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# Risk Heterogeneity and the Value of Reducing Fatal Risks: Further Market-Based Evidence

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# Risk Heterogeneity and the Value of Reducing Fatal Risks: Further Market-Based Evidence

Ikuho Kochi and Laura O. Taylor

## Abstract

The benefits associated with mortality risk reductions are a critical input for the benefit-cost analysis of economically significant federal regulations that affect health and safety. The dominant method of estimating the benefits of reducing mortality risks relies on labor markets to estimate the tradeoffs between workers' wages and occupational risk. The past literature considers all labor market risks to be equivalent, failing to recognize the inherent heterogeneity in occupational hazards. In this research, heterogeneity in the value of reducing risks is explored within the labor market context. Unique location-specific risk data are developed for over 300 U.S. cities to separately identify the wage premiums for facing two disparate occupational risks: violent assault and motor vehicle accident risks. We find that ignoring the underlying heterogeneity in risks can lead to substantial over/under-statements of the benefits of reducing any one particular risk by up to 350%. As such, caution is urged for benefits transfer exercises that apply estimates of the marginal willingness to pay for reducing labor market accident risks to policies affecting very different risks, such as public safety or environmental risks.

**KEYWORDS:** value of statistical life, risk characteristics, benefit-cost analysis

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## 1. Introduction

Methods by which we monetize the benefits associated with policies designed to reduce human mortality and morbidity risks continue to be at the core of important public policy debates. Economists advocate that benefit estimates be linked to societal measures of the willingness to pay or willingness to accept compensation for changes in the risk faced by that society. The value of a statistical life (VSL) is commonly used to represent this measure. The VSL is calculated by scaling an estimated population mean willingness to pay (WTP) for a very small reduction in the risk of death by the risk-unit base. For example, say it has been estimated that the mean WTP to reduce the annual risk of death by 1 in 100,000 from a particular hazard is $40 per year. The VSL estimate in this case would be $4 million ($40 x 100,000) and represents the total WTP for a group of 100,000 people to reduce the *probability* that one additional death among them occurs.[1] The critical input for the calculation of a VSL is the estimate of the marginal WTP for a small change in risk, $40 in the example above. Economists look to actual behavior as well as stated preferences to develop estimates of what individuals are willing to pay to reduce small risks in their lives.

The dominant revealed preference valuation method used in the U.S. to estimate the VSL is the hedonic wage method.[2] By analyzing individual tradeoffs between the risk of fatal injury on the job and wages, the worker's marginal willingness to accept a marginal increase in risk may be estimated (for recent reviews, see McConnell, 2006; Kochi et al., 2006; Viscusi and Aldy, 2003; Mrozek and Taylor, 2002). The use of labor markets to empirically estimate the VSL has received considerable attention in academic and policy circles due in large part to their important role in determining the benefit/cost ratio for economically significant federal regulations addressing public health and safety threats (Kenkel, 2003; U.S. Office of Management and Budget, 2003; U.S. Environmental Protection Agency (U.S. EPA), 2005; U.S. Department of Transportation, 2008). In addition to methodological and data quality concerns,[3] debates continue regarding whether available VSL estimates should be adjusted to

[1] The VSL term, while convenient since it expresses willingness to pay for risk reductions in a common unit ("one death"), has generated considerable controversy and misunderstanding in the popular press as it implies one is estimating the value of "a life" (statistical or not) rather than monetary tradeoffs for very small changes in risk. Several proposals exist to begin to move the academic and policy literature away from the use of the term "VSL" (e.g., Cameron, 2010), however, there is not a consensus view on alternative terminology yet.

[2] For recent alternative revealed preference approaches to estimating the VSL, see Ashenfelter and Greenstone (2004), and Blomquist (2004) for a review.

[3] See Black and Kneisner (2003), DeLeire and Timmins (2007), Hintermann, et al. (2010), and Kniesner, et al. (2011) for examples of research addressing methodological and data quality issues within the hedonic wage framework.

more closely reflect the policy to which the VSL is being applied. In particular the position is that VSL estimates should be based upon similar risks faced by a similar population that is addressed by a particular policy, to the extent possible (Robinson et al., 2010; U.S.EPA Science Advisory Board, 2000; Sunstein, 1997; U.S. Office of Management and Budget, 2003; Kenkel, 2003).

Labor market risks are typically quite different than the risks addressed in environmental, health and public-safety policies. Workplace risks generally arise from relatively routine activities such as motor vehicle or equipment operation,[4] while public safety, health and environmental policies often focus on risks that are known to inspire more fear and dread and are viewed as involuntarily assumed and less controllable (e.g., homicide and cancer risks from toxic exposures). Stated preference research generally finds that characteristics of risk affect the valuation of reducing those risks. Individuals have been found to state a higher willingness to pay (WTP) to reduce risks that involve a high degree of dread or fear, are involuntarily faced, and are less controllable (e.g., Jones-Lee et al., 1985; McDaniels et al., 1992; Savage, 1993; Carlsson et al., 2004; Chilton et al., 2006; Bosworth et al., 2010; Cookson, 2000).

While survey-based evidence suggests that risk valuation is differentiated by risk type, we have little revealed-preference evidence to help us understand the degree to which these differentials persist in market contexts, if at all.[5] Understanding how markets value heterogeneous risks is important given the skepticism with which stated preference research is often viewed. This research uses the hedonic wage model to explore how revealed preference values for reducing risks vary when multiple risks of different types are faced. Our analysis exploits the fact that labor market deaths themselves are more heterogeneous than previously acknowledged in the literature. In general, workplace risks can be placed in two categories: accident risks from routine hazards such as driving automobile or operating machinery, and violent assault risks. During the 1990s, approximately 20 percent of all workplace deaths were homicides, and for some occupations homicides comprise the majority of workplace fatality risk. With few exceptions, the past hedonic wage literature has ignored the underlying heterogeneity in workplace hazards by empirically modeling the relationship

[4] The U.S. Bureau of Labor Statistics (BLS) reports that approximately 45 percent of workplace fatalities are related to transportation accidents, while another 40 percent relate to other accidents such as falls and contact with heavy equipment.

[5] Changes in the VSL that correlate with personal characteristics, such as age, income or gender of those at risk have been extensively explored within the hedonic wage framework. See, for example, Viscusi and Aldy (2007), Aldy and Viscusi (2008), Kniesner et al. (2010), Evans and Smith (2010), Hammitt and Haninger (2010), Evans and Schaur (2010), and for a review, see Robinson (2007). Understanding how both population and risk heterogeneity interact with each other in the valuation of reducing risks is an obvious next step for research in this area, but not one we can address with the specialized sample of workers employed here, as discussed later.

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between wages and the risk of "a death", regardless of how the death occurs. The maintained assumption is that all risks are compensated equally.

We estimate the value of reducing two specific, disparate occupational hazards: violent assaults and traffic accidents. A unique database of location-specific homicide and accidental death risks is created for over 300 U.S. metropolitan statistical areas (MSAs). These risk rates are matched to a specialized sample of workers, occupational drivers, which includes truck, bus, sales, and taxi drivers. Occupational drivers are chosen because they have very similar job duties (driving) and face either traffic accident or homicide risks (or both) routinely as part of their job.[6] The combination of similar job duties and the two different risks faced makes occupational drivers an excellent sample to focus upon when attempting to isolate wage/risk premiums for these two heterogeneous risks.

Our empirical strategy combines wage data and city-specific homicide and traffic fatality risk rates in cross-sectional models that include controls for city, region, and occupation category of the driver. We first estimate the VSL as traditionally considered in the hedonic wage literature by including an aggregated, undifferentiated risk of death from all workplace hazards. The implied VSL from this model is approximately $2 million, which is within the range of estimates from prior studies and reasonable given our specialized sample of workers. Models that distinguish between assault and accident deaths, however, demonstrate that the undifferentiated VSL masks important differences in the valuation of the underlying heterogeneous risks. A strong pattern emerges from our results: assault risks (fatal or otherwise) are compensated for occupational drivers, while motor vehicle accident risks are not. If one computes a measure similar to the VSL for homicide risks only, we see a 250 percent increase in the value of avoiding this type of hazard as compared to the VSL based on an undifferentiated risk measure. And in stark contrast, our models strongly suggest that increases in automotive accident risks are not a compensated working condition for occupational drivers.

Our work supports that of Scotton and Taylor (2011) who conducts a similar analysis using a broad sample of U.S. workers matched to national averages for fatality risks for occupational accidents and homicides. While they find a significantly higher wage premium for homicides as compared to accident risks, their results are not without important qualifications and rest on

[6] Drivers generally have a higher risk of death than the average worker. Traffic accident fatality risks are higher for obvious reasons. Homicide risks for drivers are also higher than the national average for U.S. workers. This is because of the nature of the jobs. Drivers have high contact with the public (increasing the risk of assault) and move throughout metropolitan areas placing themselves in higher crime neighborhoods and/or situations than the average worker who stays at their place of work during the workday (e.g., in an office building).



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assumptions regarding segmentation of the labor market. The authors attribute some counter-intuitive results to unobserved job or worker characteristics thought to be correlated with different types of fatal risks, as well as the inherent difficulty of identifying specific types of workplace risks that are relevant to any particular occupation within the broad U.S. workforce. Our study design avoids these difficulties through a more narrow focus in the labor market. Our workers have very similar job duties (driving), use the same general equipment (on-road motor vehicles), and are very likely aware of the risks they face.[7] Importantly, our location-specific risk rates are more likely to reflect the worker's actual risk, especially for homicides, as compared to a national average risk rate used by Scotton and Taylor (2011) and by previous hedonic wage studies.

The results herein have important implications for applying past labor market VSL estimates broadly across public policy analyses. Ignoring the underlying heterogeneity in the values for heterogeneous risks can lead to substantial over/under-statements of the marginal willingness to pay to reduce specific risks. This reinforces the conclusions of the U.S. Office of Management and Budget (2003), the U.S. EPA (1997, 2005), and the U.S. EPA Science Advisory Board (2000) that the VSL used in a benefit-cost analysis should be specific to the risk context addressed by the policy. To the degree evidence continues to suggest that risk heterogeneity affects risk valuation in economically meaningful ways, the application of VSLs derived from labor market injury risks to many federal regulatory policies becomes an increasingly flawed benefits transfer exercise.

The remainder of the paper is as follows. In the next section, we present the occupational and risk data used in the analysis. The empirical models and baseline results are presented in Section 3, followed by a discussion of the robustness of the results to important model assumptions. Section 4 offers conclusions.

## 2. Occupational Risk and Labor Force Data

Statistics on occupational deaths have been maintained by various state and federal agencies for decades. However, the quality of the data collected varied substantially across states in both completeness and quality of the information reported (Drudi, 1997). To improve upon previous efforts, the U.S. Bureau of Labor Statistics (BLS) began an annual Census of Fatal Occupational Injuries (CFOI) in 1992. The CFOI is a complete census, verified by at least two independent documents such as death certificates and worker's compensation

[7] Benjamin et al. (2001) indicate that individuals predict their personal risk levels best the higher their actual risk of death from a particular source. Given the high level of risks drivers routinely face in the job, it is reasonable to assume that drivers are fairly aware of the risks they face.

reports to assure that the incident meets the criteria for inclusion as a work-related incident. To be considered a work-related incident, the worker had to be "engaged in a legal work activity, and present at the site of the incident as a job requirement".[8] Importantly, the CFOI categorizes each of these deaths according to the event leading to death using the Occupational Injury and Illness Classification System (OIICS).

Our two types of fatal events are obtained directly from the CFOI; homicides and accidental deaths. Homicides include assaults and violent acts by persons such as hitting and shooting, and do not include self-inflicted injuries (suicides) or assaults by animals. Accidental deaths include deaths from all sources other than homicide and self-inflicted injuries. Table 1 reports the total number of accidental deaths and homicides between 1998 and 2002 (Panel A, Column 1). The total number of workplace deaths between 1998 and 2002 was 28,389.[9] Accidents account for 88 percent of all workplace deaths during this period and the remaining 11 percent of workplace deaths result from homicides. The leading causes of accidental deaths on the job are motor vehicle accidents, contact with heavy equipment, falls, and electrocution or exposures. As compared to the general workforce, accidents comprise a slightly higher proportion of deaths for occupational drivers – nearly 93 percent of total fatalities (Table 1, Panel A, Column 2). For occupational drivers, approximately 80 percent of accidental deaths between 1992 and 2002 were a direct result of traffic accidents. The remaining accidental deaths arise from events such as falls and exposure to harmful substances and environments.

Table 1 also reports fatalities for each occupational driver category. Truck, bus and sales drivers all have a high proportion of their occupational deaths resulting from accidents, while taxi drivers have less than 40 percent of their deaths occurring from accidents. Homicides are the dominant fatality event for taxi drivers, comprising 61 percent of total deaths for these workers during our study period. Taxi drivers also represent 60 percent of total homicides among all occupational drivers. Truck drivers account for the next highest proportion of workplace homicides among occupational drivers (24 percent).

Occupational fatality risk rates are calculated by dividing the annual average deaths from each cause (homicide or accident) in each Metropolitan Statistical Area (MSA) for each driving occupation by the annual average employment in each MSA for each driving occupation. We use a 5-year average of the annual risk rates in our models to minimize the influence of large events and better reflect the average risk in an MSA. The number of occupational fatal

[8] BLS Handbook of Methods, September, 2008, Chapter 9, Page 36 of 49 (page numbers not included in document), available at http://www.bls.gov/opub/hom/pdf/homch9.pdf.

[9] These figures exclude suicides, which account for about 3 percent of deaths reported in the CFOI.

**Table 1. Total number of accidental and assault-related fatal and non-fatal injuries between 1998 and 2002.[a]**

| | All workers (1) | All drivers (2) | Truck drivers (3) | Sales drivers (4) | Bus drivers (5) | Taxi drivers (6) |
|---|---|---|---|---|---|---|
| *Panel A: Fatal injuries* | | | | | | |
| Total Deaths | 28,389 | 4,899 | 4,210 | 237 | 114 | 338 |
| Accidental deaths | 25,095 | 4,551 | 4,125 | 194 | 102 | 130 |
| (% of total deaths) | (88.3) | (92.8) | (97.9) | (81.8) | (89.4) | (38.4) |
| [% of total accidental deaths among all occupational drivers] | | | [90.6] | [4.2] | [2.2] | [2.8] |
| Homicides | 3,294 | 348 | 85 | 43 | 12 | 208 |
| (% of total deaths) | (11.6) | (7.1) | (2.0) | (18.1) | (10.5) | (61.5) |
| [% of total homicide deaths among all occupational drivers] | | | [24.4] | [12.3] | [3.4] | [59.7] |
| *Panel B: Non-fatal injuries*[b] | | | | | | |
| Total Injuries | 8,070,783 | 762,400 | 650,235 | 71,439 | 34,722 | 6,004 |
| Accidental injuries | 7,982,814 | 759,219 | 648,879 | 70,608 | 33,889 | 5,843 |
| (% of total injuries) | (98.9) | (99.6) | (99.8) | (98.8) | (97.6) | (97.3) |
| [% of total accidental injuries among all occupational drivers] | | | [85.5] | [9.3] | [4.5] | [0.8] |
| Assaults by person | 87,969 | 3,181 | 1,356 | 831 | 833 | 161[c] |
| (% of total injuries) | (1.1) | (0.4) | (0.2) | (1.2) | (2.4) | (2.7) |
| [% of total assault injuries among all occupational drivers] | | | [42.6] | [26.1] | [26.2] | [5.1] |

[a] All data reported exclude deaths due to suicides. Fatal injury data for all workers (Panel A, Column 1) and data for non-fatal injuries (Panel B, Columns 1-6) are obtained from the BLS *Occupational Injuries and Illnesses and Fatal Injuries Profiles* available at http://data.bls.gov (last accessed March 14, 2010). Fatal injury data for occupational drivers (Panel A, Columns 2 through 6) are obtained from non-public CFOI. Percentages do not add up to 100% due to rounding.

[b] Non-fatal injuries are defined as workplace injuries that result in at least one day away from work. Accidental injuries are defined as any workplace injury other than an injury due to assaults.

[c] The number of assault injuries for taxi drivers was not available for the year 2001 due to reporting restrictions by the BLS. Thus, the number of taxi driver assaults reported is the sum for the years 1998-2000 and 2002.

incidents by county is obtained from a restricted access CFOI file collected by the BLS for the period 1998 through 2002. The location of injury at the county level is aggregated into an MSA count of deaths using the 1999 Office of Management and Budget MSA definitions. The number of workers in each driving occupation in each MSA is collected from the Occupational Employment Statistics (OES) administered in 1998-2003 at the MSA level. The MSA risks are matched to a sample of occupational drivers (described in the next section) and the resulting mean risk rates for each event for each occupation are reported in columns (1) to (3) of Table 2. MSAs with less than 100 employees in a particular occupation are omitted from the sample to eliminate cities with very large risks due to a single event. This restriction also eliminates many zero-risk MSAs. Column (1) reports the total number of workers in each occupation over which the mean is computed. Standard deviations are presented in parentheses. The average accidental fatality risk for the occupational drivers sample is $2.12\times10^{-4}$ and the average homicide risk is $0.39\times10^{-4}$. For comparison, Scotton and Taylor (2011) report that the average accidental fatality and homicide risks for all occupations (1992-1998) were much smaller, at $0.44\times10^{-4}$ and $0.05\times10^{-4}$, respectively.

While driving occupations are generally higher risk than the U.S. labor force average, there is substantial variation in the risks across driving occupations. The average homicide risks for sales, bus and truck drivers are $0.32\times10^{-4}$, $0.16\times10^{-4}$ and $0.06\times10^{-4}$, respectively, while taxi drivers face a mean homicide risk that is more than an order of magnitude larger ($5.42\text{x}10^{-4}$). Taxi drivers also face the highest accidental fatality risk ($2.28\times10^{-4}$), however, it is very similar to the risk faced by truck drivers ($2.27\times10^{-4}$). Bus drivers have a fatal accident risk rate of $1.37\times10^{-4}$, and sales drivers face the lowest fatal accident rate among driving occupations ($0.83\times10^{-4}$). The standard deviations for the risk measures are larger than the own mean in the majority of cases of each driving occupation. We test our model robustness to low and high-risk MSAs by estimating models that exclude observations with these types of risks.

In addition to the MSA-level risks, we create state-level risk rates for each type of event for each type of occupational driver. State-level risks are created for two reasons. First, non-fatal injury rates are available at the state level only and so we create fatality risks that are consistent geographically as a robustness check. Second, we do not know the geographic extent of each worker's driving territory and so state-level fatality risks will allow us to examine the sensitivity of our results to different assumptions about the spatial extent of the relevant risks.

State-level risks are reported in columns (4) to (6) in Table 2. Compared to the MSA-level risk, the mean value of state-level homicide risk is somewhat lower for all occupations, with the largest difference being for taxi drivers. The difference for taxi drivers likely reflects that taxi drivers primarily drive within MSAs (and thus homicides on the job occur within the MSA). Conversely, the



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state-level accident risks are generally larger than MSA accident risks, with the exception being bus drivers for whom there is no practical difference in mean risk. For accident risks, the largest difference is for truck drivers, which again likely reflects the mix of driving within and outside an MSA for this occupational group. The fact that 86 percent of taxi drivers in our sample report their job location as being in an MSA, while only 63 percent of truckers do the same supports these conjectures.

**Table 2. Summary of average fatal and non-fatal injury risk rates for occupational drivers (standard deviations reported in parentheses).[a]**

| | Avg. MSA fatal risk ($x10^{-4}$) | | | Avg. State fatal risk ($x10^{-4}$) | | | Avg. State injury risk ($x10^{-4}$) | | |
|---|---|---|---|---|---|---|---|---|---|
| | N[b] | Accident | Homicide | N[a] | Accident | Homicide | N[a] | Accident | Assault |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Total | 6,915 | 2.12<br>(1.77) | 0.39<br>(1.73) | 10,534 | 3.24<br>(2.04) | 0.28<br>(1.42) | 8,705 | 489<br>(153) | 1.39<br>(4.91) |
| Truck drivers | 5,625 | 2.27<br>(1.63) | 0.06<br>(0.12) | 8,852 | 3.56<br>(1.99) | 0.05<br>(0.05) | 7,276 | 532<br>(102) | 0.54<br>(1.17) |
| Sales drivers | 359 | 0.83<br>(1.65) | 0.32<br>(0.77) | 528 | 1.19<br>(0.97) | 0.27<br>(0.37) | 426 | 407<br>(142) | 3.72<br>(8.73) |
| Bus drivers | 531 | 1.37<br>(2.27) | 0.16<br>(0.53) | 692 | 1.34<br>(1.36) | 0.15<br>(0.58) | 593 | 269<br>(153) | 9.89<br>(12.90) |
| Taxi drivers | 400 | 2.28<br>(2.15) | 5.42<br>(4.91) | 462 | 2.34<br>(1.36) | 4.78<br>(4.96) | 410 | 116<br>(94) | 1.81<br>(6.82) |

[a] Workers from all states in the continental U.S. and District of Columbia are included.
[b] The number of workers upon which the average risk rate is computed varies across columns due to differences in the geographic coverage.

Occupational non-fatal risk rates are also created for assault and accidental injuries. The count of non-fatal injuries was obtained from the 1998-2002 Survey of Occupational Injuries and Illnesses (SOII) program administered by the BLS and is only available at a state-wide level. The number of injuries is defined as the number of workers who experience at least one day away from work due to an occupational injury.[10] The risk rates are calculated by dividing the annual average count of non-fatal assault and accidental injuries by the annual average employment in each state for each driving occupation. Non-fatal injury risks will be referred to as simply "injury risks" for ease of exposition.

Columns (7) to (9) in Table 2 reports the mean state-level risk rate for assault and accidental injuries for each driving occupation. Truck and sales

[10] Not all states participate in the SOII program, and not all states report injury data for all study years. Colorado, District of Columbia, Idaho, Mississippi, New Hampshire, North Dakota, Ohio and Pennsylvania do not report injuries at all during our sample period (1998-2002), and so MSAs in these states are not included in the analysis. Wyoming does not report in 2002, and thus the average injury risks for this state are computed over four years instead of five.

drivers have the highest accidental injury risks. Five in 100 truck drivers and four in 100 sales drivers experience accidental injuries every year. Bus drivers have the highest assault injury risks among all driving occupations. Nine in 10,000 bus drivers suffer an assault injury every year. Taxi drivers experience a relatively low assault injury risk (one in 10,000), less than both bus and sales drivers. A relatively low assault injury risk combined with a high homicide risk indicates that when a taxi driver is assaulted, it tends to be fatal (Knestaut, 1997 also makes this observation).

## Labor force sample

The Outgoing Rotation Group of the Current Population Survey (CPS) provides information on wages, worker characteristics and job characteristics for drivers. We use all drivers in the CPS Outgoing Rotation Group surveyed in 1996, 1998, 2000 and 2002. The Outgoing Rotation Group is comprised of workers who are in the fourth or 16th month of their participation period, thus they appear in the same month's sample in two consecutive years. We alternate years in our sample to avoid duplication of workers. The sample is limited to non-self-employed, single job holding, full time occupational drivers who reported a valid wage to the CPS.[11] Self-employed workers are omitted for several reasons. First, our focus is on estimating hedonic wage equations resulting from wage-risk negotiations, which would not be the case for self-employed workers. Secondly, there is no employment census or employment survey for self-employed workers that allows computation of an accurate number of self-employed workers in a particular occupation and industry, and so creating a consistent risk rate for these workers is difficult. And lastly, there is evidence that the self-employed often face different work environments and as a group suffer fatal injuries more often than those working for wages and salaries (Drudi, 1997; Personick and Windau, 1995). For consistency, our risk rates do not reflect deaths of the self-employed. Workers living in Hawaii and Alaska, and workers earning less than minimum wage or whose income is top-coded by the CPS are also not included.[12]

Table 3 reports the definitions and summary statistics of the variables used to describe the base sample of drivers, which includes all drivers who live in an

[11] The CPS imputes wages of survey responders who decline to report wages. Thirty-two percent of our sample had imputed wages. This is similar to the overall CPS average of 30 percent (Bollinger and Hirsch, 2006). We also report models including workers with imputed wages.

[12] The legal minimum hourly wage for taxi drivers during our sample period was \$2.13 per hour. Minimum wage for other drivers was \$4.75 in 1996, and \$5.15 in 1998, 2000 and 2002. Per-hour minimum wage is multiplied by 35 hours to obtain minimum weekly wage, and this wage does not include tips earned by any driving occupation (we do not have this information available to us). Workers earning more than \$2,881.61 per week are top-coded by the CPS. There were 16 workers with top-coded income in our sample.

MSA in the U.S.[13] The socioeconomic descriptors constructed for the sample of workers includes age, educational attainment, race, U.S. citizenship, gender, whether the worker is salaried, their usual hours worked, union status, marital status, and location of the household (urban versus rural). Also created are occupational, Metropolitan Statistical Area (MSA), state and regional dummy variables.[14]

There are 5,867 occupational drivers in the sample, and they have an average weekly wage of $702 which is higher than the average U.S. worker's weekly wage of approximately $530.[15] The higher wage of this sample is perhaps a reflection of the relatively high participation rate of the sample in unions (26 percent) as compared to the national average (12.5 percent). Average age of the sample is 40 years old and approximately half of the sample graduated from high school, 25 percent received some college level education, and 5 percent graduated from a four year college. Compared to the national average, the educational attainment level is substantially lower.[16] Seventeen percent of the sample is of Hispanic origin, and 14 percent are African American. Most of the sample has U.S. citizenship (90 percent) and only 6 percent of the sample is female, reflecting the male dominance of the occupations upon which we focus. Fifty-three percent of the sample works overtime and sixty-four percent are married.

In addition to individual and occupational characteristics, local economic factors such as the unemployment rate may also affect wages. The MSA-level unemployment rate during the study period is obtained from the Local Area Unemployment Statistics (LAUS) administered by the BLS.[17] The average annual unemployment rate during the sample period is between four percent and six percent, however, the unemployment rate varies significantly across MSAs. For instance, during our study period, the McAllen-Edinburg-Mission MSA in Texas had unemployment rates as high as 19 percent, while the rate was two to three percent in Madison, Wisconsin over this same period.

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[13] In some model specifications in our sensitivity analysis, we include drivers who reside outside an MSA.

[14] We use nine regional divisions defined by U.S. Census Bureau: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific.

[15] All monetary values are adjusted to 2004 dollars using the consumer price index throughout the paper. Average U.S. weekly wage is reported by the BLS in the October 2005 *Employment Situation Summary*: http://www.bls.gov/news.release/history/empsit_11042005.txt.

[16] The national average during our sample period was that approximately 30 percent of the workforce had graduated from high school, 30 percent had attended a college but had no degree, and 30 percent held a bachelor's degree or more (BLS, http://www/bls/gov/cps/labor2005/chart2-1.pdf).

[17] The data are from the Local Area Unemployment Statistics (LAUS), available at the Bureau of Labor Statistics: http://www.bls.gov/lau/home.htm.

**Table 3. Variable description for base sample (N=5,867).**[a]

| | Definition | Mean | (std. dev.) |
|---|---|---|---|
| *wage* | Weekly wage (adjusted to $2004) | 702 | (331) |
| *total fatality risk* | Annual MSA-level undifferentiated fatality risk ($x10^{-4}$) | 2.52 | (2.62) |
| *total injury risk* | Annual MSA-level undifferentiated injury risk ($x10^{-4}$) | 4.94 | (1.61) |
| *homicide* | Annual MSA-level violent fatal risk ($x10^{-4}$) | 0.39 | (1.73) |
| *accidental death* | Annual MSA-level accidental death risk ($x10^{-4}$) | 2.12 | (1.77) |
| *assault injury* | Annual state-level assault injury risk ($x10^{-2}$) | 0.01 | (0.05) |
| *accidental injury* | Annual state-level accidental injury risk ($x10^{-2}$) | 4.92 | (1.61) |
| | ***Worker Characteristics*** | | |
| *age* | age in years | 39.90 | (11) |
| *college degree* | four year college degree=1, otherwise=0 | 0.05 | |
| *some college* | attended college=1, otherwise=0 | 0.25 | |
| *high school* | graduated from high school=1, otherwise=0 | 0.49 | |
| *no degree* | did not complete high school=1, otherwise=0 | 0.21 | |
| *caucasian* | Caucasian=1, otherwise=0 | 0.67 | |
| *hispanic* | Hispanic origin=1, otherwise=0 | 0.17 | |
| *black-nh* | black and non-Hispanic=1, otherwise=0 | 0.14 | |
| *other race* | Other race/ethnicity=1, otherwise=0 | 0.02 | |
| *uscitizen* | U.S. citizen=1, otherwise=0 | 0.89 | |
| *female* | Female=1, otherwise=0 | 0.06 | |
| *married* | Married=1, otherwise=0 | 0.64 | |
| *central city* | lives in central city=1, otherwise=0 | 0.29 | |
| | ***Job Characteristics*** | | |
| *salaried* | works for salary=1, otherwise=0 | 0.34 | |
| *work overtime* | usually works more than 40 hours=1, otherwise=0 | 0.53 | |
| *union* | union member or covered by union=1, otherwise=0 | 0.26 | |
| *truck* | truck driver=1, otherwise=0 | 0.80 | |
| *bus* | bus driver=1, otherwise=0 | 0.07 | |
| *taxi* | taxi driver=1, otherwise=0 | 0.06 | |
| *sales* | sales driver=1, otherwise=0 (category left out of the model) | 0.07 | |
| | ***MSA Characteristics (N = 4,842)*** | | |
| *unemployment* | annual unemployment level | 4.84 | (1.85) |
| *wholesale* | per capita sales in wholesales industry (in $1,000) | 17.52 | (9.26) |
| *retail* | per capita sales in retail industry ($1,000) | 9.32 | (1.95) |
| *transportation* | per capita sales in transportation industry ($1,000) | 1.34 | (0.71) |
| *entertainment* | per capita sales in arts-entertainment industry ($1,000) | 2.02 | (1.66) |
| *food* | per capita sales in accommodation and food service industry ($1,000) | 1.55 | (1.48) |
| *msa vmt* | per capita vehicle miles traveled | 8,493 | (2,975) |

[a] The sample excludes workers in Colorado, District of Columbia, Idaho, Mississippi, New Hampshire, North Dakota, Ohio and Pennsylvania due to non-reporting of injury statistics as discussed in footnote 10. The sample size over which fatality risks are computed is 6,915.



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Different levels of economic activity in industries important to occupational drivers could also affect the wage level of workers through different levels of demand for occupational drivers. The volume of sales in wholesale, retail, transportation, arts-entertainment, and accommodation/food-service industries in each MSA would likely affect the demand for the truck, sales, bus and taxi drivers. These data are obtained from the 1997 Economic Census administered by the U.S. Census Bureau and are available for only 1997.[18] The population of each MSA is also obtained from the 1997 Economic Census to calculate the per-capita sales volume and employment level in the above industries.

Lastly, the vehicle miles traveled (VMT) in each MSA may indicate different traffic levels, workload and stress for occupational drivers among MSAs. Increased VMT may also indicate increased urban sprawl and thus may correlate with a general increase in the cost of providing driving services. The MSA VMT per-capita are obtained from U.S. EPA (1998) which reports the 1996 VMT by county. County-level VMT is aggregated to the MSA level using the 2000 Census definition of an MSA.[19] Note, these data are available for only 188 MSAs, which reduces our sample to 4,842 workers if we include these variables in our models. As a consequence, we also estimate models using MSA fixed effects.

## 3. Empirical Model and Results

### Base Model

First we consider a hedonic wage model in which the risk of death or injury on the job is undifferentiated by the type of risk faced. In this case, the cross-sectional model we estimate is:

$$ln(wage_{ioj}) = a_0 + a_1\, total\ fatality\ risk_{oj} + a_2\, total\ injury\ risk_{oj} + X_i\beta + W_i\gamma + \theta_o + \varphi_m + \tau_t + \omega_r + \varepsilon_{ioj}, \quad (1)$$

where $wage_{ioj}$ denotes the wage of the $i^{th}$ worker in occupation $o$ in location $j$.[20] Aggregated risks are denoted *total fatality risk* and *total injury risk*, and they vary by occupation and geographic location; $X_i$ is a vector of individual worker characteristics; $W_i$ is a vector of the individual's job-related characteristics; $\theta_o$, $\varphi_m$, $\tau_t$, and $\omega_r$ are vectors of occupation, MSA, time (year) and region dummy variables, respectively; and $\varepsilon_{ioj}$ is an error term. Inference is based on robust

[18] The data are from the 1997 Economic Census: http://www.census.gov/epcd/www/econ97.html.
[19] We thank Peter Bluestone for sharing these aggregated data with us.
[20] Models are estimated using STATA statistical software, StataCorp LP, College Station, Texas.

standard errors that allow for an unknown form of heteroskedasticity. The variables included in $X$ and $W$ are discussed in the previous section and summarized in Table 3.

Model (1) in Table 4 reports estimation results for equation (1). Before discussing the results for the risk-related variables, we first briefly review results for the demographic and job characteristics. All coefficients for the demographic variables have the expected sign. Older workers earn more than younger workers, but at a decreasing rate. College and high school graduates earn more than those without a high school degree, Caucasian workers earn more than other workers although this effect is not statistically significant when comparing Caucasian to black, non-Hispanic workers. It is also the case that U.S. citizens earn more than those who are not, male workers earn more than female workers, unionized workers earn more than non-unionized workers, and married workers earn more than single workers. Among occupations, taxi drivers earn less than sales drivers, while the wages for truck and bus drivers are not significantly different than sales drivers in this model.[21] The results for the demographic and job characteristics are generally very stable across models estimated. Also included in the model, but not reported for succinctness, are fixed-effects for region and MSA of the worker, and year in which the wage data was collected.

Turning to the risk variables, the coefficient for aggregated fatality risk is positive and significant at the ten percent level, and the coefficient for aggregated injury risk is positive and significant at the five percent level.[22] For comparison to the past literature, we compute the VSL based on model (1). All estimates are reported in 2004 dollars. The implied VSL is \$1.9 million, and the implied value of a statistical injury (VSI) is \$55,000.[23] Our estimate is at the lower-end of previous estimates based on hedonic wage studies, but still in the range used for recent policy analyses (U.S. EPA, 2005) and similar to many point estimates reported in stated preference studies (Kochi et al., 2006). Our VSI estimate is in the middle of the range reported by Viscusi and Aldy (2003).

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[21] The coefficient estimate indicating that taxi drivers earn less than sales drivers is consistently significant. This is also true when comparing taxi to bus or truck drivers. The coefficient estimate that indicates that truck drivers earn more than sales drivers is significant in 11 out of 13 models presented, while the coefficient estimate indicating that bus drivers earn less than sales drivers is only statistically significant in two out of 13 models presented in the paper.

[22] Models with aggregated fatal and aggregated injury risks are sensitive to specification. The risk coefficients are significantly different than zero in approximately half the models.

[23] The VSL is calculated as follows: fatal risk coefficient × weekly average wage of the sample × 50 weeks × 10,000 (unit of the risk rate in the model). The VSI is computed as: non-fatal risk coefficient × weekly average wage of the sample × 50 weeks.



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**Table 4. Base model results.**[a]

| | Model 1 | | | Model 2 | |
|---|---|---|---|---|---|
| | Coefficient | Standard error[b] | | Coefficient | Standard error[b] |
| *Total fatality risk* | 0.0054* | 0.0033 | *homicide* | 0.0142*** | 0.0053 |
| | | | *accidental death* | -0.0045 | 0.0053 |
| *Total injury risk* | 1.5762** | 0.7875 | *assault injury* | 21.2632* | 12.2505 |
| | | | *accidental injury* | 0.7263 | 0.8686 |
| *age* | 0.0358*** | 0.0030 | *age* | 0.0359*** | 0.0030 |
| *age squared* | - 0.0003*** | 0.00003 | *age squared* | -0.0003*** | 0.00003 |
| *college degree* | 0.0897*** | 0.0267 | *college degree* | 0.0897*** | 0.0267 |
| *some college* | 0.1103*** | 0.0149 | *some college* | 0.1097*** | 0.0149 |
| *high school* | 0.0775*** | 0.0133 | *high school* | 0.0772*** | 0.0133 |
| *hispanic* | - 0.0748*** | 0.0173 | *hispanic* | -0.0730*** | 0.0173 |
| *black-nh* | - 0.0067 | 0.0153 | *black-nh* | -0.0071 | 0.0153 |
| *other race* | - 0.1087*** | 0.0366 | *other race* | -0.1097*** | 0.0364 |
| *uscitizen* | 0.1492*** | 0.0207 | *uscitizen* | 0.1506*** | 0.0208 |
| *female* | - 0.1248*** | 0.0218 | *female* | -0.1240*** | 0.0217 |
| *salaried* | 0.1195*** | 0.0111 | *salaried* | 0.1182*** | 0.0111 |
| *work overtime* | 0.2673*** | 0.0100 | *work overtime* | 0.2667*** | 0.0100 |
| *union* | 0.3157*** | 0.0113 | *union* | 0.3158*** | 0.0113 |
| *married* | 0.0939*** | 0.0106 | *married* | 0.0932*** | 0.0106 |
| *central city* | - 0.0607*** | 0.0123 | *central city* | -0.0609*** | 0.0123 |
| *truck* | 0.0377 | 0.0234 | *truck* | 0.0714*** | 0.0261 |
| *bus* | -0.0264 | 0.0304 | *Bus* | -0.0428 | 0.0337 |
| *taxi* | -0.2042*** | 0.0486 | *Taxi* | -0.2509*** | 0.0523 |
| *constant* | 5.7208*** | 0.3431 | *constant* | 5.7348*** | 0.3433 |
| $R^2$ | 0.44 | | $R^2$ | 0.44 | |
| Included dummy variables: | Year, Region, MSA | | Included dummy variables: | Year, Region, MSA | |
| | | | | Wald test p-values | |
| | | | *homicide= accidental death* | 0.0253 | |
| | | | *Assault= accidental injury* | 0.1031 | |

[a]Significance at the 1%, 5% and 10% level are represented by a ***, **, and *, respectively. Each regression is based on a sample size of 5,867 and had an average weekly wage of $702.77.
[b] Robust standard errors are reported that adjust for an unknown form of heteroskedasticity.

We now turn to the models that allow the risk of death and injury to vary according to the type of risk faced. The empirical model is:

$$ln(wage_{ioj}) = a_0 + a_1 homicide_{oj} + a_2 accidental\ death_{oj} + a_3 assault\ injury_{oj} + a_4 accidental\ injury_{oj} + X_i\beta + W_i\gamma + \theta_o + \varphi_m + \tau_t + \omega_r + \varepsilon_{ioj} \quad (2)$$

where the variables measuring occupational risk include the homicide risk (*homicide*), the risk of a fatal accident (*accidental death*), the risk of a non-fatal injury from violent assaults (*assault injury*), and the risk of a non-fatal accidental injury (*accidental injury*). The definition of variables in vectors *X, W,* $\theta_o, \varphi_m, \tau_t, \omega_r, \varepsilon$ are the same as in equation (1).

The empirical model in (2) allows us to state our hypotheses succinctly: Are the wage/risk premiums significantly different across fatal event types ($H_0^{fatal}: a_1 = a_2$) and are the wage/risk premiums significantly different across injury event types ($H_0^{injury}: a_3 = a_4$)? Due to the nature of the risks involved, we expect the wage/risk premium for violent risks to be larger than those for corresponding accidental risks. Nonetheless, we use two-sided tests for our hypothesis tests.

Model (2) in Table 4 reports coefficient estimates for equation (2). Results indicate that the coefficient estimate for *homicide* is positive and statistically significant at the one percent level and the coefficient estimate for *assault injury* is significant at the ten percent level.[24] The coefficient estimate for homicide indicates that workers are willing to accept an additional $10 per week, or $500 per year, in wages to face an increase in the risk of death by homicide by one in 10,000 when evaluated at the mean wage of the sample. If we scale this marginal value to represent a VSL-like number, the aggregate value of avoiding a statistical homicide is approximately $5 million. This value is an increase of over 250 percent from the undifferentiated measure of the VSL that was obtained in model (1). The coefficient estimate for assault injury indicates that the value of reducing the risk of an assault injury is approximately $0.7 million per avoided assault, which is over 12 times of the undifferentiated measure of the VSI obtained in model (1).

The estimated values for reducing assault risks are in the range of those estimated in previous studies. Cohen et al. (2004) conduct a contingent valuation (CV) survey and estimate that the value of reducing a statistical homicide is $10.6 million. This is approximately twice that of our estimates, although the 95 percent confidence intervals for the upper range of our point estimates overlaps

[24] We also estimated models including a second power term for homicide and accident risks. The coefficient estimates for the higher-power terms are not significant in any models.



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theirs. Our estimates for assault injury risks are very similar to those reported in prior CV studies. Cohen et al. (2004) reports an estimated willingness to pay (WTP) of $76,800 to prevent a "serious assault" (non-fatal) crime, and Ludwig and Cook (2001) report a willingness to pay of $1.39 million to prevent a non-fatal gun assault. These estimates are directly in line with our point estimates of the value of reducing a statistical assault injury.

In contrast to assault risks, the coefficient estimates reported in Table 4 for accidental deaths and injuries are not significantly different than zero. And though these coefficients are not precisely estimated, they are still significantly different than the coefficient estimates for assault risks at the five percent level for fatality risks and just misses significance at the ten percent level for non-fatal injury risks (see Table 4, Wald test p-values). At first blush, this result may seem surprising as it seems to contradict previous stated preference surveys in which respondents indicate a positive willingness to pay to reduce traffic accident risks (Hammitt and Graham, 1999; Corso et al., 2001; Persson et al., 2001). However, there are several mitigating factors that explain these results. First, our sample is, admittedly, a highly specialized sample of workers who have selected into driving occupations. Survey evidence indicates that WTP to reduce risks is lower for "less dreadful" fatality risks (e.g., McDaniels et al., 1992; Chilton et al., 2006) and that people in general view traffic accident risks as among the least dreadful risks faced (Slovic, 1980). As a result, we find it unsurprising that a marginal increase in traffic accident risk is not perceived as a compensated working condition among occupational drivers, much in the same way one might view walking up/down a flight of stairs at work a risk not in need of compensation as part of one's job.[25, 26] Homicide risks, on the other hand, are likely to be viewed very differently. Assaults are viewed as among the most highly dreaded risks (Chilton et al., 2006) and it is reasonable that occupational drivers require positive compensation to be exposed to these risks.

The key results thus far indicate that not all risks are compensated equally in the workplace. Our analysis highlights that if risk heterogeneity is ignored, important differences in the valuation of underlying heterogeneous risks are masked. In our particular application, increased assault risks are a compensated working condition, while routine automotive risks are not. Ignoring this aspect of the labor market, could lead to substantial over/under-estimates of the marginal willingness to pay to reduce specific workplace risks.

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[25] Since 1998, falls are the second most frequent cause of death on the job U.S. (after motor vehicle accidents) and account for over 10 percent of all workplace deaths.

[26] Cameron et al. (2008) also found that the willingness to pay to reduce traffic accident risks is generally substantially lower than the other types of risks such as cancer, heart disease, stroke and diabetes.

## Robustness to Model Assumptions

We now examine the robustness of the results above to a few important model assumptions including those about *(i)* the independence of the error terms across workers *(ii)* the manner in which local economic and working conditions are represented in the model;*(iii)* the sample composition; and *(iv)* the geographic level of aggregation used when computing the risk variable (such as MSA-specific risk rates or state-wide risk rates).

Table 5 presents summary results for a few key variants of the model. Model (1) replicates the heterogeneous risk model in Table 4 except that the error term is now clustered on observations within the same state. The resulting coefficient estimates replicate those reported in Table 4, model (2) and are both significant at the 5 percent level. In model (2), we replace MSA dummy variables with state dummy variables and now allow the error term to be clustered on observations within the same MSA. The results indicate somewhat larger coefficient estimates for homicide and violent injury risks, and both remain statistically significant at the 5 percent level or better. The coefficient estimates for accidental fatal and non-fatal injury risks remain not statistically significant. Similar to the base model results, the estimated coefficients for assault risks are significantly different than those for accidental risks at the ten percent level or better in Model (1) and (2). Next, we consider an alternative means for capturing local working conditions by replacing MSA dummy variables, $\varphi_m$, with the MSA characteristic vector $Z_j$, and state dummy variables, $\psi_s$. As indicated in model (3) of Table 5, the estimated homicide and assault injury coefficients are somewhat larger than in the base model, and they are statistically significant at the one and five percent level, respectively.[27] The coefficient estimates for traffic accident risks again are not significantly different than zero.

The last two models in Table 5 change the composition of workers included in the estimation. Model (4) excludes workers from states which had no homicides recorded for occupational drivers over the sample time period and those with homicide risks greater than $12.7 \times 10^{-4}$, which is approximately the 95[th] percentile for homicide risk in our sample. Model (5) includes all drivers in the CPS, including those whose wages were imputed by the Bureau of Labor Statistics. The results for these two models are consistent with previous models, although the coefficient for non-fatal assault injury risk is not significant in Model (4).

[27] Of the seven MSA characteristics included in model, *wholesale* and *msavmtp* were statistically significant at the 1 percent and 10 percent level, respectively. Increases in wholesale activity, as proxied by sales in that industry, implied higher wages as expected. Increases in per-capita VMT implied lower wages in our model.

**Table 5: Sensitivity of results to model assumptions.[a]**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *homicide* | 0.0142** | 0.0155*** | 0.0198*** | 0.0192** | 0.0110*** |
| | (0.0056) | (0.0051) | (0 .0050) | (0.0073) | (0.0033) |
| *accidental death* | -0.0045 | -0.0037 | -0.0018 | -0.0007 | 0.0008 |
| | (0.0055) | (0.0028) | (0.0039) | (0.0074) | (0.0045) |
| *assault injury* | 21.2632** | 25.7887** | 31.2563** | 7.5921 | 29.5894*** |
| | (8.4880) | (12.4511) | (13.2395) | (12.4127) | (9.7518) |
| *accidental injury* | 0.7263 | 0.0922 | -0.6199 | 0.9651 | 0.7111 |
| | (0.9689) | (0.9790) | (1.0216) | (1.1547) | (0.6780) |
| Geographic level for dummy variables: | MSA | State | State | MSA | MSA |
| Standard errors clustered on: | State | MSA | MSA | State | State |
| MSA characteristic vector, $Z_j$, included? | No | No | Yes | No | No |
| Sample | Baseline[b] | Baseline | Baseline | Exc. high/low homicide risk[c] | Inc. imputed wages |
| $R^2$ | 0.44 | 0.41 | 0.42 | 0.45 | 0.32 |
| No. Observations | 5,867 | 5,867 | 4,842 | 4,658 | 8,669 |
| <u>Wald test p-values</u> | | | | | |
| *homicide= accidental death* | 0.0695 | 0.0031 | 0.0027 | 0.1079 | 0.1501 |
| *assault injury = accidental injury* | 0.0221 | 0.0430 | 0.0197 | 0.6079 | 0.0062 |

[a] Models are identical to Model 2, Table 4, except where noted. Standard errors are reported in parentheses and significance at the 1%, 5% and 10% level is represented by a ***, **, and *, respectively.
[b] The baseline sample is all workers with non-imputed wages as reported in Model 1, Table 4. The number of observations varies for Model (3) here due to missing MSA characteristic data.
[c] Workers are excluded from states which had no homicides recorded for occupational drivers over the sample time frame, and workers with MSA-level homicide risks greater than $12.7\text{x}10^{-4}$ (MSA-level exclusion), which is approximately the 95[th] percentile for homicide risk in our sample.

The models presented thus far suggest a strong pattern: coefficient estimates for assault risks (fatal or otherwise) are significantly different than zero and coefficient estimates for accidental risks are not statistically significant. As indicated in the last two rows of Table 5, the difference in coefficient estimates for the two types of fatality risks is significant at the 10 percent level or better in three of five models, and the difference between the injury risk coefficients is significant at the 5 percent level in four of the five models.

The results presented in Table 5 are further underscored by the additional models presented in Table 6. These models vary the geographic level at which risk rates are calculated. As stated earlier, while it seems clear that taxi drivers primarily work within an MSA, truckers are likely to drive outside MSA boundaries frequently. Unfortunately, the CPS does not record any information about the geographic extent of a worker's driving territory. Our previous models assume MSA-level fatality risks are the relevant risks perceived by all workers in our sample. To test the sensitivity of our results to this assumption, we create state-level fatality risks and report results for these risks in Table 6.

**Table 6: Sensitivity of results to geographic definition underlying risk measures.** [a]

| | State-level risk for truckers; MSA-level for other drivers | | Homicides are MSA-level; all other risks are state-level | | All risks for all drivers are measured at the state level | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Homicide* | 0.0153** | 0.0158*** | 0.0141*** | 0.0155*** | 0.0185 | 0.0176** |
| | (0.0059) | (0.0055) | (0.0050) | (0.0055) | (0.0111) | (0.0076) |
| *accidental death* | -0.0070 | -0.0050 | -0.0061 | -0.0050 | -0.0012 | 0.0069 |
| | (0.0052) | (0.0052) | (0.0092) | (0.0092) | (0.0072) | (0.0045) |
| *assault injury* | 28.1970*** | 22.7605* | 20.6439** | 25.3400** | 34.0388*** | 28.7583*** |
| | (9.1572) | (12.6612) | (8.2572) | (12.1946) | (11.7452) | (11.1300) |
| *accidental injury* | -0.2987 | -0.1661 | 0.6371 | 0.0452 | 0.0731 | 0.5575 |
| | (0.6526) | (1.0315) | (0.9983) | (1.0104) | (0.4451) | (0.8510) |
| Geographic level of dummy vars.: | MSA | State | MSA | State | MSA | State |
| Std. errors clustered on: | State | MSA | State | MSA | State | MSA |
| $R^2$ | 0. 40 | 0.38 | 0.44 | 0.41 | 0.41 | 0.38 |
| No. Observations | 8,406 | 8,406 | 5,867 | 5,867 | 8,705 | 8,705 |
| Wald test p-values | | | | | | |
| *homicide= accidental death* | 0.0362 | 0.0265 | 0.0921 | 0.1042 | 0.1747 | 0.2524 |
| *assault injury = accidental injury* | 0.0042 | 0.0750 | 0.0220 | 0.0429 | 0.0068 | 0.0126 |

[a] Models include the baseline sample and are identical to Model 1, Table 4, except where noted. Standard errors are reported in parentheses and significance at the 1%, 5% and 10% level are represented by a ***, **, and *, respectively.

Models (1) and (2) in Table 6 assume state-level risks most appropriately represent truck drivers' risks, and MSA-level risks are most appropriate for taxi, bus and sales drivers. Models (3) and (4) assume homicide risks are best reflected by MSA-level aggregation, while traffic accident risks are best reflected by state-wide risks. Representing risks in this manner assumes drivers' subjective risks



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are more closely aligned with the geographic definition of risk that poses the highest risk. MSA-level homicide risks are larger than state-level homicide risks, as crime is more prevalent in urban areas. Accidental fatality risks, on the other hand, are generally larger when computed at the state level as these risks reflect more highway accidents which occur at faster speeds and are more likely to result in a fatality given an accident has occurred. The last two columns in Table 6 assume all risks are best reflected by the state-level risk measures. The difference between each pair of models is whether MSA or state dummy variables are included in the models. Standard errors are clustered on the geographic level that is not represented by dummy variables in the model, as reported directly Table 6.

Results reported in Table 6 repeat the pattern previously established using MSA-level fatality risks. The compensation for accepting assault risks in the workplace is statistically significant, while the compensation required to accept accidental fatality or injury risks is not significantly different from zero. The magnitudes of the fatal risk coefficients are stable, and the only exception to the established pattern is Model (5) in which the coefficient estimate for homicide risk narrowly misses significance at the 10 percent level (p-value = 0.1030). Across the models, the value of reducing the risk of a homicide varies between \$5.0 and \$6.9 million per avoided homicide, which is up to 3.5 larger than the estimated value of avoiding an undifferentiated (by source of risk) fatality.

For the four models that assume homicide risks are best measured at the MSA-level, three indicate a significant difference between the coefficient estimates for the two types of fatality risks, and all four indicate a significant difference between the two types of injury risks. In contrast, the two models that assume homicide risks are better measured at the state-level result in larger standard errors for the coefficient estimates, and fail to reject equality of homicide and accidental fatality risk compensation. As discussed earlier, state-level homicide risks are likely to be a poor measure of assault risks for workers and our results are consistent with this notion.

## 4. Conclusions

Our results strongly suggest that the wage premiums for accepting violent assault and traffic accident risks are significantly different from each other for occupational drivers. Averaging across models estimated, the evidence suggests that occupational drivers require approximately an additional \$500 per year to accept an increase in the risk of an occupational homicide by 1 in 10,000. If this number is scaled to be consistent with the often-reported VSL, the models indicate a value of reducing a statistical homicide of approximately \$5.0 million. In stark contrast, accident risks are not a significant predictor of wages in any model we estimate. For workers who select themselves into a driving occupation, the fact that a marginal increase in the risk of a traffic accident is not viewed as a compensated working condition is perhaps not surprising.

While our estimates could be appropriate to apply to policies designed to reduce violent assault risks, they do arise from a very specialized sample. Unless the policy-target population is occupational drivers, a benefits transfer exercise would require understanding how differences in our sample's characteristics affect the valuation of homicide risk reductions. However, our intent in this research is *not* to suggest a VSL for use in any particular policy analysis. Rather, we wish to make the point that labor markets price heterogeneous risks differentially. While survey research has generally made the point that individuals react differently to avoiding different types of fatality risks (see Robinson et al., 2010 for a recent review of this point), evidence on the degree to which these phenomena persist in market contexts is important to understand.

Two implications for benefit-cost analysis arise directly from the findings of our work. First, estimates of the VSL based on an undifferentiated, average labor-market risk is likely to be a deeply biased estimate of the value of reducing any one specific type of risk, even if that risk is itself a particular hazard faced at work. Second, we find that marginal changes in voluntarily-accepted private risks routine to a specific occupation are not necessarily compensated in the labor market. This of course does not indicate that occupational drivers (or any other sample) place a zero value on reducing *societal risks* of the same type. While our study cannot speak directly to this subject, our results for traffic accident risks certainly underscore the difficulty of applying VSL estimates based on privately-borne, voluntarily-accepted labor market risks to public policies reducing public risks.

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