Selection Against Injury Risk: Labor Supply Decisions of Los Angeles Traffic Officers

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Abstract

Workplace injury carries a large economic and human cost, yet little is known about how individual behavior impacts aggregate injury rates. This paper explores the role injury risk plays in labor supply decisions using the daily pay and workers' compensation records of 553 Los Angeles traffic officers over a 21 month period. The leave of coworkers and the size of an officer's network are used to identify how people with different injury propensity select into work. Officers supply more labor when they are less likely to be injured. Self-selection into work leads to large reductions in aggregate injury risk: the estimated population injury rate is 8.5 times larger than the injury rate observed among shifts worked. The results imply that mechanisms which assign shifts to those who value them most will reduce aggregate injury rates. Model estimates are used to compute the value of a statistical injury, which for Los Angeles traffic officers is between \$11,710 and \$23,419.

Keywords: overtime, workplace injury, workers' compensation

JEL codes: I18, J8, J32

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1 Introduction

Workplace injury represents a large burden to the US economy. In the United States, injuries on the job cost \$170.8 billion in 2018 alone. Such a cost is comparable to more well-known medical issues, like heart disease.[1] At the same time, individuals possess private information about their ability to work safely. Managers cannot know which employees slept enough the night before, which are feeling slightly sick, and which drank too much alcohol at their birthday party the day before. As a result, how workers act on their own private information influences the number of injuries that occur.

In summary, we know workplace injury is costly. We know individuals generally possess private information about their workplace injury risk. What we do not know is whether individuals use this information to make labor supply decisions. The answer to this question has implications for how organizations go about optimally assigning work and how governments regulate overtime. If individuals generally internalize their risk and choose shifts which are safer for them, then giving individuals more freedom to make labor supply decisions will reduce organizational injury rates.

As it turns out, answering the above question also helps us understand a puzzling pattern among Los Angeles traffic officers. Generally, one would expect people who work more would experience more workplace injury. Yet, in Los Angeles, traffic officers who work more are actually injured less.[2] In this paper, I argue that this is because individuals are injury-averse, and make labor supply decisions that mitigate their own injury risk.

I use administrative records detailing work hours and workers' compensation claims to make this argument. In order to trace out selection patterns, I use variation in the number of coworkers on leave and the potential size of an officer's network. As more coworkers go out on leave, more overtime opportunities present themselves, and eventually, unwilling officers are forced to work. As an officer comes into contact with more coworkers, he/she increases the number of special events overtime trading partners. This makes it easier to work extra shifts. I show that there is selection against injury risk: officers are less likely to work on days when their injury risk is high. Put another way, officers that are more hesitant to work are also more likely to be injured. As a result, the estimated population average injury rate is 8.5 times larger than the injury rate among shifts worked.[3]

[1]The CDC estimates that in 2014-2015, the annual cost of heart disease was around \$219 billion. *Heart Disease Facts* 2020

[2]This is true even if I do not count time after the first injury.

[3]The estimated population average injury rate is the injury probability of a randomly drawn officer forced to work on a randomly chosen day. The injury rate among shifts worked is the number of injuries divided by the number of shifts worked.

This paper contributes better identified estimates of injury prevalence to the interdisciplinary workplace injury literature. Although many papers analyze workplace injury across a variety of occupations and data sets (Dembe et al. 2005,Kim et al. 2016,Conway et al. 2017) none[4] present estimates which account for the endogenous nature of intensive-margin labor supply. My results imply that safe individual-days will be over-represented. Thus, observational studies which do not account for labor supply choices will generally suffer from selection bias. The true population occupational injury risk will be underestimated.

My model allows me to compute the implied value of a statistical injury using a willingness to pay approach. I find that among Los Angeles traffic officers, the value of a statistical injury is between $11,710 and $23,419. These estimates contribute to a growing literature seeking to estimate the value of a statistical injury separately from the value of a statistical life. The current practice by the Department of Transportation is to estimate the value of a statistical injury as a fraction of the value of statistical life (Moran and Monje 2016). This has also been the practice in some recent work in economics, for example Kniesner and Sullivan 2020. However, VSI's have been estimated directly. Viscusi and Aldy 2003 contains a detailed summary of estimates prior to 2000. More recently Parada-Contzen, Riquelme-Won, and Vasquez-Lavin 2013 and Kuhn and Ruf 2013 have also provided estimates of VSI's in specific contexts.

I contribute to this literature by providing VSI estimates for individuals working in a particularly important and hazardous occupation: public safety. Because I examine a single group of people working the same job in the same location, and each officer makes multiple labor supply decisions, I can analyze heterogeneity in willingness to pay that is driven by individual differences within a single occupation. I find that the distribution of willingness to pay for a 1/553 reduction in injury probability across officer-days exhibits two modes: one near $15 and another near $23.

Second, I estimate intensive margin labor supply elasticities which account for injury risk. Estimates of the intensive margin of labor supply abound in the labor economics literature, with estimates ranging from as low as 0 to as high as 0.42 (Liebman, Luttmer, and Seif 2009,Bargain, Orsini, and Peichl 2014) and synthesis of macro and micro evidence finding a consensus value of around 0.33 (Chetty 2012). I contribute to this literature by demonstrating how injury risk concerns can impact labor supply estimates. When injury is likely (as is the case in public safety occupations), labor supply is less elastic. When injury is more likely, labor is more elastic. This implies changes in labor supply elasticities over the life cycle and in aggregate over time can be due to changes in perceived injury risk rather than traditional factors.

Third, I simulate the injury risk reduction under two counterfactual assignment mechanisms. In particular, I show that assigning shifts using an auction, where officers bid a wage they are willing to work for an

[4] That I could find at the time of writing.

open shift, results in a 34 percent reduction in the injury rate compared to a random list mechanism.

My main findings lend nuance to the idea that overtime directly translates into injury. Some officers I analyze work nearly 20 percent more days than their peers; one officer even works almost everyday.[5] Despite this, officer injury rates are moderated by voluntary selection into work. My results also have significant implications for organizations trying to reduce workplace injury. The primary takeaway is that allowing greater worker discretion will generally reduce injury rates, because selection into work is positive. In my setting, this is true even though workers are covered by a workers' compensation program. Thus any moral hazard impacts of workers' compensation are dominated by an intrinsic desire to avoid high-risk shifts. My results on shift auctions imply that organizations can leverage positive selection even more by designing mechanisms which give shifts to officers who value them most.

Traffic officers are an ideal setting for exploring how injury risk affects labor supply decisions. They receive frequent opportunities to choose to work additional shifts. These take the form of special events (the Oscars, Dodger Games, presidential visits) as well as traffic-disrupting emergencies, like water main breaks. At the same time, traffic officers represent a middle ground among public safety occupations. The closest occupation with statistics on the BLS website for 2019 was crossing guards and flaggers.[6] In 2019, the nonfatal injury incidence rate was 128.6 injuries per 10,000 workers (*TABLE R98. Incidence rates for nonfatal occupational injuries and illnesses involving days away from work per 10,000 full-time workers by occupation and selected nature of injury or illness, private industry, 2019* 2020). This was above the incidence rate for firefighters (56.2) and below the incidence rate for police officers (733.8). Traffic officers are representative of occupations where hazards are present (e.g. fast-moving traffic, hot weather) but not constant (e.g. carrying a gun, investigating violent crimes). If traffic officers act to mitigate risk, it is reasonable to assume firefighters, security guards and other public safety professionals do too.

The paper proceeds as follows. First, I discuss institutional and data details. Second, the economic model is introduced and identification is discussed. Third, the results of estimation are presented. Fourth, I discuss the implications for organizations and future research. Finally, the model is used to simulate the injury rate reductions from switching to shift auctions.

[5] 601 days out of the 609 I analyze.

[6] Traffic officers are not quite crossing guards but are also not quite police officers.

2 Data and Institutional Details

In this section I present an overview of the population being studied: Los Angeles traffic officers. I first review the details of the traffic officer job, overtime assignment, and pay structure. I then present some descriptive statistics and associations observed in their pay and workers compensation data.

2.1 Institutional Details

The population of workers used for this analysis are Los Angeles traffic officers. Traffic officers are employees of the city of Los Angeles, and fall under the Los Angeles Department of Transportation. The traffic officers analyzed are union employees covered by Memorandum of Understanding 18 (MOU) between the City of Los Angeles and Service Employees International Union, Local 721.[7] According to this document, they are overtime non-exempt employees under the Fair Labor Standards Act (MOU, 28), meaning they are paid time and a half their regular rates of pay for all hours worked over 40 in a work week (Department of Labor 2017). Because the traffic officers are FSLA non-exempt and work within California, they are also covered by California overtime law. As a result, in addition to being paid a premium rate for all hours over 40 in a work week, they are also paid at least one and a half times their regular rate of pay for all hours worked over eight in a day (or any hours worked on the seventh consecutive day). Further, they are paid double their regular rate of pay for all hours worked over 12 in a day, or all hours worked over eight on the seventh consecutive day (California Department of Industrial Relations, 2017).

The Memorandum also outlines payment guidelines surrounding minimum payments and "early report" pay. The city is required to pay a minimum of fmy hours of premium pay if an employee is required to return to work "following the termination of their shift and their departure from the work location" (MOU, 30). If an officer is required to come into work earlier than their regularly scheduled time, they must be paid one and a half times their hourly rate for the amount of time worked prior to the regularly scheduled time (MOU, 32). Workers compensation rules are briefly described. For any injuries on duty, salary continuation payments "shall be in an amount equal to the employee's biweekly, take-home pay at the time of incurring the disability condition" (MOU, 59).

This paper analyzes all shifts worked by traffic officers. However, officers mainly control their labor supply by working *special events*. Special events are paid at 1.5 times the normal rate (similar to typical overtime). They are called special because they are not part of the normal job schedule of a traffic officer. Special events include things like the Los Angeles Marathon, Dodger Games, and block parties. When the

[7]The version reviewed is available online: cao.lacity.org/MOUs/MOU18-18.pdf

event is not hosted by the city itself, the bill for traffic officer overtime incurred during the events is paid by the host organization. In fiscal year 2013-2014 (a year prior to the analysis period), special events accounted for \$5.9 million in overtime paid to LADOT officers. To put this in perspective, if I divide this by \$45 (officers earn around \$30 an hour), I see this implies over 100,000 overtime hours were worked on special events. This represents a large fraction of total overtime, consider that in our analysis population for the year 2015, 150,867 hours are billed to overtime pay codes.

In regards to the assignment of overtime, the Memorandum has this to say: "Management will attempt to assign overtime work as equitably as possible among all qualified employees in the same classification, in the same organizational unit and work location" (MOU, 27). Employees must also be notified 48 hours in advance for non-emergency overtime and unofficial overtime that is not sanctioned by a supervisor is "absolutely prohibited" (MOU, 28). Workers cannot add additional hours to their shift unless authorized. For this reason my paper focuses on the decision to work additional shifts rather than the decision to work additional hours.

It is important to discuss how overtime is allocated across officers. A report by the City Controller's office states that special event overtime is assigned using a mechanism called "spinning the wheel." Each month, pre-scheduled special event overtime is randomly assigned to all officers (city-wide) who volunteer to be on an overtime list. During the month, when there are unexpected special events, overtime is randomly assigned among volunteer officers in the nearest division. This system, on first glance, seems to imply that only volunteers can be asked to work overtime. However, a city report indicates that while 192 officers signed up to volunteer in FY 2013-2014, 471 officers actually ended up working special events overtime. This implies that while volunteering increases the likelihood of working overtime, the department still asks non-volunteers to work extra shifts. We take this to be evidence that the department forces some officers to work overtime.

Although the wheel system is fair in theory, the Controller report found that an enormous amount of overtime was being worked by a small group of officers. This group is colloquially called "the cartel." The Controller's office explains how this cartel arose in the following way: "Traffic Officers may be able to receive more overtime if they have nurtured relationships and know how to network, treating overtime assignments as a privilege that can be traded." Although the wheel provides equal *opportunity* for special event overtime, officers with enough determination can bargain with the winners of the wheel spin to work shifts beyond those that they themselves one. This leads to ex-post differences in the number of extra shifts worked. The cartel is an extreme example of this.

These two features of overtime assignment are an essential part of my identification strategy. Because initial assignments are randomized monthly, all officers start with the same opportunity to work special events. If an officer wants to work a special event but was not selected, they can bargain with coworkers for an opening. An officer who is well connected will have an easier time finding a trading partner. In the opposite case, if enough people are out on leave and there is a surge in demand, the city will need to force non-volunteers to work.[8]

2.2 Data

The worker's compensation and payroll data was provided by the City of Los Angeles. The data was de-identified, and spans from 2014 to 2016. It was first provided to a city employee, who performed the de-identification and merged together the two sources. Originally, only the worker's compensation files contained information on employee age and hire date. To the extent an employee was never injured, there would be no age information. A third file was acquired and merged on to fill in gaps of information for employees that were not injured.

The workers' compensation data includes the date of the injury[9], the date on which the employee gained knowledge of the injury, the nature of the injury, and the cause of the injury. After removing duplicate records, there are 351 distinct worker compensation claims across 246 traffic officers in the time period. Of these, 295 have a non-zero value for "Med Pd" suggesting some sort of expense was paid out to the employee. Figure 2 displays the distribution of claims across the period. The claim counts appear abnormally low prior to January 2015 and after September 2016.

The pay data includes records for each type of pay received on each day. It also includes the number of hours, amount of pay, rate of pay, division worked, and *Variation Description*. Variation Description is a pay code which describes the reason for a payment. I use Variation Description to classify records as work-related, leave-related, or neither. Table A.3 displays the classification process.

For analysis, I aggregate the pay and workers' compensation records into an officer-day panel data set with measures of daily hours worked and hours taken as leave. This process is non-trivial, and requires some assumptions which are outlined in the data-building section of the Appendix. I then perform several important exclusions to create the working sample. First, I limit the data to workdays and injuries between January 1, 2015 through September 1, 2016. This is due to the missing claims issue observed in the last paragraph. Second, I exclude all part-time employees.[10] This is because these employees have very irregular schedules. I include only officer-days where the officer works or does not work, and exclude days where they

[8] `https://lacontroller.org/wp-content/uploads/2019/07/dotovertimespecialevents.pdf`

[9] It also includes time of injury, but this field says 12:00 AM the majority of the time, suggesting it is not reliable.

[10] The methodology for determining who is part-time is listed in the Appendix. I do include these employees in my measures of leave worked by others in division.

are on leave. I do this to focus on the decision of working a shift, not on the decision of using a sick or vacation day. Finally, I exclude all days between the date of injury up to and including the first observed work day. The reason for this is that the decision of when to return to work after an injury is separate from the decision to work when an officer is not injured. I do not model the return to work decision.

In the analysis population, the distribution of injuries across officers is described in Table 1. Some officers are never injured, some are injured once and others are injured several times. Tables 3 and 4 present the distribution by Claim Cause (reason for injury) and nature of injury (type of injury). The distribution of Claim Cause helps paint a picture of the hazards faced by the traffic officers. Most injuries are related to the fact that traffic officers work outside in heavy traffic: they can be sideswiped, get into car accidents, or suffer heat-induced injuries. The distribution of the Nature of Injuries reveals that while some injuries are minor and perhaps superficial (things like strains or mental stress) many injuries are quite serious.

Table 5 contains labor supply statistics related to the number of hours worked daily. Table 6 contains labor supply statistics on the shift margin: days worked in four-week periods. To adjust for the fact that injury causes officers to miss work, Table 6 is restricted to 4 week periods prior to the first injury. From these labor supply tables two things are apparent. First, the shift margin has much more variation than the daily hours margin. The inter-quartile range of shift length is 0, while the inter-quartile range of days worked in 4 weeks is 5. Second, employees who experience injury tend to work fewer days per month than those who do not. Note that this is excluding fmy week periods come after an injury. These two patterns are why this paper focuses on the decision to work an additional shift (rather than an additional hour), and the role of selection on injury risk.

Table 7 documents the distribution of shifts by day of the week. There seems to be less need for officers on the weekends, especially Sunday. This is in line with many street parking spots being free on Sundays, so there is less need for enforcement. Although this is hard to capture in a table, shift patterns are highly irregular. Some officers work everyday for as many as 14 days and others work 3 day stints with single days off in between. I do not observe any data on what is considered a person's regular shift. As a result, I include a set of day of the week controls in all models.

Table 9 contains aggregate pay statistics, including rates and typical weekly pay amounts, and what percentage of pay is overtime-related pay. Most individuals earn a wage that is a little less or a little more than \$30 per hour. This is consistent with the common wage schedule which is set during negotiations between the union and the city. Overtime on average represents 12 percent of pay, but this masks a highly skewed distribution. At least 50 percent of officer-weeks do not have overtime pay, while 10 percent are more than 33 percent overtime pay. Again these statistics indicate that schedules vary most in terms of number of days worked rather than number of hours worked per day.

3 Preliminary Evidence of Selection Against Injury

In the next section, I will introduce a formal model of daily labor supply. However, before adding any structure, I think it is helpful to see the selection effect in a very simple way. I can summarize my empirical approach and the fundamental idea behind my identification this way: I use variation in the leave of other employees to encourage officers to work. Some officers on some days are less likely to work, and their willingness may very well be related to factors which also impact their likelihood of injury. But when enough coworkers are out on leave, even extremely unwilling officers will need to work, or else they risk their relationship with their supervisors and disciplinary action. Similarly, as officers come into contact with more officers outside their division, they build a network. The more expansive their network, the easier it is to find special events trading partners.

Even without a formal model, I can see evidence of this selection by comparing the ordinary least squares (OLS) regression of injury on work to the two-stage least squares (2SLS) regression of injury on work with leave of others and cumulative contacts as instruments. I hypothesize that the coefficient on work should be much higher in the 2SLS regression than in OLS, because officers are selecting not to work when they are most likely to be injured (officers are on average injury averse).

As hypothesized, the OLS estimate turns is 0.108% while the 2SLS estimate is 0.905%.[11] Intuitively, the observed injury rate among worked shifts (OLS estimate) is much lower than the injury rate I would observe if officers came into work at random (2SLS estimate). This is evidence of positive selection: officers do not work on days they are more likely to be injured, and go to work on days they are more likely to be injured.

4 Empirical Strategy

4.1 Model and Conceptual Framework

There are N officers indexed by i who make myopic daily decisions to work on dates $t = 1, 2, .., T$. Denote the binary work decision w_{it} and the binary injury outcome y^*_{it}. Injury is determined by the below equation:

$$y^*_{it} = \begin{cases} 1 \text{ if } \zeta_2 + X'_{it}\beta + \underbrace{c_{i2} + u_{it2}}_{\text{unobservable injury propensity}} \geq 0 \\ 0 \qquad \text{otherwise} \end{cases} \tag{1}$$

[11]The 2SLS estimate is reported in Table A.4 column 3 and the OLS estimate is in Table 10 column 3.

In this equation c_{i2} represents time invariant propensity to be injured and u_{it2} represents idiosyncratic conditions that make a particular officer more likely to be injured on a particular day. I assume that the officer may have information about $c_{i2} + u_{it2}$, but this is unobserved by the analyst. c_{i2} is determined by factors like chronic health conditions (obesity, heart disease, diet, etc) and demographics. u_{it2} is determined by factors an officer may know about before coming to work (the quality of sleep the night before, whether the officer has a slight cold) as well as things that happen during the shift that could not have been predicted (car crashes, water main bursts, road conditions).

If an officer does not work then y^*_{it} is not observed (it is counterfactual). As a result there is a selection problem: the analyst only observes injury outcomes among individuals who go to work. Denote y_{it} as the injury outcome that is observed. Then I have that:

$$y_{it} = \begin{cases} y^*_{it} \text{ if } w_{it} = 1 \\ 0 \qquad \text{otherwise} \end{cases} \tag{2}$$

I assume the officer is an expected utility maximizer, and decides to work if the expected utility of work is greater than not working. Denote the utility of work less the utility of not working U_{it}, and assume that it takes the form $U_{it} = Z'_{it}\alpha + \zeta_1 + c_{i1} + u_{it1}$. Then the decision to work is given by:

$$w_{it} = \begin{cases} 1 \text{ if } Z'_{it}\alpha + \zeta_1 + \underbrace{c_{i1} + u_{it1}}_{\text{unobservable utility}} \geq 0 \\ 0 \qquad \text{otherwise} \end{cases} \tag{3}$$

c_{i1} and u_{it1} are both fully observed by the officer, but unobserved by the analyst. Similar to the injury outcome, c_{i1} represents unobserved time invariant taste for work, due to things like a greater enjoyment from the job, or a lower value of leisure. u_{it1} represents unobserved time varying taste for work, driven by factors like wealth shocks, wanting to watch ymy child's soccer game, or not getting enough sleep the night before.

The example of sleep is a good way to illustrate how the work decision is connected to the injury outcome. If too little sleep causes officers to dislike working more and it also increases injury risk, then this would enter as a negative correlation between u_{it2} and u_{it1}. This could be because the officer dislikes injury risk, and then u_{it1} can be interpreted as a private signal of elevated injury risk. It could also be because it is generally less pleasant to drive around Los Angeles on less sleep, and this happens to also make an officer a worse driver. As a result, equation 3 should be viewed as a simplified way of capturing how an officer uses information, preferences and risk to decide whether to supply labor on date t.

4.2 Identification

If one is willing to ignore Equation 1 and instead assume a linear probability model for the injury outcome, my model would be a special case of the switching model described in Chen, Zhou, and Ji 2018. Then I could achieve non-parametric identification with a single exclusion restriction and a symmetry condition on the unobservables. But I am not willing to make this simplification, because unlike in other applications, injury for a particular officer on a particular day is quite unlikely, so that $Pr(y_{it}) \approx 0$. Because there are continuous covariates in X_{it}, $X_{it}'\beta$ is unlikely to be bounded between $[0, 1]$ almost surely. According to Horrace and Oaxaca 2006, this the linear probability model rather implausible .

Given these circumstances, I achieve identification by making the assumption that the unobservables are jointly normally distributed, and are independent of all other variables conditional on the person specific means of all time-varying observables $\bar{Z}_i$. This is formally written in Assumption 1.

Assumption 1 *Conditional on Z_i, X_i:*

$$\begin{pmatrix} c_{i1} + u_{i1} \\ c_{i2} + u_{i2} \end{pmatrix} \sim N\left(\begin{bmatrix} \bar{Z}_i\gamma_1 \\ \bar{Z}_i\gamma_2 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right)$$

where $-1 \leq \rho \leq 1$

Notice that this assumption is *weaker* than assuming full independence of the instruments from the unobservables. As an example, suppose officers sort into work locations based on the supervisor's reputation for approving leave. Suppose less healthy (more injury-prone) officers sort into locations with more lenient supervisors. Then injury outcomes would be correlated with the mean of the leave of coworkers. In this case, my specification will still deliver consistent estimates of all parameters. Further, I could check the sign of the estimate of γ_2 to see if there is evidence of sorting.

Suppose Assumption 1 holds. If there exists at least one time-varying element in Z_{it} that is not in X_{it} (an excluded instrument), then Semykina and Wooldridge 2018 prove constructive identification of the model.[12] Intuitively, identification of the unobserved correlation, ρ, is driven by the excluded instrument effectively tracing out the patterns of selection. In this case the number of coworkers on leave currently and a proxy for the size of an officer's network (cumulative potential contacts) are the excluded instruments. I will argue in the next sections that these two instruments are both relevant to the work decision and do not directly impact injury risk.

[12]Indeed my model is motivated by Semykina and Wooldridge 2018.

4.3 Model Comments

In my model, I cannot separate the idiosyncratic (u) and individual parts (a) of the unobservables. However, I can analyze the sums $c_{i1} + u_{it1}$ and $c_{i2} + u_{it2}$. Estimation of my model yields the following characteristics of the joint distribution of $(c_{i1} + u_{it1}, c_{i2} + u_{it2})$:

1. $Cov(c_{i1} + u_{it1}, a_{i2} + u_{it2})$: This is captured by ρ, and it the main focus of the paper.

2. $\bar{Z}_i\gamma_1$: This is similar to an individual fixed effect for work propensity. It captures part of officer i's time invariant desire to work. $Var(\bar{Z}_i\gamma_1)$ represents a lower bound of the variance in utility from work captured by individual effects. I can compare this variance to 1, which is the variance of $c_{i1} + u_{it1}$.

3. $\bar{Z}_i\gamma_2$: This is similar to an individual fixed effect for injury propensity. It captures part of officer i's time invariant propensity to be injured. $Var(\bar{Z}_i\gamma_2)$ represents a lower bound of the variance in injury propensity captured by individual effects. I can compare this variance to 1, which is the variance of $c_{i1} + u_{it1}$.

4. $Cov(\bar{Z}_i\gamma_1, \bar{Z}_i\gamma_2)$: This covariance represents the time-invariant dependence between utility from work and injury propensity.

With this framework in mind, I take a moment to introduce an important definition.

Definition 1 *The marginal probability of injury (denoted MPI) is the injury probability of an officer who is indifferent between working and not working.*

This concept is similar in spirit to the marginal treatment effect formalized in Heckman and Vytlacil 2005. It allows us to fully capture the utility-based selection using a single concept. Formally, consider officer-days where officers are just indifferent between working and not working. That is, situations where $z'_{it}\alpha + \zeta_1 + \bar{z}'_i\gamma_1 = v_{it1}$ (see Equation 3). Denote the left-hand-side as $\tilde{v}$. $\tilde{v}$ can be interpreted as unobserved resistance to work. Then the marginal probability of injury given unobserved resistance to work $\tilde{v}$, covariates x_{it}, and Equations 1 and 2 is:

$$MPI(x_i, \tilde{v}, \bar{z}_i) = \Phi\left(\frac{\zeta_2 + x'_i\beta + \bar{z}'_i\gamma_2 - \rho\tilde{v}}{(1-\rho^2)^{1/2}}\right) \tag{4}$$

The average marginal probability of injury is the expectation of 4 with respect to $x_i, \bar{z}_i$:

$$AMPI(\tilde{v}) = E_{x_i,\bar{z}_i}\left[\Phi\left(\frac{\zeta_2 + x'_i\beta + \bar{z}'_i\gamma_2 - \rho\tilde{v}}{(1-\rho^2)^{1/2}}\right)\right] \tag{5}$$

The key question I answer in this paper is whether average marginal probability of injury is increasing in $\tilde{v}$. The following Lemma states that this depends only on ρ.

Lemma 1 *If and only if $\rho < 0$, the sample analogue of the average marginal probability of injury is strictly increasing in $\tilde{v}$.*

The lemma follows directly from the fact that the normal distribution CDF is strictly increasing and the denominator of Equation 4 is always positive. Thus MPI is increasing if and only if ρ is negative. As long as we can apply the dominated convergence theorem and take the derivative inside the integral, average MPI is increasing if and only if MPI is increasing. From the lemma, I can test whether MPI is increasing by testing the null hypothesis that $\rho = 0$. If $\rho < 0$ I say there is *selection against injury.* If $\rho > 0$ I say there is *selection into injury.*

4.4 Estimation

In the estimated model, X_{it} includes a federal holiday indicator, age, amount of rain in inches, the maximum daily temperature, the officer's wage,[13] division indicators (with small divisions grouped together), day of the week indicators and month indicators.

The excluded instruments which help us achieve identification without relying on functional form include two variables:

- **Leave of Coworkers in Division:** The number of other officers in officer i's division (work location/station) who take leave on date t.
- **Cumulative Potential Contacts:** The number of colleagues an officer could have physically encountered. This is measured as the number of other unique officers the target officer has worked in the same division as on the same day in the past. This is a proxy measure for the potential size of an officer's network. For some officer i in division j, this measure will be constant until either a new officer joins division j, an officer in division j terminates, or officer i works in a division other than division j. Intuitively, it can be thought of as an address book of active officers which officer i may have encountered in the past.
- **Seniority Rank:** The rank of officer i in terms of number of years since hire among all officers in the current division.

Z_{it} includes all the variables in X_{it} as well as the these three instruments. $\bar{Z}_i$ includes officer-specific time averages of leave of coworkers, cumulative potential contacts, age and the wage. Seniority rank, division,

[13]A quadratic specification for wage was tried, but a Wald test failed to reject that the coefficient on the quadratic term was different from 0.

day of the week, month, and weather variables are excluded from $\bar{Z}_i$ because they did not vary enough (either temporally or across officers). For example, for two officers who were present throughout the analysis window, averages of day of the week indicators would be the same.[14]

Estimation proceeds using partial maximum likelihood, with the expressions of the likelihood presented in Appendix Section A.1. As pointed out in Semykina 2012, models of the type specified are pooled Heckman-selection probit models. As a result, I estimate the parameters using Stata's built-in 'heckprobit' command with the addition of person-specific means $\bar{Z}_i$ in the selection and outcome equations. Standard errors are clustered at the officer level to account for within-officer serial-correlation.

4.5 Instrument Validity

Identification of my model requires leave of coworkers to be a valid instrument. Validity means the instruments satisfy two requirements. First, they must be properly *excluded* from the injury equation. Second, they must be relevant to the work decision. In other words, they must be properly *included* in the work equation. I support provide theoretical and statistical evidence that these assumptions are satisfied in the following two subsections.

4.5.1 Exclusion Restrictions

Conditional on x_{it} and $\bar{z}_i$[15], leave of others must only impact injury through the decision to work. For many forms of leave, like bereavement and jury duty, this seems likely to be satisfied. The death of an elderly family member of an officer's colleague is unlikely to be related to own work conditions or own health status. For other forms of leave, like vacation or floating holidays, I argue this is conditionally satisfied. That is, people may take vacations during times of the year with certain weather conditions (i.e., summer) that can impact injury risk (through heat exhaustion perhaps). But I control for holiday and monthly effects, and conditional on these controls, there is likely no dependence. For sick leave, there is a concern of contagion and also violation of the exclusion restriction (sick leave causes the remaining pool of available workers to be on average more healthy). To address these concerns I estimate the main parameters using a leave instrument that does not include sick time. These estimates are in Appendix Table A.1 and are discussed in more detail in the robustness section.

[14] As a result of the collinearity/lack of variation, trying to include these variables causes convergence problems.

[15] Conditioning on individual means allows for some violations of exclusion. For example, more injury-prone employees may be in divisions with other employees who often get sick. This would mean that on average sick leave in division may be correlated with injury probability. This is dealt with by conditioning on $\bar{z}_i$

Conditional on x_{it} and $\bar{z}_i$, cumulative contacts must not impact injury propensity other than through the work decision. Some variation in cumulative potential contacts comes from *own* division changes. When this happens, the officer has a spike in the number of cumulative contacts, because he/she now has a history at two divisions. Officers with higher injury propensity might be more likely to change divisions. To account for this, we include the time average of cumulative potential contacts in both equations. This allows for correlation between the mean of cumulative potential contacts and injury. Some variation also comes from other officers changing division, leaving the job entirely, or joining the force. Because the main part of the job is not team-based (patrolling parking meters and directing traffic) there is little reason to think this variation is correlated with injury propensity. It might be that more dangerous divisions have more personnel changes due to injuries. To account for this, I include division indicators in both the work and injury equations. Conditional on these indicators, it is hard to think of a reason why the instrument would impact injury directly.

I know turn to formal statistical tests of instrument independence/exclusion. There are several papers proposing tests of instrument validity in traditional sample selection models where the outcome is continuous and the data is cross-sectional. However, at the time of writing, I could not find any papers suggesting tests for instrument validity when the outcome is binary (i.e. when the link function is not the identity function). As a result, I implement an instrument validity test that is meant for continuous outcomes. First, I implement a modified version of the test designed in Semykina 2012. The procedure uses a flexible control function method to correct for selection. In my implementation, I use the semi-parametric estimator proposed in Gallant and Nychka 1987 with a fourth-degree polynomial for the selection equation and then insert the selection correction into the outcome equation using a linear spline with 5 knots. I then test whether the instruments from the selection equation, in my case *seniority rank* and *leave of others in division* satisfy over-identifying moment restrictions. The null hypothesis is the variables do satisfy the restrictions, and thus are uncorrelated with the injury outcome errors. Failing to reject the null hypothesis provides evidence that the variables satisfy the exclusion restriction. The test returns a J-statistic of 1.40 and a p-value of 0.496. Therefore I fail to reject the null hypothesis at the 0.05 level.[16]

Another way to test instrument independence is to examine the balance of other officer-day characteristics across values of the instruments. One such variable is *medical expenses paid*, which is included in the workers' compensation data for each documented injury. Medical expenses are a proxy for the seriousness of injury. For example, injuries with *Claim Cause* "Repetitive Motion - Other" had an average expense of \$2,726,

[16]The current test ignores the uncertainty and variance coming from the first-stage estimation of the selection correction because the computational burden of the flexible first-stage is large.

while those with "Collision or Sideswipe" had an average expense of $3,385. In theory, leave of others and cumulative potential contacts should only impact injury by inducing more people to go into work. Both instruments should not impact the severity of the injury. If they do, then there is reason to suspect the exclusion restriction. In Table 12, I regress medical expenses paid on the leave instrument with different sets of controls. In all specifications, the coefficient on leave is not statistically significantly at the 0.05 level.

4.5.2 Relevance

Next I discuss instrument relevance. Officers vary substantially in their number of shifts worked, as can be seen in Table 6. Since the Memorandum of Understanding requires equitable opportunity for overtime, it is reasonable to attribute a good deal of this variation to officer choice. Given this, the question remains: do the instruments encourage officers to work? That is, are the instruments *relevant* to the work decision?

If LADOT at least partially substitutes officers on leave for off-duty officers, then the answer is yes. Under the "spin the wheel" system, officers who volunteer are randomly chosen for overtime. If more individuals call out sick or for bereavement, the supervisor will need to select a larger number of volunteers. Conditional on volunteering, the probability of working an extra shift rises. Even if an officer does not volunteer, there is nothing in the memorandum of understanding preventing supervisors from forcing officers to work if the volunteer pool is exhausted. In fact, the MOU uses the word "required" to describe some overtime, implying that management can force officers to work under threat of discipline. The MOU also states that many rules are suspended during emergencies, meaning it is reasonable to assume the city can force officers to work during times of crisis (incidents like water main breaks, earthquakes, etc). As a result, work probability conditional on not volunteering should also be weakly increasing in the number of other officers on leave.

Second, does a higher level of potential cumulative contacts encourage work? This measure approximates the size of an officer's network. Being at the same physical location (division) as another officer increases the chance an officer will form a connection. Thus, potential cumulative contacts represents an upper bound on the number of colleagues an officer meets on the job. As the audit states, a cartel of well-connected officers was trading with other officers to get access to special events overtime. Because this overtime is generally desired, and everyone who volunteers has an ex-ante equal chance of being chosen, having a larger network implies a greater chance at least one colleague in an officer's network gets a shift. In effect, a bigger network reduces the search cost of finding a trading partner.

To test these two theories, I present F-statistics of a linear probability model of work on the leave of others and potential cumulative contacts in Table 11. I include seniority rank within division even though the audit and memorandum of understanding do not explicitly mention seniority as a factor because it is likely that seniority could have an informal influence. All F-statistics are greater than 170. The coefficient on Division Leave (of others) is also highly significant in all specifications. In my preferred specification, which is in column 4, has an F-statistic of 255 and significant positive coefficient on seniority rank. Overall the table suggests instrument relevance is satisfied. This is best seen in the first panel of Figure 3. The figure displays a local linear regression of injury probability among groups of officers binned according to their leave of coworkers and then by cumulative potential contacts. The line is generally upward sloping, indicating a positive relationship between the instruments and work probability.

For linear models, there are many formal under-identification, over-identification, and weak instrument tests. Unfortunately, my model is nonlinear. In Appendix Table A.4, I report results from what I call the "proxy" model. It is a fixed effects 2SLS specification (the model I would fit if y_{it} was not binary). Across all specifications, using the Kleinbergen-Paap rK LM test, I reject the null hypothesis of under-identification. Using the Hansen-J test of overidentification, I fail to reject the null hypothesis that my moment restrictions are satisfied for all instruments. Using the Kleinberg-Paap rk Wald F test, I reject the null hypothesis that my instruments are weak. Overall I find no evidence that the identifying assumptions are violated in the proxy model.

I can use the proxy model to see how instrument strength impacts the coefficients. Using the tables presented in Stock and Yogo 2002, for my preferred specification (the third model in Table A.4) the maximum relative bias of the IV estimator is 10% (relative to OLS). The Cragg-Donald F-Statistic of my preferred specification is 213.6. According to Lee et al. 2020, this means I can safely use the 1.96 critical-value for testing hypotheses while maintaining a Type 1 error of 5 percent. Therefore, in my preferred specification, I can reject the null hypothesis that the coefficient on work is 0. This loosely means I have sufficient instrument strength to reject the null hypothesis of random selection into work.

5 Results

The coefficient estimates for my injury and labor supply model are reported in Table 13. Coefficients on leave of coworkers and cumulative potential contacts are positive and significant at the 0.05 level. Age also has a statistically significant and negative coefficient in the utility from work equation, suggesting that officer's utility from work declines over time. Rain and temperature variables do not have significant coefficients. The indicator for federal holidays has a negative coefficient in the injury equation and a positive coefficient in the work equation, suggesting that holidays are less dangerous and also more desirable (likely due to a pay multiplier). The coefficients $\bar{z}_i$ are the coefficients corresponding to the variables prefixed by "Avg.". Importantly, the coefficient estimates of average coworker leave and average cumulative potential contacts are both significantly different from 0 in the injury equation. This implies that full exclusion/independence does not hold.

Due to the non-linear nature of the model, I also report average elasticities of the work probability with respect to several variables in Tables 15. I find large wage elasticities: a 1 percent increase in the wage increases the probability a worker takes a shift by 2.27 percent. Leave of coworkers and cumulative potential contacts have positive but more moderate elasticities: a 1 percent increase in the leave of coworkers results in a 0.04 percent increase in the probability of working. Table 16 reports average elasticities of injury conditional on work (the observed injury rate). These can be interpreted as the expected percent change in the probability of injury after a 1 percent change in a variable given the officer works. Again, wage has a large effect: a 1 percent increase in the wage increases the probability of injury conditional on work by 12.82 percent. A percent increase in cumulative potential contacts increases the probability of injury conditional on work by 0.17 percent.

Other structural estimates, including $\hat{\rho}$, are presented in Table 14. Similar to the 2SLS results presented in Section 3, the unconditional probability of injury is around 9 times larger than the probability of injury conditional on working. This is due to significant unobserved negative correlation between injury propensity and utility from work, reflected by an estimate of ρ of -0.60, which is statistically significant. Applying the Lemma, the marginal probability of injury is increasing in v for all covariate values, meaning there is *selection against injury risk*.

There is also correlation between the unobserved time-invariant components, reflected by the negative sign of $Cor(\bar{Z}_i\gamma_1, \bar{Z}_i\gamma_2)$ in Table 14. Because $\bar{Z}_i\gamma_1, \bar{Z}_i\gamma_2$ can be loosely thought of as individual fixed effects, this means the types of officers who prefer not to work are more likely to be injured. To visualize this, Figure 4 plots the fixed effect pairs for all 553 officers.

I graphically demonstrate selection against injury several ways. In Figure 5 I plot the conditional probability of injury at different fixed values of leave of coworkers. The upward sloping line means that the pool of officers working on a day when more coworkers are on leave will be more injury prone. As the department has to dig deeper into the pool to fill open slots, it has to rely on officers who are both less willing to work and more likely to be injured. The story is much the same in Figure 6. It is easier to access special event overtime when an officer has more connections. As a result, all else equal, a more connected officer will be willing to work under more risky conditions than a less connected officer.

I plot the average marginal probability of injury, as defined in 5, for different resistances to work in Figure 9. -0.5 corresponds to a person at the 32.5th percentile of resistance to work, while 0 corresponds to the 50th percentile. I plot the marginal probability of injury only on this limited domain because the standard error becomes very large outside this region due to the need to average over many covariate values. The graph highlights that MPI is upward sloping, starting close to 0 and sloping towards 0.2 percent (about double the observed injury rate).

To get a sense of how selection impacts heterogeneous officers, consider the case where there are two officers, both of which decide to work. Suppose one officer is *a willing worker*, in the sense that he/she is in the 25th percentile of unobserved resistance to work. Suppose the other is *a hesitant worker*, in the sense that he/she is in the 50th percentile of unobserved resistance to work. The willing worker is 85 percent less likely to be injured than the hesitant worker.

It is important to keep in mind that I cluster standard errors at the employee level in all of my models, and include a rich set of controls in my model (division, month and day of the week fixed effects). As a result, I have limited power, especially over the tails of the unobserved distributions. Figure 3 makes this point clear: most of my observations have low values for leave of coworkers and potential contacts. When I compute the marginal probability of injury for high resistances I am implicitly relying on a small number of observations.

6 Robustness

I perform several versions of my analysis to test sensitivity to assumptions and address potential threats to identification. A summary of major parameter estimates under each version is provided in Appendix Table A.2. I report the coefficient on the main instrument, leave of coworkers, as well as $\hat{\rho}$ and the percentage difference in injury probability of a marginal employee at the 75th percentile of willingness to work compared to an officer at the median.

First, I construct a more conservative version of the leave instrument, which excludes sick time. I do this out of concern that sick leave violates the exclusion restriction: perhaps when there is more sick leave people are more prone to injury due to contagious diseases caught from coworkers. Alternatively, increased sick leave might make the remaining pool of officers on average more healthy. This conservative instrument has considerably less variation, because sick time represents a fourth to a third of leave.[17] Additional coefficient estimates are provided in Appendix Table A.1.

Second, I test the sensitivity of my results to changes in the definition of injury. Because I measure injuries as workers' compensation claims, there is a concern that false reporting of injuries might be biasing my results. Claims are verified by medical professionals, but for hard to verify injuries, like strains and mental stress, over-reporting might still be a concern. If this is true, the selection I observe could just be because officers who are more likely to file false claims also prefer to work less. To address this, I estimate my

[17] See Table 8

model again with claims described as "Strains" not considered injuries. Out of 243 injuries, 118 are classified as a "Strain." Given this removes almost 50 percent of injuries, it is not surprising that my estimates fall in magnitude and statistical significance. What is reassuring is that all estimates remain the same sign: $\hat{\rho}$ remains negative and the change in probability is still negative.

Finally, I run the analysis classifying injuries based on thresholds of medical expenses. The idea here is that more expensive claims are more serious injuries, and more serious injuries are less likely to be falsely reported. I report results where injuries incurring \$0, less than \$200, and less than \$400 are not counted as injury. Surprisingly, $\hat{\rho}$ actually rises as I raise the minimum expense threshold. Similarly, the percentage increase also rises in magnitude. This suggests that if there is fraudulent reporting of workplace injury, it is likely causing us to underestimate selection against risk.

7 Discussion

My main result is that $\hat{\rho} < 0$, so by Lemma 1, the marginal probability of injury is increasing in resistance to work (or decreasing in willingness to work). As I show in section 6, this is quite robust to alternative specifications. Despite injury being a relatively rare occurrence, and despite the existence of a worker's compensation system, officers still try to avoid injury. This is consistent with the idea that officers have information about their own personal injury risk on a given day, and they avoid working on days when this risk is elevated. In terms of application, this means that systems which award shifts to those most willing to work them will tend to reduce injury more than systems which award shifts randomly. I discuss this further in Section 8, paying special attention to shift auctions.

There is some evidence of officer sorting into divisions. The negative and statistically significant coefficient on average coworker leave implies that officers who work in divisions with more coworker leave also tend to get injured less. This suggests that less injury-prone officers slot into divisions where overtime is more plentiful.

The officers I analyze are employed by the Los Angeles Department of Transportation. In this department, special event overtime (a main source of extra shifts) is generally assigned by "spinning the wheel." This system essentially amounts to randomly allocating extra shifts among those who volunteer. In practice, there is some trading that occurs, but it is not formally part of the system. Thus, the current system is suboptimal in the sense that it does not always give shifts to the people who want them most. Given this, it is surprising how much positive selection I observe. The observed injury rate, defined as the number of injuries divided by the number of person-days worked, is around 0.14%. That is, there is around 1.4 injuries in every 1,000 person-days worked. However, my model suggests that the population unconditional injury rate, defined as the probability of injury if I forced a random officer to work on a random day, is on average 1.2%. If I were to randomly draw 1,000 person-days, I would expect 10 injuries. Selection, even in the current imperfect mechanism, is responsible for making the observed injury rate 8.5 times smaller than the true underlying rate.

This result is especially interesting given news coverage of overtime among public safety professionals. Many articles are alarmed by the massive amount of overtime worked by certain fire fighters and police officers (Ashton and Reese n.d., Steinbach 2019). I analyze 553 officers over 609 days. The median number of days worked is 379, but the top 10 percent of officers work more than 447. One officer worked 601 of the 609 days. My data cannot speak to the quality of the work performed by an officer who works almost everyday. However, I can say that allowing officers discretion in working overtime helps reduce workplace injury. If the objective is to reduce workplace injury, it is not necessarily a good idea to regulate excessive overtime (for example, by putting a cap on voluntary overtime).

Many descriptive analyses have shown a positive relationship between excessive work and workplace injury. These include studies using the NLSY (Dembe et al. 2005), a survey of fire fighters in Korea (Kim et al. 2016) and an analysis using the PSID (Conway et al. 2017). Importantly, these studies do not distinguish between mandatory and voluntary overtime. My paper fills this gap. In my model, I can think of mandatory overtime as shifts worked when resistance to work is high. I have shown unobserved resistance to work is positively correlated with injury propensity. This means mandatory overtime is more dangerous than voluntary overtime.

To illustrate this last point: consider the probability of injury conditional on working as a proxy for the injury risk from voluntary work. The unconditional probability of injury can be thought of as a proxy for mandatory overtime, because it is the injury probability I would expect if I randomly forced an officer to work. As stated previously, the conditional probability is 0.001, while the unconditional probability is 0.01. This means that in my population, mandatory overtime is 8.5 times more dangerous than voluntary overtime. Because of this, analyses which lump mandatory and voluntary overtime together will always be estimating a weighted average of the mandatory and voluntary effect, with the mandatory effect usually being much larger than the voluntary effect. Additionally, two identical companies employing identical populations of employees could still have completely different observed injury rates if they allocate additional work differently. Organizations which rely on voluntary mechanisms will tend to have lower injury rates, while organizations which force employees will tend to have higher rates.

The idea that mandatory overtime is much more dangerous than voluntary overtime highlights the importance of expectations and planning. At baseline, my results suggest there is a natural alignment between the preferences of officers and an injury-minimizing social planner. This is because when individuals work planned, voluntary overtime, they can organize their time before and after the shift to allow for additional rest. When overtime is unexpected and induced using either incentives (additional pay) or penalties (discipline) the natural alignment is broken and individuals begin trading off risk for money.

Anecdotally, I have heard several stories which support my finding that workers in high risk environments select against injury. An older nurse who is a cancer survivor turned down overtime shifts with $700 bonuses during the December COVID-19 surge. A young healthy paramedic volunteered to leave a safe county to work a two week period in a dangerous, overwhelmed county. This illustrates another point. While it is generally illegal to give preferential access to overtime based on factors like age and past medical conditions, individuals incorporate this information into their decision making. In this sense, greater employee choice can have a protective effect, even when it leads to inequitable overtime worked.

A long literature in economics asks under what conditions prices aggregate private information. Although this has often been applied to asset evaluation, I argue that it applies equally to injury propensity. Individuals possess both time invariant private information about themselves and temporal private information about their specific job and life circumstances. My results imply that market dynamics can induce more revelation of this private information.

7.1 Labor Supply Elasticities

It follows directly from the results section that, all things constant, officers on the margin will require more pay for more injury risk. Another interesting question is how risk impacts average labor supply elasticities. My model allows us to estimate the elasticity of the probability of working a shift with respect to the wage conditional on different unobserved propensities to be injured. This allows me to see how elasticities vary at different levels of risk. Formally, I calculate the quantity:

$$e_{wage}(z_{it}, v) = \frac{wage_{it}}{Pr(w_{it}|z_{it}, v_{2it} = v)} \frac{\partial}{\partial wage_{it}} Pr(w_{it}|z_{it}, v_{2it} = v)$$

and average over observed z_{it}. This yields an average labor supply elasticity for each value of v. I plot this relationship in Figure 1 and see that the elasticity is declining in unobserved injury propensity. Individuals with an injury propensity around the 16th percentile will have an elasticity of around 4.9, while those with an injury propensity around the 84th percentile will have an elasticity of around 1.4. Intuitively, an additional dollar in earnings is less enticing when an officer knows they will have work after staying up all night.

Even when injury is relatively likely, labor supply is still elastic (greater than 1). This has implications for how wage multipliers impact injury rates. Companies frequently use wage multipliers to encourage workers to take shifts on holidays and during periods of high demand. While my results suggest wage multipliers are an effective way to encourage work, they are not effective at encouraging the right employees to work. This is because even relatively risky employees have highly elastic labor supply. Consider the case when an organization offers a wage multiplier for working Christmas. It decides that if more people volunteer than needed, it will randomly choose who gets the shift. The wage multiplier will induce all types of employees to volunteer, and conditional on volunteering, the random allocation mechanism is just as likely to give it to a high risk volunteer as a low risk volunteer. What this mechanism is missing is a way to leverage competition among workers to optimally allocate the shift to the least risky employee. An example of such a mechanism is a shift auction, which I describe fully in Section 8.

7.2 The Value of a Statistical Injury

I use an approach similar to the literature (Kniesner and Viscusi 2019) and define the *value of a statistical injury* (VSI) as the amount of money an officer would be willing to pay to accept a shift with an additional 1/553 risk of injury, multiplied by 553.[18] In my setting, variation in wages allows us to back out the implied willingness to pay. Since unobserved injury risk is negatively correlated with utility and the coefficient on wages in utility is positive, the typical officer will require a positive payment to take on injury risk. Before presenting the VSI, I briefly state my methodology for calculating willingness to pay using my model.

In my model, an officer who is choosing to work is ex-ante indifferent between a $\$q$ increase in the wage and an increase of $\alpha_w q$ in v_{it1}. This increase in v_{it1} translates into injury probability because it is correlated with v_{it2}. Thus the shift in v_{it1} results in an expected shift in v_{it2} by $\rho\alpha_w q$. The proportional change in the probability of injury for an officer with covariates x_{it} and initial value of v_{it1} of v is:

$$\Delta(x_{it}, q, v) := \Phi\left(\frac{\zeta_2 + x'\beta + \bar{z}_i'\gamma_2 - \rho v + q(\beta_w - \rho\alpha_w)}{(1-\rho^2)^{1/2}}\right) - \Phi\left(\frac{\zeta_2 + x'\beta + \bar{z}_i'\gamma_2 - \rho v}{(1-\rho^2)^{1/2}}\right)$$

The willingness to pay for a 1/553 increase in injury probability for an officer with covariates x_{it} and unobserved resistance to work v is then given by $q(x_{it}, v)$ which solves:

$$\Delta(x_{it}, q(x_{it}, v, p), v) = \frac{1}{553}$$

This is uniquely defined because the CDF is strictly increasing. Solving for q (willingness to pay) yields:

$$q(x_{it}, v) = -\frac{1}{\beta_w - \rho\alpha_w}\left((\zeta_2 + x_{it}'\beta + \bar{z}_i'\gamma_2 - \rho v) - (1-\rho^2)^{1/2}\Phi^{-1}\left\{\Phi\left(\frac{\zeta_2 + x_{it}'\beta + \bar{z}_i'\gamma_2 - \rho v}{(1-\rho^2)^{1/2}}\right) + \frac{1}{540}\right\}\right)$$

[18] I use 540 because this is the number of unique officers in my data. Typically VSL's use 10,000 but my study does not have enough power to assess risk changes that are this small.

To calculate VSI, I assume that officers expect to work 8 hours ex-ante. Finally, the value of a statistical injury is given by:

$$VSI = M \cdot 553 \cdot 8 \cdot E_{x,v}[q(x,v)]$$

where note that I have integrated out v, the unobserved utility from work.[19] M represents a multiplier on the wage. For some shifts, officers will expect to be paid their typical wage rate, so $M = 1$. For others, officers may expect to be paid an overtime or special events premium, so $M = 1.5$ or $M = 2$. Because the coefficient on wage is positive, I can bound the VSI from above by setting $M = 2$ and below by setting $M = 1$. The upper and lower bounds of the average VSI (and the associated willingness to pay) for Los Angeles traffic officers are presented in Table 17. I estimate that on average, the implied value of a statistical injury for Los Angeles traffic officers is between \$11,710 and \$23,419.

These aggregate figures mask significant individual and temporal heterogeneity. To visualize the heterogeneity, I plot the willingness to pay using each individual officer-day (rather than averaging over all officer-days). Figure 7 displays a density plot of these estimates. The distribution exhibits two peaks, one around \$23 and another around \$17. The vast majority of officer-days have a willingness to pay which is between \$10 and \$30. Such heterogeneity in willingness to pay implies significant heterogeneity in individual VSI. This heterogeneity is a cautionary tale: even though I analyze a single occupation in specific city, there are large differences in preferences over injury risk.

In the last 20 years, many papers reporting the value of a statistical life have increased the granularity of their estimates by computing values for different age groups and different occupations. As more studies calculate VSI's, it is likely that these estimates will also become more refined. However, it is important for researchers and policymakers to understand that even within an occupation and age, there may be significant individual heterogeneity in the value of a statistical injury.

On the one hand, significant heterogeneity in a homogeneous population might seem surprising. On the other hand, traffic officers have a large amount of control over how much they work. One interpretation of the heterogeneity is that choice over shifts allows many different types of people to work the same job. Thus, for similar jobs (delivery drivers, crossing guards, etc), my results suggest that as working arrangements become more flexible (through gig-economy growth and the transition to contractor employment), I may expect workplace injury to fall. My results also support the idea that schedule flexibility is a valuable amenity.

My estimates fall near the lower end of VSI estimates in the literature. Kuhn and Ruf 2013 find a value of approximately \$39,000 while Viscusi and Aldy 2003 list values ranging between \$20,000 and \$30,000. My

[19] For my estimates, I integrate out v using Gauss-Hermite quadrature with 5 nodes.

upper bound lies in this range, but it is in 2015 dollars, meaning it is inflated and would not lie in the range if I corrected for inflation.

7.3 Limitations

The largest limitation of my analysis is the absence of demographic information. It is well known that gender and race can be quite influential on injury rates.[20] If this information was incorporated in the model, it would probably greatly increase the precision of the estimates, and allow a better disentangling of time-invariant effects from idiosyncratic effects.[21]

A second limitation is dynamics. The model I estimate assumes officers are myopic: they care only about maximizing utility today. I made this modeling choice out of a desire for parsimony. The cost of dynamics in a binary choice model is complexity. For traffic officers deciding whether to work a shift, dynamics seems to be a second-order concern. However, it might be that officers think about how taking a trade today might impact their ability to get a shift in the future. They might want to smooth earnings. A potential extension of this work would be to incorporate work schedule choice into a dynamic framework. Indeed, such an extension would allow the researcher to better understand internal labor markets.

A third limitation is the decision to leave the job. I chose to leave this as exogenous, but it is possible that this is another dimension of selection which might be important.

8 Application: Shift Auctions

The main finding, that all else equal, officers with higher unobserved injury risk prefer to work less, implies there are gains from allowing individuals more freedom over which shifts they work. Currently and when the data was collected, Los Angeles traffic officers are assigned to additional shifts using a a *spin the wheel* mechanism, which is described earlier. The format of this mechanism gives officers some freedom to select against risk. Indeed, this is reflected by the fact that the observed injury rate is much lower than the unconditional injury rate. However, the list mechanism is sub-optimal in terms of minimizing the injury rate. The wage the officer expects to receive is fixed at the normal wage or the overtime wage, and officers are given take it or leave it offers in a random order.

In the last section, I discussed how officer labor supply is increasing in the wage. This means on average,

[20]For example, Simpson and Severson 2000 finds that African American hospital workers have 2.3 times higher risk than white workers.

[21]In a linear panel data model, I could have accounted for this using fixed effects.

officers who are less likely to be injured on a given day will require a lower wage. This motivates a potential improvement over the list mechanism: shift bidding. By shift bidding, I refer to a process where a manager posts the available shifts, and officers may place a wage bid for the shift if they satisfy the requirements (additional requirements could be seniority priority, etc). The shift is then assigned to the officer who bids the lowest wage. Although shift auctions may seem like an unusual practice, many scheduling software companies publicly list it as a built-in option.[22] In the below analysis, I explore the benefits of utilizing shift bidding as compared to a list mechanism. I do not explicitly compare to the spin the wheel mechanism because the data do not contain information about who volunteers.

Before providing simulation evidence, I consider the equilibria of the two mechanisms. For shift bidding, I restrict attention to $k+1$-price auctions, where the k overtime shifts in a division are assigned to the lowest k bidders and they are paid the bid of the $k+1$ lowest bidder. Assuming independent values, the unique Bayesian Nash Equilibrium is clearly for each officer to bid their value. The winner in equilibrium will be the officers with the k lowest values. Further, since injury risk is negatively correlated with value, the k winners will have the lowest injury risks among all bidders. In the list mechanism, officers will accept the shift if they are offered it and their value exceeds their outside option. If their value does not exceed their outside option, the shift passes to the next person. Whenever there are more officers willing to work at their normal wage then there are shifts to fill, the officers selected from an auction will have a lower expected injury rate than from the random list. If there are more shifts than officers, and it is assumed that in both mechanisms the shortage is filled by forcing employees to work, then the mechanisms deliver ex-ante the same injury rates. As a result, injury rates will be weakly lower with shift auctions.

To formalize this, consider a fixed day t, where from here on I suppress the t subscript. Denote the monetary value of a shift to officer i as θ_i. I can derive the monetary value by setting utility equal to 0 and solving for the wage variable. This yields: $\theta_i := (z_i'\alpha + \zeta_1 + \bar{z}_i'\gamma_1 - v_{i1})/\alpha_{wage}$ where z_i does not include the wage variable and α_{wage} is the coefficient on the wage variable. The utility from working at bid wage b_i is given by $U_i = \theta_i + b_i$. Recall that the injury outcome is denoted y_i. θ_i and y_i are correlated both through the shared elements of z_i that enter both the work and injury outcomes and through unobserved correlation.

There are a number of complexities related to how overtime shifts can be assigned. I abstract from these complexities, and consider a simple situation where each division on each date requires $s_{d,t}$ officers, where $s_{d,t}$ is determined as the number of people observed working. Denote total shifts in the the entire analysis period in division d as S_d. I assume that some number of the positions, denoted $r_{d,t}$ are filled by regular

[22] Some examples: Stay Staffed, which produces a nurse scheduling software; Celayix Software, a multi-industry workforce management software company; EPay Software, a human capital management provider.

officers. The remainder, denoted $k_{d,t}$, are filled with additional officers. Because I do not observe how many shifts are regularly scheduled, I assume that, within each division, it can be approximated as the number of hours coded as "CURRENT ACTUAL HOURS WORKED ONLY" divided by 8.[23] Call this numbers R_d. I also assume the fraction of shifts which are regular is time invariant. This allows us to approximate $r_{d,t}$ as $R_d/S_d \times s_{d,t}$ rounded to the nearest whole number. $k_{d,t}$ is then $s_{d,t} - r_{d,t}$. With these in hand, the simulation procedure I use to obtain injury rates under the random list and shift auctions is as follows:

1. For all officer-days, randomly draw i.i.d. pairs of (v_{it1}, v_{it2}). Then, within each division-date, do steps 2-4.

2. To simulate the list mechanism, randomly select $s_{d,t}$ officers from among those with $z_i'\alpha+\zeta_1+\bar{z}_i'\gamma_1-v_{i1} > 0$ with wage included in z_{it}. If there are not enough officers that satisfy the criteria, fill the remaining slot with randomly chosen officers. Calculate the list-mechanism injuries using the v_{it2} draws of the selected officers.

3. To simulate a shift auction, order the officers according to $z_i'\alpha + \zeta_1 + \bar{z}_i'\gamma_1 - v_{i1}$. Assign the $r_{d,t}$ shifts to the "winners", the lowest $r_{d,t}$ officers. Calculate the shift auction injuries using the v_{it2} draws of the auction winners.

4. Compute the injury rate change as the difference in the number of injuries under the two systems divided by the total number of officer-work days.

I repeat this process 1,000 times. On average, shift auctions reduced the number of injuries by 34.26 percent. The effect was 30.26 percent and 38.11 percent at the 5th and 95th percentiles respectively. In terms of percentage point changes, shift auctions reduced the injury rate on average by 0.1220 percentage points. In this setting, shift auctions lead to lower injury rates compared to the list mechanism.

I also compare shift bidding to what I term the *full information benchmark*. The full information benchmark is the injury rate that would be observed if I could assign the additional $k_{d,t}$ shifts directly to the employees with the lowest injury risk. To simulate it, I randomly assign regular shifts among officers who are willing to work, and then I assign the additional shifts to the officers with the lowest values of $\zeta_2 + \bar{z}_i'\gamma_2 + x_{it}'\beta - v_{it2}$ (essentially, I give the shifts to those who I know will not be injured). The full information benchmark decreases injuries by 27.36 percent compared to shift auctions.

The simulation results are summarized in Figure 8. The figure displays the simulated injury rate under all three regimes plotted for 1,000 simulations (assuming the number of shifts worked is constant). The

[23] This code appears to correspond to regular hours, or non-overtime, hours.

shift bidding injury rate distribution is sandwiched between the much better full information benchmark and much worse random list mechanism. This exercise highlights the importance of the main result: positive selection on the part of officers can be leveraged by an organization to reduce the aggregate injury rate. Shift auctions accomplish this goal while also being available in several scheduling software packages.

9 Conclusion

This paper explores how individuals make shift-level labor supply decisions. It asks whether injury risk factors into traffic officer work decisions. I answer this question using a detailed panel of Los Angeles traffic officers. I find officers do indeed account for their own injury risk. Specifically, there is *selection against injury:* officers prefer to work when they have lower injury risk. Selection effects are large. I estimate the population average injury rate is 8.5 times larger than the observed injury rate.

My results hold implications for several important topics in labor economics. They imply that even within occupations and geographic locations, individuals have very different willingness to pay for injury risk reduction. Additionally, estimates of workplace injury rates which do not account for worker labor supply will generally underestimate the population average probability of injury. Finally, they imply estimates of labor supply elasticities will vary greatly depending on the level of risk faced by the population and date of interest.

The idea that self-selection into work reduces injury rates is important for organizations seeking to reduce injury rates. For some organizations it may be unsavory that self-selection results in inequitable distribution of overtime. But ex-post inequality is the cost of the injury reduction coming from self-selection. My analysis supports the idea that it is mandatory overtime, not voluntary overtime, which leads to greater workplace injury. Organizations concerned about high injury rates should consider not just how much their employees work, but also why they work. Is it by choice or is it by force? The answer matters for overall safety. If an employer wants to reduce injury, it can design mechanisms which leverage how officers trade-off risk for earnings. One such mechanism is a k-price shift auction, which assigns shifts to the workers willing to work for the lowest wages.

Overall, this paper challenges the idea that injury risk within a job is exogenous. Rather, it is a choice over which some workers exercise a good deal of control. Recognizing the factors which impact this choice and the institutions that facilitate it is crucial for both safety regulations and our understanding of workplace injury.

Table 1: Number of Unique Injuries

Injury Count	Officer Count	% of Total
0	366	66.18
1	134	24.23
2	39	7.05
3	12	2.17
4	1	0.18
5	1	0.18
Total	553	100.00

Distribution of injuries across officers. Most officers experience no injuries or one injury.

Table 2: Basic Characteristics of Officers

	Mean	Std. Dev.	p5	p10	p25	p50	p75	p90	p95
Not Injured									
Age	44.48	10.09	28.24	30.11	37.30	44.06	52.05	58.43	60.16
Tenure (years)	13.11	8.63	1.94	2.86	7.20	12.41	17.80	26.49	28.21
Divisions Worked In	1.26	0.46	1.00	1.00	1.00	1.00	1.00	2.00	2.00
Injured									
Age	46.43	8.88	34.30	35.13	39.79	46.63	52.81	58.31	62.38
Tenure (years)	14.26	8.24	3.42	6.20	8.19	11.99	19.60	26.49	27.77
Divisions Worked In	1.24	0.45	1.00	1.00	1.00	1.00	1.00	2.00	2.00
Total									
Age	45.14	9.73	28.72	32.03	38.61	44.65	52.22	58.31	60.23
Tenure (years)	13.49	8.51	2.39	3.42	8.19	11.99	18.18	26.49	27.92
Divisions Worked In	1.25	0.46	1.00	1.00	1.00	1.00	1.00	2.00	2.00
Observations	553								

Tenure, age and division changes broken down among officers who are injured and those who are not. Age and tenure are as of first day observed in the analysis period.

Table 3: Injuries by "Claim Cause"

	Frequency	Percent
Strain or Injury By, NOC	53	20.95
Collision or Sideswipe w	40	15.81
Repetitive Motion - Other	24	9.49
Fall, Slip, Trip, NOC	18	7.11
Motor Vehicle, NOC	16	6.32
Other-Miscellaneous, NOC	12	4.74
Animal or Insect	10	3.95
Object Being Lifted or	8	3.16
Other Than Physical Cause	8	3.16
Fellow Worker, Patient, or	7	2.77
Person in Act of a Crime	7	2.77
Cumulative, NOC	5	1.98
Dust, Gases, Fumes or	5	1.98
Exposure, Absorption,	4	1.58
Twisting	4	1.58
Foreign Matter in Eye(s)	3	1.19
Struck or Injured, NOC	3	1.19
Using Tool or Machinery	3	1.19
Bicycling	2	0.79
Broken Glass	2	0.79
Lifting	2	0.79
Pushing or Pulling	2	0.79
Repetitive Motion - Carpal	2	0.79
Temperature Extremes	2	0.79
Caught In, Under or	1	0.40
Contact With, NOC	1	0.40
Cut, Puncture, Scrape,	1	0.40
From Different Level	1	0.40
Hand Tool or Machine in	1	0.40
Holding or Carrying	1	0.40
Object Handled by Others	1	0.40
On Same Level	1	0.40
Running/Jogging/Walking	1	0.40
Stationary Object	1	0.40
Striking Against or Stepping	1	0.40
Total	253	100

This table lists the distribution of injuries by their Claim Cause.

Table 4: Injuries by "Nature of Injury"

	Frequency	Percent
Strain	119	47.04
Contusion	32	12.65
Sprain	30	11.86
Mental Stress	14	5.53
No Physical Injury	11	4.35
Inflammation	7	2.77
All Other Specific Injuries,	5	1.98
Bee Sting	4	1.58
Dermatitis	4	1.58
Foreign Body	4	1.58
Heat Prostration	4	1.58
Multiple Physical Injuries	4	1.58
Carpal Tunnel Syndrome	3	1.19
All Other Cumulative	2	0.79
Infection	2	0.79
Respiratory Disorders (e.g.,	2	0.79
Asbestosis	1	0.40
Bloodborne Pathogens	1	0.40
Hypertension	1	0.40
Laceration	1	0.40
Mult Injuries Incl Both	1	0.40
Stroke	1	0.40
Total	253	100.00

This table lists the distribution of injuries by their Nature of Injury.

Table 5: Daily Hours Worked Summary Statistics

	Mean	Std. Dev.	p5	p10	p25	p50	p75	p90	p95
Not Injured	9.00	2.70	7.00	8.00	8.00	8.00	8.00	13.00	15.00
Injured	8.94	2.62	8.00	8.00	8.00	8.00	8.00	13.00	15.00
Total	8.98	2.67	8.00	8.00	8.00	8.00	8.00	13.00	15.00
N	183659								

This table describes the distribution of hours worked among officers who are injured and those who are not. The sample is restricted to days with positive hours worked.

Table 6: Days Worked in 4 Week Periods

	Mean	Std. Dev.	p10	p25	p50	p75	p90
Not Injured	18.15	4.44	13.00	16.00	19.00	21.00	23.00
Injured	17.54	4.24	12.00	16.00	18.00	20.00	22.00
Total	18.03	4.41	13.00	16.00	19.00	21.00	23.00
N	8378						

This table describes the distribution of days worked among officers who are injured and those who are not. The unit of observation is officer-4 week period. The sample is restricted to 4 week periods with at least one day with positive hours worked.

Table 7: Days Worked by Day of the Week

	Frequency	Percent
Tuesday	32364	17.62
Wednesday	31548	17.18
Thursday	31329	17.06
Monday	30933	16.84
Friday	29757	16.20
Saturday	16478	8.97
Sunday	11250	6.13
Total	183659	100.00

This table describes the distribution of officer-days by day of the week.

Table 8: Number of Officers on Leave By Division

	Mean	Std. Dev.	p10	p25	p50	p75	p90
811							
Officers with Positive Leave	4.54	3.67	1.00	2.00	4.00	6.00	8.00
Officers with Positive Sick	1.57	1.45	0.00	0.00	1.00	2.00	4.00
Total Leave Hours	52.35	34.17	2.00	24.50	52.00	76.00	94.00
812							
Officers with Positive Leave	11.25	7.55	1.00	3.00	12.00	17.00	20.00
Officers with Positive Sick	3.54	2.79	0.00	1.00	3.00	5.00	7.00
Total Leave Hours	112.26	76.29	6.00	32.00	123.00	168.00	203.00
814							
Officers with Positive Leave	16.76	10.15	1.00	5.00	21.00	25.00	28.00
Officers with Positive Sick	5.59	3.61	0.00	2.00	6.00	8.00	10.00
Total Leave Hours	169.11	101.10	16.00	56.00	203.50	243.00	281.00
816							
Officers with Positive Leave	9.37	5.93	0.00	3.00	11.00	14.00	16.00
Officers with Positive Sick	2.40	2.04	0.00	1.00	2.00	4.00	5.00
Total Leave Hours	90.70	58.55	0.00	35.50	104.00	132.00	155.00
818							
Officers with Positive Leave	4.75	3.35	0.00	1.00	5.00	7.00	9.00
Officers with Positive Sick	1.49	1.39	0.00	0.00	1.00	2.00	3.00
Total Leave Hours	47.69	33.65	0.00	16.00	49.00	72.00	88.00
819							
Officers with Positive Leave	17.01	10.49	1.00	4.00	21.00	24.00	28.00
Officers with Positive Sick	5.79	3.79	1.00	2.00	6.00	8.00	10.00
Total Leave Hours	173.82	106.87	16.00	53.00	206.00	246.00	293.00
800 - 810, 824, 828,							
Officers with Positive Leave	1.48	1.42	0.00	0.00	1.00	2.00	3.00
Officers with Positive Sick	0.63	0.81	0.00	0.00	0.00	1.00	2.00
Total Leave Hours	16.14	15.82	0.00	0.00	16.00	24.00	40.00
Other							
Officers with Positive Leave	2.42	1.77	0.00	1.00	2.00	4.00	5.00
Officers with Positive Sick	0.68	0.84	0.00	0.00	0.00	1.00	2.00
Total Leave Hours	24.28	18.55	0.00	8.00	24.00	32.50	48.00
Total							
Officers with Positive Leave	8.45	8.66	0.00	2.00	5.00	14.00	23.00
Officers with Positive Sick	2.71	3.05	0.00	0.00	2.00	4.00	7.00
Total Leave Hours	85.79	86.87	0.00	16.00	52.00	138.00	227.00
Observations	4864						

This table describes the distribution of the number of officers on leave by division. It gives a sense of how leave varies spatially (differences in the distribution across divisions) and temporally (variation within division across time). Other contains several small division codes.

Table 9: Pay Statistics

	Mean	Std. Dev.	p10	p25	p50	p75	p90
Hourly Wage	30.10	2.33	26.56	30.54	30.54	30.54	32.22
Regular Pay	1236.11	716.25	244.00	873.50	1220.00	1573.00	2135.00
Overtime Pay	287.60	488.18	0.00	0.00	0.00	435.00	967.00
Proportion OT	0.11	0.14	0.00	0.00	0.00	0.24	0.33
Observations	43004						

Overtime and straight time are classified based on Variation Description. Wage is the maximum observed base wage during that day. During non-work days it is interpolated.

Table 10: OLS Estimates of Injury on Work

	(1)	(2)	(3)	(4)
Work=1	0.00140***	0.00142***	0.00113***	0.00116***
	(0.000100)	(0.000103)	(0.000106)	(0.000109)
Age	0.0000108	0.0000118	0.0000120	0.0000121
	(0.00000769)	(0.00000779)	(0.00000780)	(0.00000785)
Observations	259861	259861	259861	259861
F-Stat.	97.78	10.54	5.748	.
Division FE	No	Yes	Yes	Yes
Day of Week/Month FE	No	No	Yes	No
Date FE	No	No	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents results of ordinary least squares regressions of injury on work. The coefficient on work provides a naive estimate of the observed injury rate. Each column adds additional controls. Standard errors are clustered at the officer level.

Table 11: Linear Probability Models of Work Decision

	(1)	(2)	(3)	(4)	(5)
Leave of Coworkers (count)	0.0267***	0.0265***	0.0280***	0.00347***	0.00370***
	(0.000468)	(0.000451)	(0.000469)	(0.000631)	(0.000642)
Cumulative Officer Potential Contacts	0.0000624	-0.000175	0.000465*	0.000349	0.000395*
	(0.000345)	(0.000307)	(0.000222)	(0.000190)	(0.000195)
Seniority Rank	-0.000497*	-0.000342	0.000306	0.000391*	0.000390*
	(0.000242)	(0.000235)	(0.000193)	(0.000187)	(0.000188)
Wage		0.0707***	0.0523***	0.0378***	0.0380***
		(0.00442)	(0.00469)	(0.00323)	(0.00321)
Observations	259861	259861	259861	259861	259861
First-Stage F.	559.7	548.4	179.6	255.0	220.4
Division FE	No	No	Yes	Yes	Yes
Day of Week FE	No	No	No	Yes	Yes
Month FE	No	No	No	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents estimates of a linear probability model of the work decision. Time averages of age, leave of coworkers, cumulative officer potential contacts, seniority rank and wage are included in all specifications. The table suggests that the instruments are relevant to the work decision. Each column adds additional controls. Standard errors are clustered at the officer level.

Table 12: Balance Test: Regression of Medical Expenses Paid on Instruments

	(1)	(2)	(3)	(4)
Leave of Coworkers (count)	3.849	26.04	84.99	106.4
	(29.66)	(47.53)	(64.66)	(66.27)
Cumulative Officer Potential Contacts	-5.590	-1.467	-2.044	-4.170
	(6.702)	(6.974)	(7.144)	(7.774)
Seniority Rank	-6.425	1.949	-0.908	-1.276
	(9.588)	(9.083)	(9.538)	(9.553)
Observations	257	257	257	257
F.	0.409	.	.	.
Division FE	No	Yes	Yes	Yes
Day of Week FE	No	No	Yes	Yes
Month FE	No	No	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents regressions of medical expenses on the instruments. Time averages of age, leave of coworkers, cumulative officer potential contacts, seniority rank and wage are included in all specifications. This is a balance test of the instruments, and if the exclusion restriction holds we would see no relationship between each variable and the outcome. The lack of significant coefficients is evidence in favor of the exclusion restriction. Each column adds additional controls. Standard errors are clustered at the officer level.

Table 13: Labor Supply Model: Select Parameter Estimates

	Injury	Work
Avg. Coworker Leave	-0.0559***	0.0235***
	(0.00917)	(0.00673)
Avg. Wage	-0.0324	-0.150***
	(0.0600)	(0.0157)
Avg. Age	-0.0212	0.0309**
	(0.0402)	(0.0101)
Avg. Cum. Potential Contacts	0.00165*	-0.00121
	(0.000671)	(0.000837)
Age	0.0227	-0.0287**
	(0.0399)	(0.0101)
Holiday	-0.679**	1.758***
	(0.245)	(0.132)
Amount Rain (in.)	-0.134	-0.0229
	(0.125)	(0.0220)
Max. Daily Temp.	-0.000197	-0.000131
	(0.00285)	(0.000453)
Wage	0.0434	0.150***
	(0.0606)	(0.0135)
Leave of Coworkers (count)		0.0189***
		(0.00242)
Cumulative Officer Potential Contacts		0.00192*
		(0.000767)
Seniority Rank		0.00152
		(0.000781)
Observations	259861	
Rho	-0.624	
Rho 95% CI	(-0.16, -0.863)	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table displays the main coefficient estimates of the injury and work equations, estimated using a pooled Heckman Probit procedure. “Avg.” variables are time averages within person. Rho represents the unobserved correlation between injury propensity and work utility. The negative sign and confidence interval that does not contain 0 indicate there is selection against injury: more injury-prone officers are less likely to work. Standard errors are clustered at the officer level.

Table 14: Beyond Coefficients: Additional Model Estimates

Description	Analytical Representation	Estimate
Conditional Injury Probability	$E_{z_{it}}[Pr(y_{it=1}\|w_{it} = 1\,\&\,z_{it})]$	.0013 (.00009)
Unconditional Injury Probability	$E_{v,z_{it}}[Pr(y_{it=1}\|z_{it}\,\&\,v)]$	.0119 (.01323)
Unobserved Idiosyncratic Correlation (ρ)	$Cor(a_{i1} + u_{it1}, a_{i2} + u_{it2})$	$-.6241$ (.17803)
Variance Time-Invariant Work Utility	$Var(\bar{Z}_i\gamma_1)$	.1503 (.)
Variance Time-Invariant Injury Propensity	$Var(\bar{Z}_i\gamma_2)$	.1108 (.)
Correlation Time-Invariant Components	$Cor(\bar{Z}_i\gamma_2, \bar{Z}_i\gamma_2)$	$-.4664$ (.)
Total Correlation Unobserved Utility/Injury	$\frac{\rho+Cov(\bar{Z}_i\gamma_2,\bar{Z}_i\gamma_2)}{1+Var(\bar{Z}_i\gamma_1)^{1/2}Var(1+\bar{Z}_i\gamma_2)^{1/2}}$	$-.6053$ (.)

This table contains additional structural quantities of interest. In particular, the unconditional injury probability is the chance of injury if we forced a random officer to work a random shift. The fact that the unconditional injury probability is much smaller than the conditional injury probability demonstrates that selection moderates observed injury rates. Probabilities are averages over all officer-days, with standard errors accounting for sampling of covariates. Some quantities involve a mixture of model parameters and covariate variances, so I do not report standard errors.

Table 15: Average Elasticities: Labor Supply

Effect	Analytical Representation	Model Estimate
Wage	$E_{z_{it}}[\frac{wage_{it}}{Pr(w_{it}=1\|z_{it})}\frac{\partial Pr(w_{it}=1\|z_{it})}{\partial wage_{it}}]$	2.270 (.21450)
Leave of Coworkers	$E_{z_{it}}[\frac{leave_{it}}{Pr(w_{it}=1\|z_{it})}\frac{\partial Pr(w_{it}=1\|z_{it})}{\partial leave_{it}}]$	.0429 (.00551)
Cum. Potential Contacts	$E_{z_{it}}[\frac{contacts_{it}}{Pr(w_{it}=1\|z_{it})}\frac{\partial Pr(w_{it}=1\|z_{it})}{\partial contacts_{it}}]$	.0510 (.02052)
Seniority	$E_{z_{it}}[\frac{senior_{it}}{Pr(w_{it}=1\|z_{it})}\frac{\partial Pr(w_{it}=1\|z_{it})}{\partial senior_{it}}]$	.0229 (.01175)

This table reports averages elasticities of the work outcome. Elasticities have a more meaningful interpretation than the raw coefficient estimates. The elasticities are averages over all covariates and officer-days, with standard errors account for sampling of covariates. The values can be interpreted as a 1% increase in the variable changes the probability of working by x%. These estimates can be thought of as shift labor supply elasticities.

Table 16: Average Elasticities: Injury Conditional on Working

Effect	Analytical Representation	Model Estimate
Wage	$E_{z_{it}}[\frac{wage_{it}}{Pr(y_{it}=1\|w_{it}=1,z_{it})}\frac{\partial Pr(y_{it}=1\|w_{it}=1,z_{it})}{\partial wage_{it}}]$	12.82 (5.8296)
Leave of Coworkers	$E_{z_{it}}[\frac{leave_{it}}{Pr(y_{it}=1\|w_{it}=1,z_{it})}\frac{\partial Pr(y_{it}=1\|w_{it}=1,z_{it})}{\partial leave_{it}}]$	.2500 (.13539)
Cum. Potential Contacts	$E_{z_{it}}[\frac{contacts_{it}}{Pr(y_{it}=1\|w_{it}=1,z_{it})}\frac{\partial Pr(y_{it}=1\|w_{it}=1,z_{it})}{\partial contacts_{it}}]$	.1695 (.11043)
Seniority	$E_{z_{it}}[\frac{senior_{it}}{Pr(y_{it}=1\|w_{it}=1,z_{it})}\frac{\partial Pr(y_{it}=1\|w_{it}=1,z_{it})}{\partial senior_{it}}]$	.0779 (.06158)

This table reports averages elasticities of the injury outcome conditional on working. These have a more meaningful interpretation than the raw coefficient estimates. The elasticities are averages over all covariates and officer-days, with standard errors account for sampling of covariates. The values can be interpreted as a 1% increase in the variable changes the conditional probability of injury by x%. The conditional injury rate can be thought of as the injury rate among shifts worked.

Table 17: Marginal Value of Injury Risk

Lower Bound (M = 1)	
Willingness to Pay	VSI
\$21.18	\$11,709.9
(11.20)	(6193.9)

Upper Bound (M = 2)	
Willingness to Pay	VSI
\$42.35	\$23,419.8
(22.40)	(12387.7)

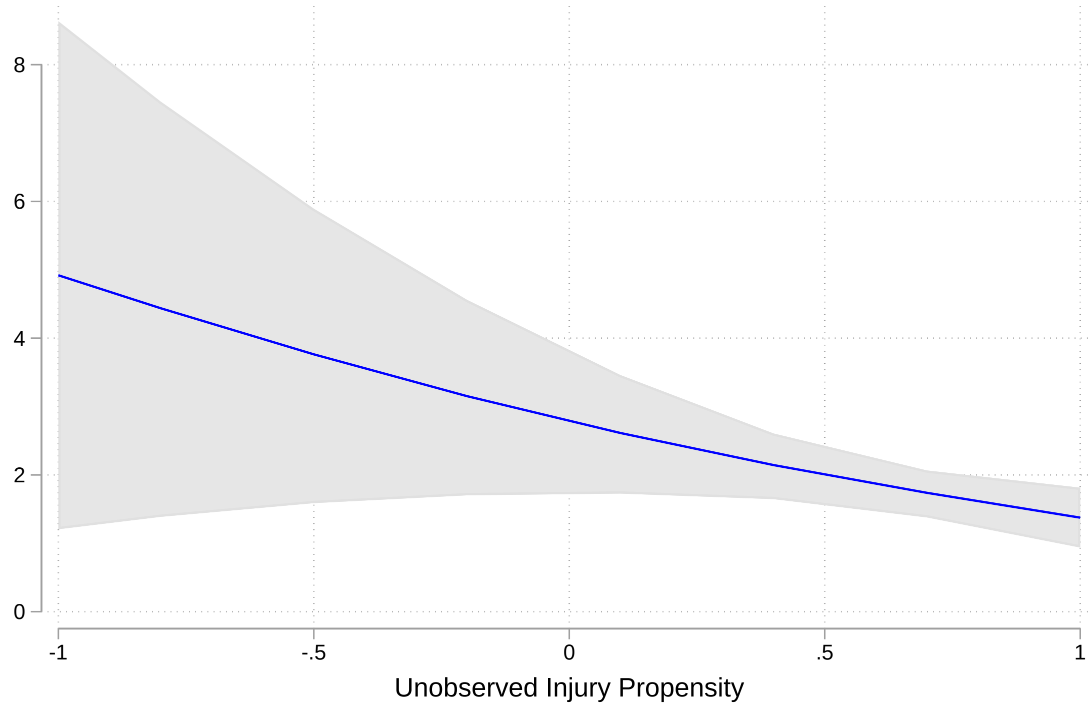
This table displays the willingness to pay for an injury risk reduction, which is the average amount an officer who is indifferent between working and not would pay to reduce injury risk by 1/553. The value of a statistical injury (VSI) is the willingness to pay multiplied by 553.

Table 18: Labor Supply Elasticities

Unobserved Injury Propensity	Labor Supply Elasticity
-1.0	4.920
	(1.895)
-0.8	4.424
	(1.550)
-0.5	3.741
	(1.098)
-0.2	3.131
	(0.729)
0.1	2.594
	(0.442)
0.4	2.126
	(0.245)
0.7	1.722
	(0.175)
1.0	1.376
	(0.223)

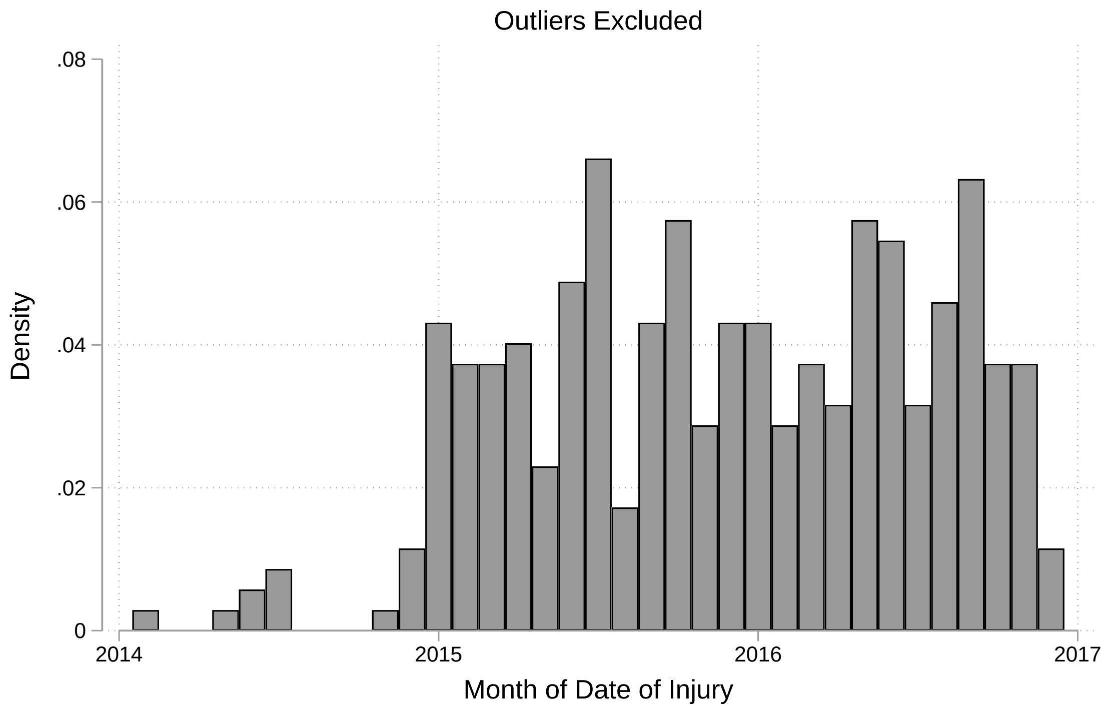
The table displays the average work probability (labor supply) elasticity conditional on different values of unobserved injury propensity. Labor supply becomes less elastic as injury propensity rises.

Figure 1: Average Labor Supply Elasticity By Injury Risk Propensities

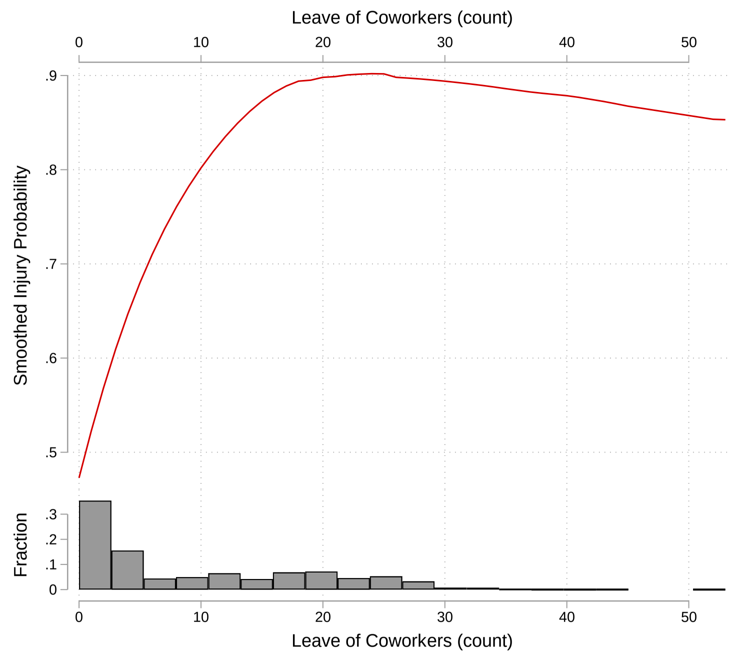


The figure displays the average work probability (labor supply) elasticity conditional on different values of unobserved injury propensity. Labor supply becomes less elastic as injury propensity rises. The gray band represents a 95 confidence interval with a Bonferroni correction for multiple hypothesis testing.

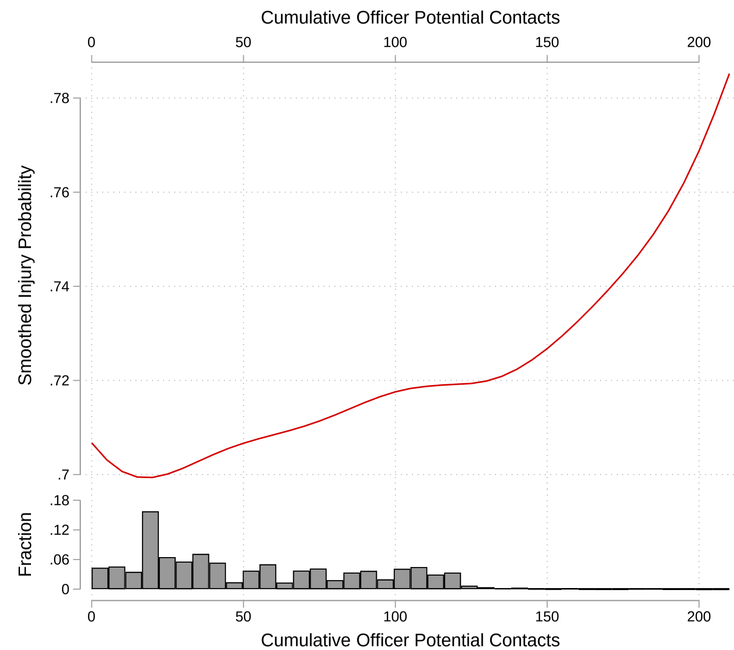
Figure 2: Workers' Compensation Claims by Month



The figure plots the number of workers' compensation by month. There is a distinct drop off in claims prior to January 2015. This is why the analysis window is limited to January 1, 2015 to September 1, 2016.



(a) Leave of Coworkers

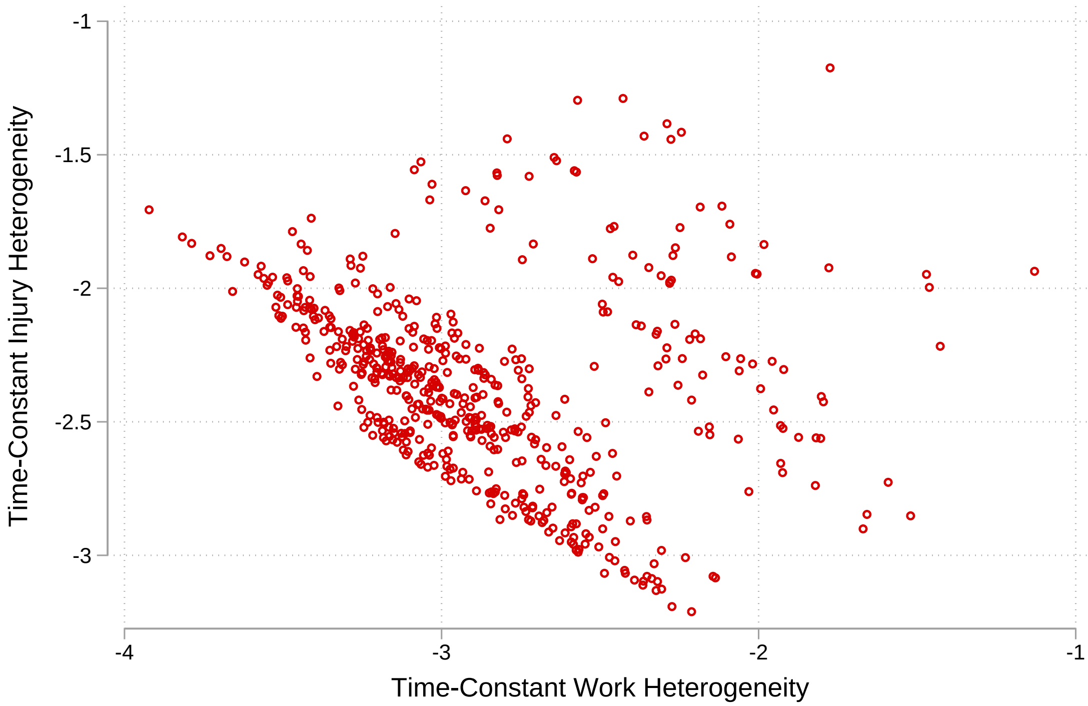


(b) Cumulative Potential Contacts

Figure 3: Instrumental Relevance: Increasing the Probability of Working

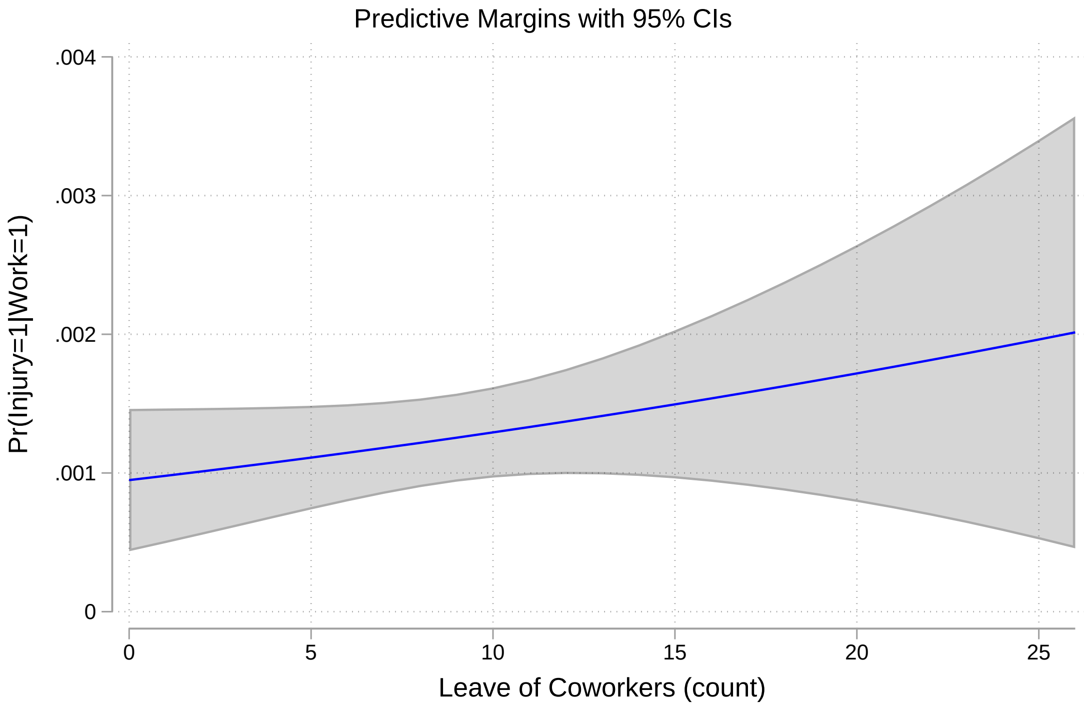
The figure visualizes the relationship between the two main instruments and the probability of working. Observations are binned based on the leave of coworkers in panel A and number of potential contacts in panel B. The probability of working is calculated for each bin. The line is locally weighted regression fit to the aggregated observations. A histogram showing the distribution of each instrument is displayed under each plot. There is generally a positive relationship between both instruments and work probability.

Figure 4: Scatterplot of Estimated Time-Constant Heterogeneity



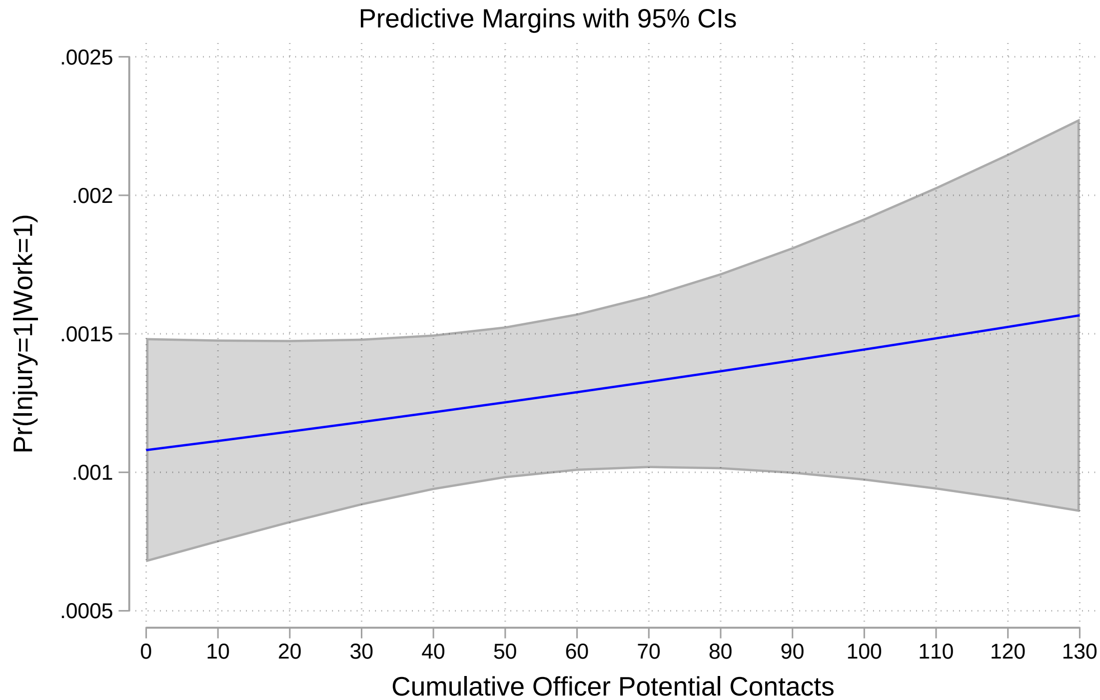
The figure plots the 553 time constant heterogeneity values ($\gamma_1 \bar{z}_i$ and $\gamma_2 \bar{z}_i$). These estimates can loosely be thought of as individual fixed effects for work utility and injury propensity. There is a negative correlation between the estimates, meaning that the types of officers which work less also tend to be injured more.

Figure 5: Average Probability of Injury By Leave of Coworkers



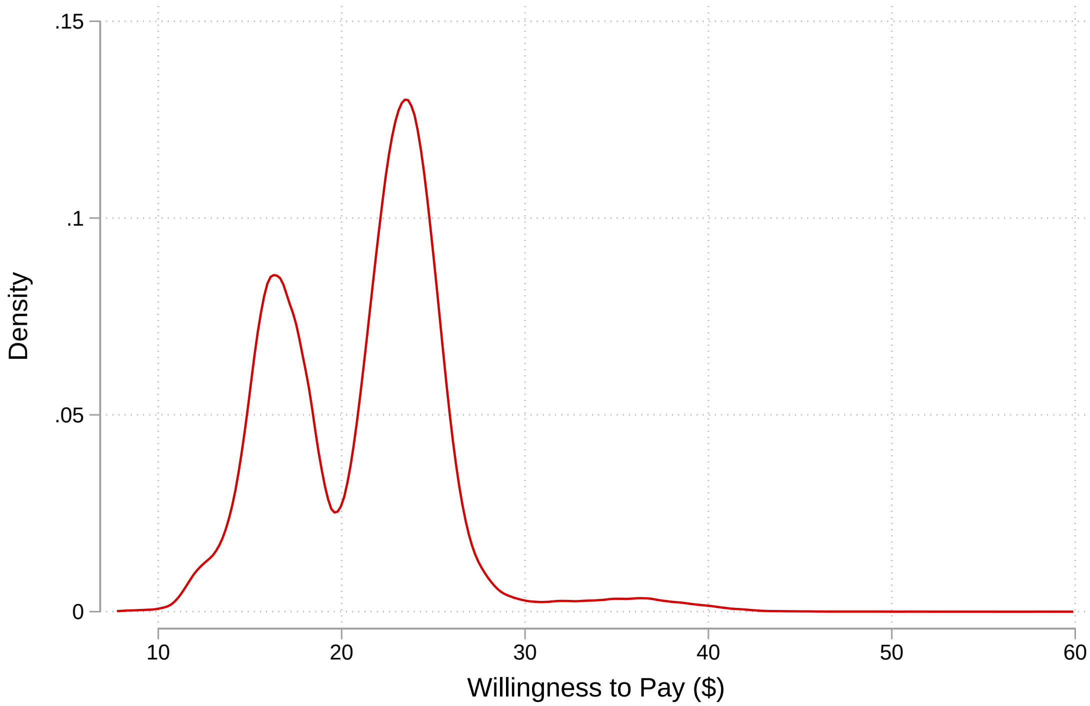
The figure displays the estimated relationship between leave of coworkers and the observed injury rate. Point estimates are averages of both unobserved heterogeneity and covariates. The figure shows that officers who work when leave of coworkers is high tend to have higher injury rates. This is because the pool of officers becomes more negatively selected. The gray band represents a 95 confidence interval with a Bonferroni correction for multiple hypothesis testing.

Figure 6: Average Probability of Injury By Cumulative Potential Contacts



The figure displays the estimated relationship between cumulative potential contacts and the observed injury rate. Point estimates are averages of both unobserved heterogeneity and covariates. The figure shows that officers who work when they have a larger network tend to have higher injury rates. This is because the pool of officers becomes more negatively selected: a larger network lowers the cost of finding special events overtime. The gray band represents a 95 confidence interval with a Bonferroni correction for multiple hypothesis testing.

Figure 7: Distribution of Officer-Day Marginal Values of Injury

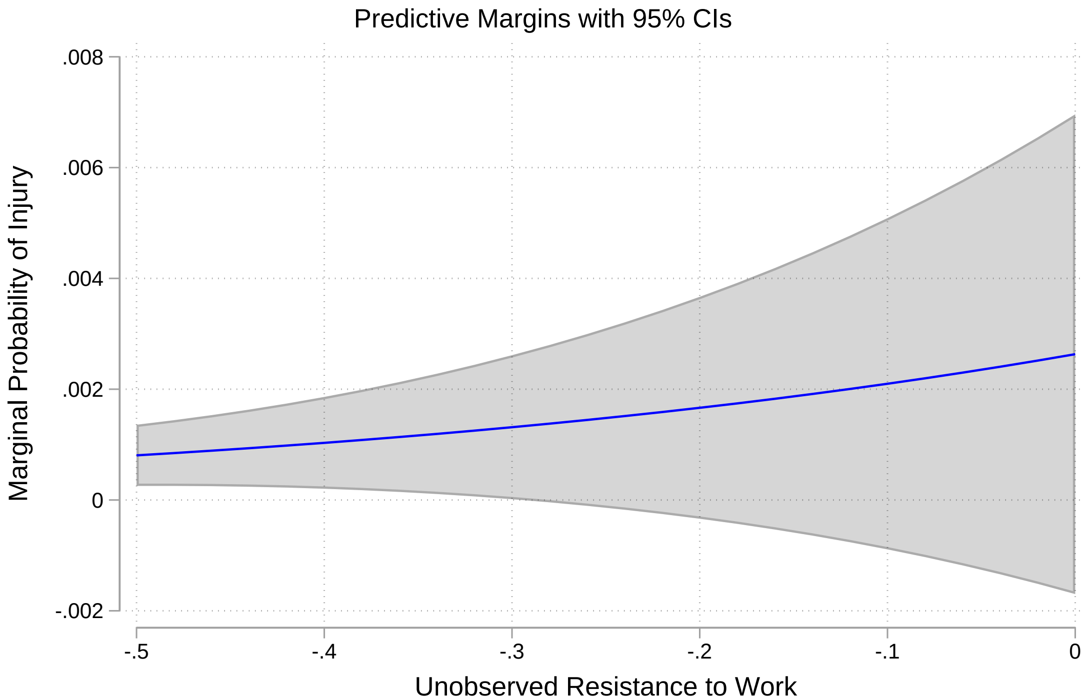


The figure plots the distribution of willingness to pay for a 1/553 reduction in risk. The unit of observation is officer-day. The Epanechnikov kernel is used to estimate the density. The distribution is two-peaked. There is significant heterogeneity in willingness to pay.

Figure 8: Simulated Injury Rate Distributions

The figure plots the simulated distribution of the injury rate under three different overtime assignment mechanisms. The full information mechanism is the ideal case, when a planner assigns shifts to the officers with the lowest risk. The random list mechanism is similar to the mechanism currently used by the City of Los Angeles, where shifts are given randomly to everyone who volunteers. The shift auction assigns extra shifts to the officers who bid the lowest wage. The simulated distributions use 1,000 draws. The plot shows that the shift auction mechanism is much closer to the full information benchmark than the list mechanism.

Figure 9: Average Marginal Probability of Injury



The figure plots the marginal probability of injury for different unobserved resistances to work. The marginal probability of injury is the injury probability of an officer given that the officer is indifferent between working and not working. MPI rises with resistance to work, indicating that there is selection against injury risk: officers desire to work declines hen they are more likely to be injured.

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A Appendix

A.1 The Partial Likelihoods

$$Pr(y_{it}=1|w_{it}=1,Z_i) = \frac{1}{\Phi(Z'_{it}\alpha+\zeta_1+\bar{z}'_i\gamma_1)}\int_{-\infty}^{Z'_{it}\alpha+\zeta_1+\bar{Z}'_i\gamma_1}\Phi\left(\frac{\zeta_2+X'_{it}\beta+\bar{Z}'_i\gamma_2+\rho v}{(1-\rho^2)^{-1/2}}\right)\phi(v)dv$$

$$Pr(y_{it}=0|w_{it}=1,Z_i) = \frac{1}{\Phi(Z'_{it}\alpha+\zeta_1+\bar{z}'_i\gamma_1)}\int_{-\infty}^{Z'_{it}\alpha+\zeta_1+\bar{z}'_i\gamma_1}\left[1-\Phi\left(\frac{\zeta_2+X'_{it}\beta+\bar{Z}'_i\gamma_2+\rho v}{(1-\rho^2)^{1/2}}\right)\right]\phi(v)dv$$

$$Pr(w_{it}=1|Z_i) = \Phi(Z'_{it}\alpha+\zeta_1+\bar{Z}'_i\gamma_1)$$

$$Pr(w_{it}=0|Z_i) = 1-\Phi(Z'_{it}\alpha+\zeta_1+\bar{Z}'_i\gamma_1)$$

Table A.1: Model Parameters with Sick Time Excluded

	Injury	Work
Avg. Wage	-0.0343	-0.152***
	(0.0620)	(0.0156)
Avg. Age	-0.0213	0.0212*
	(0.0408)	(0.0103)
Avg. Cum. Potential Contacts	0.00169*	-0.00126
	(0.000682)	(0.000843)
Avg. Leave (No Sick)	-0.0813***	0.0334***
	(0.0136)	(0.00992)
Age	0.0227	-0.0189
	(0.0404)	(0.0103)
Holiday	-0.655**	1.716***
	(0.248)	(0.132)
Amount Rain (in.)	-0.135	-0.00620
	(0.126)	(0.0216)
Max. Daily Temp.	-0.000235	-0.000101
	(0.00289)	(0.000453)
Wage	0.0469	0.151***
	(0.0624)	(0.0135)
Division Leave (No Sick)		0.0247***
		(0.00309)
Cumulative Officer Potential Contacts		0.00197*
		(0.000771)
Seniority Rank		0.00151
		(0.000784)
Observations	259861	
Rho	-0.603	
Rho 95% CI	(-0.12, -0.857)	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table displays results of a number of robustness analyses. The first row provides the reference values from the primary specification. The second row removes sick time from the leave instrument. The third row does consider strains to be non-injuries. The fourth through sixth rows recode injuries with medical expenditures less than different amounts as non-injuries. Estimates of ρ remain negative across all specifications. Estimates remain significantly different from 0 in all specifications except the analysis which does not consider strains injuries. Thus the finding that marginal probability of injury is increasing in resistance to work is robust to several alternative specifications.

Table A.2: Robustness Analyses

	Leave Coef.	Coef SE	Rho	Rho SE	%. Incr.	% SE
Base Model	0.0189	0.0024	-0.6233	0.1782	-0.8521	0.1440
Sick Time Excluded from Leave	0.0247	0.0031	-0.6035	0.1883	-0.8358	0.1581
Strains Not Considered Injuries	0.0189	0.0024	-0.5676	0.3368	-0.8238	0.2899
Med Exp $\leq$0 Not Injury	0.0189	0.0024	-0.7220	0.1257	-0.9285	0.0749
Med Exp $\leq$200 Not Injury	0.0189	0.0024	-0.7386	0.1153	-0.9387	0.0637
Med Exp $\leq$400 Not Injury	0.0189	0.0024	-0.7407	0.1208	-0.9417	0.0645

Table A.3: Variation Descriptions

Work	Leave	Other
ADJUSTMENT PERMANENT VARIATION IN RATE	100% SICK TIME (CREDIT OR CHARGE)	100% SICK TIME BALANCE PAID AT RETIREMENT
CURRENT ACTUAL HOURS WORKED ONLY	75% SICK TIME (CREDIT OR CHARGE)	50% SICK TIME BALANCE PAID AT RETIREMENT
DAY SHIFT HOURS WORKED	ABSENT WITHOUT PAY (POS OR NEG)	ADJUST VACATION EARNED BALANCE (+) OR (-)
HOLIDAY HOURS (CREDIT OR CHARGE)	ABSENT WITHOUT PAY - BANKED EXCESS SICK TIME	ADJUST VC MAX BALANCE (-) WAIVED
LIGHT DUTY RETURN TO WORK PROGRAM	ABSENT WITHOUT PAY - CPTO	BANKED EXCESS SICK TIME - PAID AT TERMINATION/RETIREMENT
NIGHT OR GRAVE PAY 5.5% NOT FOR SWORN	ABSENT WITHOUT PAY - FAMILY ILLNESS ¿ 40.0 HOURS	BANKED EXCESS SICK TIME - TIME OFF
OVERTIME (1.0) WORKED AND PAID	ABSENT WITHOUT PAY - FAMILY LEAVE-C CLASS	BIKE/WORK NON-TAX REIMBURSEMENT
OVERTIME (1.5) WORKED AND PAID	ABSENT WITHOUT PAY - FLOATING HOLIDAY	BIKE/WORK TAXABLE REIMBURSEMENT
OVERTIME WORKED (1.5)	ABSENT WITHOUT PAY - OVERTIME OFF 1.5	BONUS OR MARKSMANSHIP
OVERTIME WORKED (STRAIGHT)	ABSENT WITHOUT PAY - PREVENTIVE MEDICINE ¿ LIMIT	CALIFORNIA STATE TAX ADJUSTMENT (POS OR NEG)
PAID OVERTIME (HOLIDAY 1.5)	ABSENT WITHOUT PAY - SICK LEAVE	CASH-IN-LIEU PAYMENT
SEDENTARY DUTY	ABSENT WITHOUT PAY - VACATION	CATASTROPHIC TIME TRANSFERRED FROM BANK TO RECEIVING EMPLO
TEMPORARY VARIATION IN RATE - UP	ADDITIONAL BEREAVEMENT LEAVE OUT OF SICK TIME	CATASTROPHIC TIME USED BY CIVILIAN FROM CATASTROPHIC
	ADMINISTRATIVE LEAVE WITH PAY (POS OR NEG)	CPTO - CHANGE PERMANENT BALANCE + OR -
	BEREAVEMENT LEAVE (POS OR NEG)	CURR YR IOD CONVERSION ADJUSTMENT
	CPTO - COMPENSATED PERSONAL TIME OFF	ELECTRONIC PARKING SENSORS
	DECEASED EMPLOYEE / HOURS DID NOT WORK	FEDERAL TAX ADJUSTMENT (POS OR NEG)
	FAMILY ILLNESS (POS OR NEG)	FICA/MEDICARE YTD WAGE ADJUSTMENT (POS OR NEG)
	FML USING 1.0 BANKED OT	FLOATING HOLIDAY ACCRUED HOURS BALANCE (REPLACE)
	FML USING 1.5 BANKED OT	FLOATING HOLIDAY HOURS TAKEN THIS PAY PERIOD
	FML USING 100% SICK	Floating Holiday Lost
	FML USING 75% SICK	GROSS WAGE ADJUSTMENT
	FML USING FAMILY ILLNESS	NEW HIRE CODE / HOURS NO PAY IN INITIAL PAY PERIOD
	FML USING FLOATING HOLIDAY	OVERTIME (1.5) BALANCE PAID AT TERMINATION/RETIREMENT
	FML USING HOLIDAY	OVERTIME (STRAIGHT) BALANCE PAID AT TERMINATION/RETIREMENT
	FML USING VACATION	OVERTIME PAYMENT CONVERTED FROM OT (1.5)
	FML WITHOUT PAY	PMT OF EXES SICKLEAVE OVER 800 HRS AT 100% PAID AT 50
	JURY DUTY	PRIOR YR IOD CONVERSION ADJUSTMENT
	LEAVE WITH PAY (POS OR NEG)	PROFESSIONAL DEVELOPMENT STIPEND
	LEAVE WITHOUT PAY (POS OR NEG)	REDUCTION FROM TERMINATION PAYOUTS BAL OWED- CURR YR IOD CONV ADJ
	MILITARY LEAVE WITH PAY (POS OR NEG)	REDUCTION FROM TERMINATION PAYOUTS BAL OWED- PRIOR YR IOD CONV ADJ
	MILITARY LEAVE WITHOUT PAY (POS OR NEG)	REFUND DEDUCTION
	NET IOD (POS OR NEG)	SETTLEMENT
	OVERTIME TAKEN OFF (1.5)	SICK 100% ACCUMULATED
	OVERTIME TAKEN OFF (STRAIGHT)	SICK 100% CURRENT
	PREVENTIVE MEDICINE (POS OR NEG)	SICK 75% ACCUMULATED
	SUSPENSION (POS OR NEG) / HOURS NO PAY	SICK 75% CURRENT
	UNION NEGOTIATION TIME	STRAIGHT MONEY ADJUSTMENT OR EMPLOYEE EARNINGS (PO
	UNION RELEASE TIME	TERMINATION CODE / HOURS NO PAY
	VACATION (POS AND NEG)	TRANSIT BENEFIT ADJUSTMENT DOLLAR AMOUNT (NET PAY BENEFIT)
	WORKERS' COMPENSATION (POS OR NEG)	TRANSIT SPENDING SUBSIDY POSTTAX
		TRAVEL ALLOWANCE
		UNIFORM ALLOWANCE
		VACATION BALANCE PAID AT TERMINATION/RETIREMENT
		W2 MEDICAL SUBSIDY ADJUSTMENT
		YTD IMPUTED GROUP TERM LIFE - W2

The table lists the way each Variation Description is categorized. Variation Descriptions are pay codes describing the reason for payment. “Work” codes are used to construct hours worked and determine which days were worked. “Leave” codes are used to construct the leave instrument.

Table A.4: Fixed Effects IV: Testing Instrument Validity

	(1)	(2)	(3)	(4)
work	0.00271***	0.00244***	0.0101**	0.00458*
	(0.000340)	(0.000304)	(0.00362)	(0.00229)
N	259861	259861	259861	259861
Underid K-P LM-stat	340.5	347.0	36.67	64.04
C-G F-Stat	20617.6	22900.0	230.6	506.6
Weak id. K-P F-stat	1167.4	1191.9	13.47	26.31
Hansen J	5.189	2.995	0.929	.
Hansen J p	0.0747	0.224	0.628	
Division FE	No	Yes	Yes	Yes
Day of Week/Month FE	No	No	Yes	No
Date FE	No	No	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table displays estimates from a fixed effects instrumental variables regression. Work is instrumented with leave of coworkers, seniority and cumulative potential contacts. Column 4 is called the proxy model in the paper, as it denotes the model which would have been estimated if the outcome was continuous. Several weak instrument and overidentification tests are displayed under the coefficient estimates. Each column adds additional controls. Standard errors are clustered at the officer level.

B Data Cleaning and Population Definition

The analysis population is limited to all officers with at least one work-related pay record between January 1, 2015 and September 1, 2016.

1. **Part-Time Officers:** I exclude officers which had more than 3 periods of part-time work (defined as having less than 60 hours of leave and work hours in a 4 week period).

2. I exclude non-work officer-days that occur after an injury but before the first day worked after injury. I also exclude the first day worked after injury. The idea is that the decision to return to work after an injury is a separate process. The days off work may be medically required. The first day returned also is part of the worker's compensation process and not subject to the normal labor supply decision process.

3. 10 injuries occurred on dates without positive work hours. 4 of these injuries are associated with the day prior (it appears that the work may have crossed over midnight). 6 injuries are assumed to have happened immediately, and the date is considered worked.