risks faced by workers which is not captured by the occupation and industry dummies. Consequently, there is not enough variation left in the data to identify any significant effects that job risk has on wages.

It is interesting that only unionised female workers were found to have statistically significant CWDs for fatal risk[24]. Although, publication bias in VSL estimates which are computed from hedonic wage equations may lead one to believe that the insignificant results found here far more uncommon than what is the case (Doucouliagos et al., 2011; Stanley &

[24] As mentioned earlier in this study, wage bargaining power may be better reflected by workers who report having their wage determined through an enterprise agreement, rather than the use of a dummy variable for union membership as employers cannot pay CWDs to union members only. When the union dummy in the current study is replaced by a dummy for enterprise agreements, the study finds no significant CWDs for risk (the interaction between EA and risk is insignificant, as is the linear sum of coefficients). This is true for both male and female groups.

Doucouliagos, 2014). It is noted that this study does not account for the possible endogeneity of risk (Garen,1988), union status (Arabsheibani and Marin, 2000) or labour mobility (Lavetti and Schmutte, 2018). As noted by Purse (2004), if the risk variable is endogenous, studies which attempt to estimate the CWD using an exogenous risk variable will underestimate the true return for risk. Perhaps more importantly, not controlling for the possibility of endogenous job mobility may have reduced the estimated CWDs to zero (Leigh, 1991; Leigh, 1995; Dorman and Hagstrom, 1998). As noted earlier, when Lavetti and Schmutte (2018) switched from a typical panel model (such as the one used in this study), to a model which has controls for endogenous job mobility, the estimated CWDs for fatal risk increased from 3.7% to 17% for their sample of male workers. It is thus likely that the inability of this study control for the possibility of endogenous labour mobility, or endogeneity of risk, has resulted in insignificant CWD estimates for Australian workers.

Conclusion

The theory of equalising differences dates back to Adam Smith's *The Wealth of Nations* and is the basis for the well-researched theory of CWDs for job risk. In order to equalise the net attractiveness of all jobs, firms must compensate workers with higher earnings for undesirable job characteristics, such as the risk of death (fatal risk) and injury (non-fatal risk). Only two studies have examined whether Australian workers are paid CWDs for job risk. Both studies are unquestionably outdated and are likely to exhibit estimation bias known to affect cross-sectional studies. More recent research has concluded that labour market efficiency and union status are key variables in understanding CWD payments. The omission of such variables from previous Australian studies would also lead one to believe that CWD estimates in Australia can be improved upon.

The introduction of the HILDA survey has allowed for a much larger degree of worker and workplace information to be acquired than what was previously available, and it has also made panel estimation possible with Australian data. Using yearly death and injury statistics published by Safe Work Australia, the current study constructs a risk variable which is representative of both the industry and occupation of each worker in the sample. Constructing a risk variable that reflects the worker's industry and occupation is becoming popular as it gives researchers the ability to compute estimates that better reflect the true compensation paid for workplace risk.

Using a sample of 45,353 observations across eight years, CWDs for job risk are estimated for Australians. The current study finds small wage premiums to male union members (around 2.2%) and modest wage premiums to females who work in the public sector (as high as 4.3%). The study finds no evidence that changes in fatal risk alone leads to changes in a worker's wage. There is a lack of support for the proposition that the risk of injury (non-fatal risk) alone plays a role in determining a worker's wage. Individually, the tightness of the labour market (proxied by the unemployment rate) has no impact on CWDs for fatal and non-fatal risk. The only group for which a statistically significant CWD was found is female union members. The results show that female union members who face the average risk of fatality receive, on average, a 0.68% increase in their current wage rate for a 1/100,000 increase in fatal risk. When evaluated at the sample means of unemployment, hours worked and wage rate, this corresponds to a VSL estimate of $47.9 million. While this value looks large when compared to those found in previous studies, this estimate is unique as it applies to only female union members and is the result of the significant linear combination of coefficients for fatal risk and its interaction terms. A lack of statistical significance for the non-fatal risk variable means that a CWD for injury risk and a corresponding VSI estimate are not computed. Switching to a three-year moving average of fatal risk results in a reduction of the CWD for female union members to 0.51%. This implies a VSL of $35.4 million when evaluated at sample means.

When extending the framework to include the influence of worker-provided safety investments, the results indicate that there is a small trade-off between worker safety investments and earnings for males. For each additional day of training (for the reasons of health and safety), male workers in Australia experience a reduction in their current wage rate of 0.1%. No penalty for worker-provided safety investments is found for female workers. When the interaction between risk and worker safety investments are included in the model there is little change to the extent that Australian workers are compensated for job risk. When safety investments are included in the model, the fatal risk CWD for female union members increases to 0.72% (from 0.68% when worker safety investments were not included) when evaluated at sample means. The switch to a three-year moving average increases the CWD for female union members of average fatality risk to 0.55% (from 0.51%) when evaluated at sample means. Thus, there is some evidence that allowing for workers to invest in their own safety does increase the CWD, but only for female union members who experience a non-zero level of fatal risk. Overall, this study concludes that there is little evidence that Australian workers receive CWDs for job risk. Whilst the estimates reported in this study are less likely to be biased compared to previous Australian estimates, they can be further improved by allowing for endogeneity of the risk variables and by making allowances in the hedonic wage model for endogenous labour mobility.

This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the author and should not be attributed to either DSS or the Melbourne Institute.

Appendix

Table 9: Sample means of real hourly wage for males and females across categories

Variable	Male	Female		Variable	Male	Female	
Combined	35.48	30.36					
Union	36.92	32.59	**	Higher education			
Non-union	35.06	29.62	**	Tertiary[a]	45.32	35.74	**
Not public sector	34.53	28.02	**	Diploma[b]	41.49	32.87	**
Public sector	38.83	34.72	**	Certificate[c]	31.99	24.87	**
Married (yes)	39.45	32.63	**	Year 12	29.77	25.79	**
Married (no)	30.98	28.76	**	≤ Year 11	27.34	24.93	**
Australia	34.91	29.92	**				
Main Lang. English	39.54	34.17	**	Industry			
Other	36.02	30.63		1	23.90	22.26	**
				2	48.82	34.41	**
Full-time contract				3	32.31	26.32	**
Fixed term	39.75	32.54	**	4	42.01	33.06	**
Casual	27.50	24.80	**	5	33.62	29.19	**
Permanent	35.79	30.47	**	6	32.20	26.31	**
				7	24.76	22.36	**
Wage setting				8	24.31	21.56	**
Collective	36.10	31.97	**	9	32.62	27.22	**
Individual	38.12	31.26	**	10	41.25	33.66	**
Combination [d]	35.20	30.68	**	11	49.66	34.51	**
Award only	27.54	26.96		12	34.13	26.55	**
				13	43.72	32.01	**
Location				14	28.13	25.77	**
Sydney	38.21	32.86	**	15	38.97	36.60	**
Balance of NSW	32.73	29.68	**	16	38.31	33.50	**
Melbourne	36.42	30.87	**	17	37.70	30.53	**
Balance of Victoria	31.35	27.36	**	18	30.34	27.59	
Brisbane	36.08	29.99	**	19	27.60	28.33	
Balance of Qld	32.82	26.42					

Variable	Male	Female	
Adelaide	31.57	29.54	**
Balance of SA	29.52	28.92	**
Perth	41.53	32.93	**
Balance of WA	36.15	25.83	**
Tasmania	28.77	27.44	**
NT	38.24	32.27	
ACT	44.01	36.21	**
Firm size (employees)			
< 20	30.41	25.71	**
20–99	33.19	28.08	**
100–499	37.48	30.05	**
500–999	38.63	31.67	**
1,000–4,999	40.59	33.12	**
5,000–19,900	40.52	33.27	**
≥20,000	38.11	32.17	**

Variable	Male	Female	
Occupation			
1	44.42	36.76	**
2	43.54	35.53	**
3	32.34	23.94	**
4	31.33	24.75	**
5	31.00	26.59	**
6	25.68	22.69	**
7	29.30	24.66	**
8	25.44	22.21	**

[a] Includes bachelor's, honours, master's and doctoral degrees. [b] Includes diplomas, graduate/advanced diplomas and graduate certificates. [c] Includes certificates III and IV.
[d] Combination of collective/enterprise agreement and individual agreement.
* and ** indicate a significant difference in mean real hourly wage between the two groups at 5% and 1% respectively.

Table 10: Full estimation results from models (1) and (2) for male and female workers with single-period risk rates

	Model (1) for fatal risk				Model (2) for non-fatal risk			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Human capital covariates								
Worker experience [a]	0.072***	0.010	0.052***	0.010	0.074***	0.011	0.052***	0.010
Worker experience square [a]	0.000***	0.000	0.000***	0.000	0.000***	0.000	0.000***	0.000
Tenure (employment) [a]	0.001	0.001	0.001**	0.001	0.001	0.001	0.001**	0.001
Tenure (occupation) [a]	0.001**	0.000	0.000	0.000	0.001**	0.000	0.000	0.000
Age [a]	-0.011	0.010	0.008	0.009	-0.012	0.010	0.008	0.009
Married/De facto	0.016**	0.008	0.018**	0.008	0.016**	0.008	0.018**	0.008
Public sector	0.018	0.012	0.034***	0.011	0.016	0.013	0.043***	0.011
Education (base Year 11)								
Tertiary	0.005	0.039	0.011	0.035	0.009	0.039	0.017	0.035
Diploma	0.042	0.031	0.025	0.030	0.041	0.031	0.034	0.031
Certificate	-0.003	0.024	-0.016	0.026	-0.008	0.024	-0.015	0.027
Year 12	-0.060*	0.032	-0.005	0.034	-0.064**	0.032	-0.003	0.034
Age of dependent children (base 10–14 years)								
0–4 years	0.002	0.007	-0.029***	0.011	0.002	0.007	-0.029***	0.011
5–9 years	0.000	0.006	-0.004	0.010	0.001	0.006	-0.004	0.010

	Model (1) for fatal risk				Model (2) for non-fatal risk			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Contract (base Casual) [b]								
Permanent worker (full-time)	-0.042***	0.010	-0.043***	0.013	-0.039***	0.010	-0.041***	0.013
Fixed term (full-time)	-0.013	0.012	-0.026*	0.014	-0.010	0.012	-0.023	0.014
Firm Size (base < 20 employees)								
20–99	0.005	0.008	0.000	0.009	0.004	0.008	0.001	0.009
100–499	0.026***	0.008	0.019**	0.008	0.024***	0.008	0.020**	0.008
500–999	0.041***	0.009	0.019**	0.009	0.041***	0.009	0.021**	0.010
1,000–4,999	0.048***	0.008	0.030***	0.008	0.051***	0.008	0.033***	0.008
5,000–19,999	0.055***	0.008	0.028***	0.008	0.057***	0.008	0.030***	0.008
≥20,000	0.054***	0.009	0.026***	0.008	0.058***	0.010	0.029***	0.008
Region (base Northern Territory)								
Sydney	-0.072	0.053	0.119*	0.068	-0.072	0.055	0.117*	0.070
Other New South Wales	-0.137**	0.053	0.092	0.075	-0.144***	0.055	0.089	0.076
Melbourne	-0.067	0.057	0.067	0.070	-0.071	0.059	0.062	0.072
Other Victoria	-0.058	0.062	0.017	0.077	-0.067	0.064	0.012	0.078
Brisbane	-0.082	0.055	0.039	0.069	-0.094*	0.056	0.035	0.071
Other Queensland	-0.089*	0.052	0.004	0.076	-0.098*	0.054	0.000	0.077
Adelaide	-0.046	0.064	0.075	0.080	-0.056	0.065	0.061	0.081

	Model (1) for fatal risk				Model (2) for non-fatal risk			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Other South Australia	-0.052	0.065	0.078	0.097	-0.050	0.066	0.074	0.098
Perth	-0.052	0.058	0.036	0.079	-0.061	0.059	0.034	0.081
Other Western Australia	0.064	0.068	0.040	0.095	0.076	0.070	0.043	0.097
Tasmania	-0.193***	0.069	0.038	0.089	-0.200***	0.071	0.028	0.088
Australian Capital Territory	-0.096*	0.057	0.203***	0.071	-0.094	0.059	0.210***	0.073
Wave (base 10)								
11	0.000	0.005	0.002	0.005	0.001	0.005	0.002	0.005
12	0.030***	0.005	0.012**	0.005	0.031***	0.005	0.011**	0.005
13	0.015***	0.005	0.004	0.005	0.016***	0.005	0.003	0.005
14	0.011**	0.006	0.001	0.006	0.012**	0.006	-0.001	0.006
15	0.011**	0.005	0.010*	0.006	0.011**	0.005	0.009	0.006
16	0.011***	0.004	0.014***	0.005	0.011***	0.004	0.013***	0.005
Occupation (base managers)								
2	-0.002	0.008	0.003	0.010				
3	-0.003	0.011	-0.043**	0.019				
4	-0.037**	0.016	-0.041***	0.013				
5	-0.023***	0.009	-0.031***	0.010				
6	-0.044***	0.013	-0.008	0.013				

	Model (1) for fatal risk				Model (2) for non-fatal risk			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
7	-0.010	0.013	-0.022	0.032				
8	-0.024**	0.012	0.017	0.021				
Industry (base Agriculture, forestry and fishing)								
2	0.172***	0.039	0.021	0.057				
3	0.054	0.034	0.000	0.047				
4	0.112***	0.038	-0.027	0.052				
5	0.067**	0.033	0.005	0.048				
6	0.027	0.034	0.001	0.047				
7	0.015	0.036	-0.051	0.048				
8	-0.036	0.040	-0.050	0.050				
9	0.036	0.032	0.015	0.046				
10	0.069*	0.038	-0.014	0.050				
11	0.092**	0.038	0.007	0.049				
12	-0.002	0.040	-0.076	0.051				
13	0.047	0.034	-0.020	0.047				
14	0.020	0.035	-0.036	0.046				
15	0.053	0.035	0.019	0.046				
16	0.022	0.040	0.036	0.050				

	Model (1) for fatal risk				Model (2) for non-fatal risk			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
17	0.024	0.037	-0.017	0.047				
18	0.017	0.038	-0.079	0.053				
19	0.033	0.036	-0.028	0.049				
Risk								
Risk	-0.0004	0.002	-0.000	0.002	-0.0002	0.0003	0.000	0.001
Unemp	-0.004	0.005	-0.003	0.005	-0.004	0.006	0.001	0.006
Unemp × Risk	0.000	0.000	-0.001	0.001	0.000	0.000	-0.001	0.000
Union	0.022**	0.009	-0.000	0.008	0.015	0.012	-0.002	0.011
Union × Risk	0.001	0.001	0.007**	0.003	0.001	0.001	0.001	0.001
Constant	2.700***	0.193	2.224***	0.205	2.731***	0.192	2.178***	0.200

Note. SE = standard error. Unemp = centred unemployment rate.

[a] Measured in years. [b] Employment contract for full-time workers only.

* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$. Clustered standard errors are used and reported.

Table 11: Full estimation results from models (1) and (2) for male and female workers with three-year moving-average risk rates

	Model (1) for fatal risk (MA)				Model (2) for non-fatal risk (MA)			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Human capital covariates								
Worker experience [a]	0.072***	0.010	0.052***	0.010	0.074***	0.011	0.052***	0.010
Worker experience squared [a]	0.000***	0.000	0.000***	0.000	0.000***	0.000	0.000***	0.000
Tenure (employment) [a]	0.001	0.001	0.001**	0.001	0.001	0.001	0.001**	0.001
Tenure (occupation) [a]	0.001**	0.000	0.000	0.000	0.001**	0.000	0.000	0.000
Age [a]	-0.011	0.010	0.008	0.009	-0.012	0.010	0.008	0.009
Married/De facto	0.016**	0.008	0.018**	0.008	0.016**	0.008	0.018**	0.008
Public sector	0.018	0.012	0.034***	0.011	0.016	0.013	0.043***	0.011
Education (base Year 11)								
Tertiary	0.005	0.039	0.010	0.035	0.009	0.039	0.017	0.035
Diploma	0.043	0.031	0.024	0.031	0.041	0.031	0.034	0.031
Certificate	-0.003	0.024	-0.016	0.026	-0.008	0.024	-0.015	0.027
Year 12	-0.060*	0.032	-0.005	0.034	-0.064**	0.032	-0.003	0.034
Age of dependent children (base 10–14 years)								
0–4 years	0.002	0.007	-0.029***	0.011	0.003**	0.007	-0.029	0.011
5–9 years	0.000	0.006	-0.004	0.010	0.001	0.006	-0.004	0.010

	Model (1) for fatal risk (MA)				Model (2) for non-fatal risk (MA)			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Contract (base Casual) [b]								
Perm Worker	-0.042***	0.010	-0.043***	0.013	-0.039***	0.010	-0.041***	0.013
Fixed Term	-0.013	0.012	-0.026*	0.014	-0.010	0.012	-0.023	0.014
Firm size (base < 20 employees)								
20–99	0.004	0.008	-0.001	0.009	0.004	0.008	0.001	0.009
100–499	0.026***	0.008	0.019**	0.008	0.024***	0.008	0.020**	0.008
500–999	0.041***	0.009	0.020**	0.009	0.041***	0.009	0.020**	0.010
1,000–4,999	0.048***	0.008	0.031***	0.008	0.051***	0.008	0.033***	0.008
5,000–19,999	0.055***	0.008	0.028***	0.008	0.057***	0.008	0.030***	0.008
≥20,000	0.054***	0.009	0.026***	0.008	0.058***	0.010	0.029***	0.008
Region (base Northern Territory)								
Sydney	-0.072	0.053	0.119*	0.069	-0.072	0.055	0.116*	0.070
Other New South Wales	-0.136**	0.053	0.093	0.075	-0.144***	0.055	0.088	0.076
Melbourne	-0.067	0.057	0.068	0.070	-0.071	0.059	0.062	0.072
Other Victoria	-0.058	0.062	0.017	0.077	-0.067	0.064	0.011	0.078
Brisbane	-0.082	0.055	0.040	0.069	-0.094*	0.056	0.034	0.070
Other Queensland	-0.088*	0.052	0.005	0.076	-0.098*	0.054	-0.001	0.077

	Model (1) for fatal risk (MA)				Model (2) for non-fatal risk (MA)			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Adelaide	-0.046	0.064	0.076	0.080	-0.056	0.065	0.061	0.081
Other South Australia	-0.051	0.065	0.078	0.097	-0.050	0.066	0.073	0.098
Perth	-0.052	0.058	0.036	0.079	-0.060	0.059	0.034	0.081
Other Western Australia	0.064	0.069	0.041	0.095	0.076	0.070	0.043	0.097
Tasmania	-0.193***	0.069	0.039	0.089	-0.200***	0.071	0.027	0.088
Australian Capital Territory	-0.096*	0.057	0.203***	0.071	-0.095	0.059	0.209***	0.073
Wave (base 10)								
11	0.000	0.005	0.002	0.005	0.001	0.005	0.002	0.005
12	0.030***	0.005	0.012**	0.005	0.031***	0.005	0.011**	0.005
13	0.015***	0.005	0.004	0.005	0.016***	0.005	0.003	0.005
14	0.011*	0.006	0.001	0.006	0.012**	0.006	-0.001	0.006
15	0.011**	0.005	0.010*	0.006	0.011**	0.005	0.008	0.006
16	0.011**	0.004	0.014***	0.005	0.011***	0.004	0.013***	0.005
Occupation (base manager)								
2	-0.003	0.008	0.002	0.010				
3	-0.003	0.011	-0.042**	0.019				
4	-0.037**	0.016	-0.041***	0.013				
5	-0.023***	0.009	-0.033***	0.010				

	Model (1) for fatal risk (MA)				Model (2) for non-fatal risk (MA)			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
6	-0.044***	0.013	-0.010	0.013				
7	-0.007	0.013	-0.009	0.032				
8	-0.023*	0.012	0.021	0.021				
Industry (base agriculture, forestry and fishing)								
2	0.169***	0.038	0.004	0.055				
3	0.050	0.033	-0.019	0.044				
4	0.107***	0.038	-0.045	0.050				
5	0.063*	0.033	-0.012	0.046				
6	0.022	0.034	-0.018	0.044				
7	0.010	0.036	-0.070	0.045				
8	-0.041	0.040	-0.070	0.047				
9	0.035	0.031	0.005	0.044				
10	0.065*	0.038	-0.033	0.048				
11	0.087**	0.038	-0.012	0.047				
12	-0.006	0.039	-0.094*	0.048				
13	0.043	0.034	-0.039	0.044				
14	0.016	0.035	-0.054	0.044				
15	0.049	0.034	0.000	0.044				

	Model (1) for fatal risk (MA)				Model (2) for non-fatal risk (MA)			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
16	0.017	0.040	0.017	0.048				
17	0.020	0.037	-0.037	0.044				
18	0.013	0.038	-0.097*	0.051				
19	0.029	0.036	-0.047	0.046				
Risk MA								
Risk MA	-0.001	0.001	-0.001	0.001	-0.000	0.000	0.000	0.001
Unemp	-0.004	0.005	-0.003	0.005	-0.004	0.006	0.001	0.006
Unemp × Risk MA	0.000	0.000	-0.001	0.001	0.000	0.000	-0.001	0.000
Union	0.023***	0.009	-0.001	0.008	0.015	0.012	-0.002	0.011
Union × Risk MA	0.000	0.001	0.006**	0.003	0.001	0.001	0.001	0.001
Constant	2.690***	0.194	2.248***	0.205	2.730***	0.192	2.180***	0.200

Note. SE = standard error. Unemp = centred unemployment rate. MA = moving average.
[a] Measured in years. [b] Employment contract for full-time workers only.
* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$. Clustered standard errors are used and reported.

Table 12: Full estimation results from models (7) and (8) for male and female workers with single-period risk rates

	Model (7) for fatal risk				Model (8) for non-fatal risk			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Human capital covariates								
Worker experience [a]	0.071***	0.010	0.052***	0.010	0.074***	0.011	0.052***	0.010
Worker experience squared [a]	0.000***	0.000	0.000***	0.000	0.000***	0.000	0.000***	0.000
Tenure (employment) [a]	0.001	0.001	0.001**	0.001	0.001	0.001	0.001**	0.001
Tenure (occupation) [a]	0.001**	0.000	0.000	0.000	0.001**	0.000	0.000	0.000
Age [a]	-0.010	0.010	0.008	0.009	-0.012	0.010	0.008	0.009
Married/De facto	0.016**	0.008	0.017**	0.008	0.016**	0.008	0.018**	0.008
Public sector	0.018	0.012	0.033***	0.011	0.016	0.013	0.043***	0.011
Education (base Year 11)								
Tertiary	0.006	0.039	0.011	0.035	0.009	0.039	0.017	0.035
Diploma	0.042	0.031	0.025	0.030	0.041	0.031	0.034	0.031
Certificate	-0.003	0.024	-0.016	0.026	-0.008	0.024	-0.015	0.027
Year 12	-0.059*	0.032	-0.005	0.034	-0.063**	0.032	-0.003	0.034
Age of dependent children (base 10–14 years)								
0–4 years	0.002	0.007	-0.029***	0.011	0.003	0.007	-0.029***	0.011
5–9 years	0.000	0.006	-0.004	0.010	0.001	0.006	-0.004	0.010

	Model (7) for fatal risk				Model (8) for non-fatal risk			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Contract (base casual) [b]								
Permanent worker (full-time)	-0.042***	0.010	-0.042***	0.013	-0.039***	0.010	-0.041***	0.013
Fixed term (full-time)	-0.013	0.012	-0.025*	0.014	-0.010	0.012	-0.022	0.014
Firm Size (base < 20 employees)								
20–99	0.005	0.008	-0.001	0.009	0.004	0.008	0.001	0.009
100–499	0.026***	0.008	0.019**	0.008	0.024***	0.008	0.020**	0.008
500–999	0.041***	0.009	0.019**	0.009	0.042***	0.009	0.020**	0.010
1,000–4,999	0.048***	0.008	0.030***	0.008	0.051***	0.008	0.033***	0.008
5,000–19,999	0.055***	0.008	0.027***	0.008	0.057***	0.008	0.030***	0.008
≥20,000	0.055***	0.009	0.026***	0.008	0.058***	0.010	0.029***	0.008
Region (base Northern Territory)								
Sydney	-0.072	0.053	0.119*	0.068	-0.072	0.055	0.116*	0.070
Other New South Wales	-0.136**	0.053	0.093	0.075	-0.144***	0.055	0.090	0.076
Melbourne	-0.067	0.057	0.067	0.070	-0.071	0.059	0.062	0.072
Other Victoria	-0.058	0.062	0.016	0.077	-0.067	0.064	0.011	0.078
Brisbane	-0.082	0.055	0.039	0.069	-0.094*	0.056	0.035	0.071
Other Queensland	-0.089*	0.052	0.005	0.076	-0.098*	0.054	0.000	0.077

	Model (7) for fatal risk				Model (8) for non-fatal risk			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Adelaide	-0.047	0.064	0.075	0.080	-0.057	0.065	0.062	0.081
Other South Australia	-0.052	0.065	0.078	0.097	-0.050	0.066	0.074	0.098
Perth	-0.052	0.058	0.036	0.079	-0.060	0.059	0.035	0.081
Other Western Australia	0.064	0.069	0.040	0.095	0.076	0.070	0.044	0.097
Tasmania	-0.193***	0.069	0.038	0.089	-0.200***	0.071	0.027	0.088
Australian Capital Territory	-0.095*	0.057	0.202***	0.071	-0.094	0.059	0.210***	0.073
Wave (base 10)								
11	0.000	0.005	0.002	0.006	0.001	0.005	0.002	0.005
12	0.030***	0.005	0.012**	0.005	0.031***	0.005	0.011**	0.005
13	0.015***	0.005	0.004	0.005	0.016***	0.005	0.003	0.005
14	0.011**	0.006	0.001	0.006	0.012**	0.006	-0.001	0.006
15	0.012**	0.005	0.010*	0.006	0.011**	0.005	0.009	0.006
16	0.011**	0.004	0.014***	0.005	0.011***	0.004	0.013***	0.005
Occupation (base manager)								
2	-0.002	0.008	0.003	0.010				
3	-0.003	0.011	-0.043**	0.019				
4	-0.036**	0.016	-0.040***	0.013				
5	-0.022***	0.009	-0.032***	0.010				

	Model (7) for fatal risk				Model (8) for non-fatal risk			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
6	-0.044***	0.013	-0.009	0.013				
7	-0.010	0.013	-0.024	0.033				
8	-0.023*	0.012	0.017	0.021				
Industry (base agriculture, forestry and fishing)								
2	0.173***	0.039	0.019	0.057				
3	0.054	0.034	-0.002	0.046				
4	0.112***	0.038	-0.029	0.052				
5	0.067**	0.033	0.004	0.048				
6	0.027	0.034	0.000	0.047				
7	0.015	0.036	-0.054	0.048				
8	-0.035	0.040	-0.052	0.050				
9	0.036	0.032	0.013	0.046				
10	0.069*	0.038	-0.016	0.050				
11	0.092**	0.038	0.005	0.049				
12	-0.002	0.040	-0.077	0.051				
13	0.047	0.034	-0.022	0.047				
14	0.020	0.035	-0.037	0.046				
15	0.054	0.035	0.018	0.046				

	Model (7) for fatal risk				Model (8) for non-fatal risk			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
16	0.022	0.040	0.035	0.050				
17	0.024	0.037	-0.019	0.046				
18	0.018	0.038	-0.078	0.053				
19	0.033	0.036	-0.029	0.049				
Risk								
Risk	-0.000	0.001	0.000	0.001	-0.000	0.000	-0.000	0.000
Unemp	-0.004	0.005	-0.003	0.005	-0.004	0.006	0.001	0.006
Unemp × Risk	0.000	0.000	-0.001	0.001	0.000	0.000	-0.001	0.000
Union	0.023***	0.009	-0.001	0.008	0.015	0.012	-0.002	0.011
Union × Risk	0.001	0.001	0.007**	0.003	0.001	0.001	0.001	0.001
WT	-0.001*	0.001	-0.001	0.001	-0.001**	0.001	-0.002	0.002
WT × Risk	0.000	0.000	-0.001	0.001	0.000	0.000	0.000	0.000
Constant	2.672***	0.193	2.232***	0.205	2.726***	0.192	2.183***	0.199

Note. SE = standard error. Unemp = centred unemployment rate. WT = worker training.
[a] Measured in years. [b] Employment contract for full-time workers only.
* *p* < 0.1. ** *p* < 0.05. *** *p* < 0.01. Clustered standard errors are used and reported.

Table 13: Full estimation results from models (7) and (8) for male and female workers with three year moving-average risk rates

	Model (7) for fatal risk (MA)				Model (8) for non-fatal risk (MA)			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Human capital covariates								
Worker experience [a]	0.072***	0.010	0.052***	0.010	0.074***	0.011	0.052***	0.010
Worker experience squared [a]	0.000***	0.000	0.000***	0.000	0.000***	0.000	0.000***	0.000
Tenure (employment) [a]	0.001	0.001	0.001**	0.001	0.001	0.001	0.001**	0.001
Tenure (occupation) [a]	0.001**	0.000	0.000	0.000	0.001**	0.000	0.000	0.000
Age [a]	-0.011	0.010	0.007	0.009	-0.012	0.010	0.008	0.009
Married/De facto	0.016**	0.008	0.017**	0.008	0.016**	0.008	0.018**	0.008
Public sector	0.018	0.012	0.033***	0.011	0.016	0.013	0.043***	0.011
Education (base Year 11)								
Tertiary	0.006	0.039	0.010	0.035	0.009	0.039	0.017	0.035
Diploma	0.043	0.031	0.025	0.031	0.041	0.031	0.034	0.031
Certificate	-0.003	0.024	-0.016	0.026	-0.008	0.024	-0.015	0.027
Year 12	-0.059*	0.032	-0.006	0.034	-0.064**	0.032	-0.003	0.034
Age of dependent children (base 10–14 years)								
0–4 years	0.002	0.007	-0.029***	0.011	0.003	0.007	-0.029***	0.011
5–9 years	0.000	0.006	-0.004	0.010	0.001	0.006	-0.004	0.010

	Model (7) for fatal risk (MA)				Model (8) for non-fatal risk (MA)			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Contract (base casual) [b]								
Permanent worker (full time)	-0.042***	0.010	-0.042***	0.013	-0.039***	0.010	-0.041***	0.013
Fixed term (full time)	-0.013	0.012	-0.025*	0.014	-0.010	0.012	-0.022	0.014
Firm size (base < 20 employees)								
20–99	0.005	0.008	-0.001	0.009	0.004	0.008	0.001	0.009
100–499	0.026***	0.008	0.019**	0.008	0.024***	0.008	0.020**	0.008
500–999	0.041***	0.009	0.019**	0.009	0.041***	0.009	0.020**	0.010
1,000–4,999	0.048***	0.008	0.031***	0.008	0.051***	0.008	0.033***	0.008
5,000–19,999	0.055***	0.008	0.028***	0.008	0.057***	0.008	0.030***	0.008
≥20,000	0.055***	0.009	0.026***	0.008	0.058***	0.010	0.029***	0.008
Region (base Northern Territory)								
Sydney	-0.072	0.053	0.119*	0.068	-0.072	0.055	0.116*	0.070
Other New South Wales	-0.136**	0.053	0.093	0.075	-0.144***	0.055	0.089	0.076
Melbourne	-0.066	0.057	0.067	0.070	-0.071	0.059	0.062	0.072
Other Victoria	-0.057	0.062	0.017	0.077	-0.067	0.064	0.011	0.078
Brisbane	-0.082	0.055	0.040	0.069	-0.094*	0.056	0.034	0.070
Other Queensland	-0.088*	0.052	0.005	0.076	-0.098*	0.054	-0.001	0.077

	Model (7) for fatal risk (MA)				Model (8) for non-fatal risk (MA)			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Adelaide	-0.047	0.064	0.076	0.080	-0.057	0.065	0.061	0.081
Other South Australia	-0.052	0.065	0.078	0.097	-0.050	0.066	0.073	0.098
Perth	-0.052	0.058	0.036	0.079	-0.060	0.059	0.034	0.081
Other Western Australia	0.064	0.069	0.041	0.095	0.076	0.070	0.043	0.097
Tasmania	-0.193***	0.069	0.038	0.089	-0.200***	0.071	0.027	0.088
Australian Capital Territory	-0.095*	0.057	0.203***	0.071	-0.094	0.059	0.209***	0.073
Wave (base 10)								
11	0.000	0.005	0.002	0.005	0.001	0.005	0.002	0.005
12	0.030***	0.005	0.012**	0.005	0.031***	0.005	0.011**	0.005
13	0.015***	0.005	0.004	0.005	0.016***	0.005	0.003	0.005
14	0.011*	0.006	0.001	0.006	0.012**	0.006	-0.001	0.006
15	0.011**	0.005	0.010*	0.006	0.011**	0.005	0.008	0.006
16	0.011**	0.004	0.014***	0.005	0.011***	0.004	0.013***	0.005
Occupation (base manager)								
2	-0.002	0.008	0.003	0.010				
3	-0.003	0.011	-0.042**	0.019				
4	-0.037**	0.016	-0.041***	0.013				
5	-0.023***	0.009	-0.033***	0.010				

	Model (7) for fatal risk (MA)				Model (8) for non-fatal risk (MA)			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
6	-0.044***	0.013	-0.010	0.013				
7	-0.007	0.013	-0.013	0.032				
8	-0.023*	0.012	0.021	0.021				
Industry (base agriculture, forestry and fishing)								
2	0.169***	0.038	0.002	0.055				
3	0.050	0.033	-0.020	0.043				
4	0.107***	0.038	-0.046	0.049				
5	0.063	0.033	-0.013	0.045				
6	0.022	0.034	-0.018	0.043				
7	0.010	0.036	-0.072	0.045				
8	-0.040	0.040	-0.070	0.047				
9	0.035	0.031	0.003	0.044				
10	0.065*	0.038	-0.033	0.047				
11	0.087**	0.038	-0.012	0.046				
12	-0.006	0.039	-0.094	0.048				
13	0.043	0.034	-0.040	0.044				
14	0.016	0.035	-0.054	0.043				
15	0.049	0.034	-0.001	0.043				

	Model (7) for fatal risk (MA)				Model (8) for non-fatal risk (MA)			
	Male		Female		Male		Female	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
16	0.017	0.040	0.017	0.047				
17	0.020	0.037	-0.037	0.043				
18	0.013	0.038	-0.094	0.051				
19	0.029	0.036	-0.047	0.046				
Risk MA								
Risk MA	-0.001	0.001	-0.001	0.001	-0.000	0.000	0.000	0.001
Unemp	-0.004	0.005	-0.003	0.005	-0.004	0.006	0.001	0.006
Unemp × Risk MA	0.000	0.000	-0.001	0.001	0.000	0.000	-0.001	0.000
Union	0.024***	0.009	-0.001	0.008	0.015	0.012	-0.003	0.011
Union × Risk MA	0.000	0.001	0.006**	0.003	0.001	0.001	0.001	0.001
WT	-0.001*	0.001	0.000	0.001	-0.001**	0.001	-0.002	0.002
WT × Risk MA	0.000	0.000	-0.001	0.001	0.000	0.000	0.000	0.000
Constant	2.683***	0.194	2.257***	0.205	2.725***	0.192	2.185***	0.199

Note. SE = standard error. MA = moving average. Unemp = centred unemployment rate. WT = worker training.
[a] Measured in years. [b] Employment contract for full-time workers only.
* p < 0.1. ** *p* < 0.05. *** *p* < 0.01. Clustered standard errors are used and reported.

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