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

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Abstract

We employ a novel data set of 219,000 workers' compensation claims and pay records to understand whether traffic officers account for injury risk when making daily labor supply decisions. We use variation in the leave of coworkers as an instrument inducing officers to work. We find that officer appear to mitigate their own injury risk: on average an officer at the 60th percentile of willingness to work is 2.6 times more likely to be injured as an officer at the 60th percentile. Using variation in hourly wages, we also calculate the marginal value of injury risk, defined as the value of a 1 percentage point reduction in injury probability for officers that are indifferent between working and staying home. A 1 percentage point decrease in injury risk is valued on average between $31 and $67 in earnings. Using our model, we simulate the benefits of switching to a shift-auction mechanism of shift assignment. We find that shift auctions more fully leverage officer's natural tendency to select against risk, and as a result reduce the injury rate by 38 percent compared to a random list mechanism.

1 Introduction

This paper is motivated by a puzzle observed in a long panel of Los Angeles Traffic Officers: officers that tend to work more tend to be injured less. This is true even if we ignore the time after the injury. At face value, this contradicts the conventional wisdom, that more time at work increases the probability of workplace injury. Numerous studies in both economics and epidemiology document a positive association between workplace injury and excessive work. Our paper suggests a simple story that reconciles the puzzle with past literature: self-selection.

Theoretically, this story is compelling. Individuals have private information about their own health status and their ability to work safely on any given day. As an example, parents may have had a particularly sleepless night caring for a newborn. As long as the disutility of injury outweighs any workers compensation and leisure benefits, individuals will have an incentive to mitigate risk. On the other hand, recent developments in behavioral economics suggest individuals do not always behave rationally in the expected utility sense when it comes to low-probability outcomes.(Barberis 2013) In the setting of public safety, the way in which selection would work is even less clear. People that choose public safety careers could be more risk-loving, and as a result they may prefer to work even when they have high injury risk.

In light of these ideas, we seek to answer the following questions in this paper: How do individuals trade-off injury risk with extra pay when making the decision to work additional shifts? Do they account for their own injury risk, or are they myopic? If there is selection, how can the mechanisms used to assign shifts best take it into account?

To answer these questions, we consider the case of Los Angeles Traffic Officers. Using detailed daily pay records from a one and a half year period we examine how officers choose to work shifts and how this selection impacts injuries filed as workers' compensation claims. In general, factors unobservable to the analyst but observable to the officer will impact both the decision to work and workplace injury. To address this problem we employ an identification strategy which takes number of coworkers on leave as an instrument in the work decision.[1]

Using this identification strategy, we specify and estimate a discrete choice panel data model, which captures the decision to work while also allowing for nonrandom selection. The specification permits unobservable correlation between the determinants of the work decision and injury outcome. Parameter estimates confirm the presence of positive selection in terms of both observable and unobservable factors: officers are more likely to work when injury is less likely. I quantify the magnitude of the selection graphically, and show that it is economically meaningful.

Finally, I use this model to compute a willingness to pay metric, which I interpret as the Los Angeles Traffic Officer's *marginal value of injury risk.* I find, despite significant evidence of positive selection, officers are quite willing to trade injury risk for small amounts of money. On average, officers value a 1 percentage point increase in injury risk between \$31 and \$67. I use this idea to motivate a simulation examining the effect of shift auctions n injury rates. I find assigning additional shifts using auctions more fully leverages officer's tendency to avoid risk, and reduces overall injury rates by 38 percent.

This paper is organized as follows. First we review the multidisciplinary literature on overtime and injury. We place our paper within this context and establish its contribution. Next we discuss our data and the institutional details of the traffic officers. We then introduce the labor supply model and estimate it. In the discussion section we put our results in context and apply them to calculate the implied value of injury risk

[1] I also use changes in seniority rankings as an instrument, but leave of others turns out to be the strongest instrument.

and the benefits of shift auctions.

2 Literature Review

In this section, I review three relevant strands of literature. The first strand is the *value of health risks* literature. This encompasses papers estimating the value of a statistical life as well as studies examining the revealed preferences over health risks that are not fatal. The second strand is the *workers' compensation* literature. The third strand is the *injury risk* literature, which is based mainly in epidemiology. These papers estimate the associations between injury and overtime across different populations.

2.1 Value of Health Risks

The oldest question in this literature is evaluating how people value their life, famously known as the calculation of the *statistical value of life (VSL)*. All VSL papers take a similar approach: examine choices of individuals or groups between two options with differing fatality risk, and use the difference in compensation to infer the VSL. The difference is in which choices they examine, and which groups they consider.

Ashenfelter and Greenstone 2004 examine the implied VSL from the adoption of speed limits by states. They consider a representative voter who trades-ff time savings for fatality risk. They recover a state-level VSL of $1.5 million per fatality. An earlier methodology involves looking at the risk premium associated with more risky jobs. As described in Viscusi and Aldy 2003, this usually involves estimating wage regressions and examining the coefficient on fatality risk, which is sometimes called the *compensating wage differential*. Implicitly, this is looking at the revealed preferences of occupation choice, where occupation is a lottery over money and death. Interestingly, a major confounding issue in this literature is dealing with self-selection by unobserved type. More risk loving individuals tend to select into risky occupations. Not accounting for this self-selection will cause an underestimate of the overall VSL.

Some more recent papers have dealt with this confounding directly. One example is León and Miguel 2017, which studies transportation choices to the airport in Sierra Leone. They make the argument that there is little self-selection into the decision itself because if one wishes to travel they must get to the airport. They explicitly invoke a revealed preference framework, and use a mixed logit specification to get a VSL of $577,000 for African travelers.

It is also possible that individual choices over risk may have externalities. In the VSL literature, Li 2012 calculate the VSl implied by demand for light-trucks, which confer a safety benefit to the user but an accident severity cost on society. They estimate a $244 million externality imposed by light truck purchases.

Finally, there is new work looking to find the *value of non-fatal injury*. This parameter is related to our study, since by definition most workers' compensation injuries are not fatal. Cameron and DeShazo 2013 find that VSL-type estimates for non-fatal injuries are significantly lower than that for fatal injuries, on the order of $3 million for non-fatal compared to $6.76 million for fatal.

2.2 Workers' Compensation

A key feature of my setting is that injury is proxied by workers' compensation claims. Because workers' compensation is a form of insurance against risk, there is the potential for moral hazard in choice behavior, both in terms of reporting an injury and in terms of returning to work. The marked increase in strains and less verifiable injuries in the 1990s led to a concern over workers' compensation costs, especially because it is well known that strains or "soft-tissue" injuries are hard to verify.

Butler, Durbin, and Helvacian 1996 attribute nearly 30 percent of the rise in soft-tissue claims in the 1980s to moral hazard, that is the increased incentive to report an injury when there is little ability to verify the injury. Bronchetti and McInerney 2012 find that using more recent data, and controlling for past earnings results in little sensitivity of claims to benefit levels. On the other hand, the same author finds that when examining the consumption smoothing objective of workers' compensation, it seems that benefits are higher than optimal (Bronchetti 2012). This suggests that workers' compensation benefits replace more than lost counterfactual income.

A working paper by Cabral and Dillender 2020 use a sharp increase in benefits in texas to examine worker behavior. They find no claim response but large changes in claim duration and expense. Interestingly, they perform a welfare analysis and find that increasing benefits does not result in higher welfare.

2.3 Overtime and Injury Risk

There is a large number of studies, most outside of economics, looking at associations between some definition of overtime or excessive hours and injury. Wooden, Warren, and Drago 2009 summarizes this body of research well by noting that most studies involve specific populations (as this one does) and have mixed results depending on the outcome and the level of care taken to control for confounding influences. Wooden does state that among nationally representative samples there does seem to be a positive relationship between excessive hours (defined differently depending on the study) and workplace injury. Many of these studies lack a clear identification strategy, and as a result they do not account for any type of selection into overtime.

An influential, nationally representative study in this vein is Dembe et al. 2005. They employ survey data from the NLSY where respondents answered questions related to their work. Dembe et al. find a statistically significant association between overtime work in general and extended hour schedules in particular with injury. Specifically, they find a 61 percent higher injury hazard rate for those working "overtime" schedules, a 23 percent higher injury hazard rate for those working 60 or more hours a week, and a 37 percent higher injury hazard rate for those working 12 or more hours in a day. These results were derived using a Cox proportional hazard model.

3 Contribution

My approach and data allow me to contribute to all three of the strands of literature mentioned above. Because my research design explicitly accounts for selection, it contributes to the overtime and injury literature by establishing whether selection causes large biases in observed injury rates. My results indicate that selection is positive, which means that observational studies that do not account for selection will generally underestimate the true impact of overtime on injury because the individuals who choose to work tend to be at lower risk. Within the VSL and value of health risks literature, I will contribute another estimate of the implied value of nonfatal injury. With respect to the workers' compensation literature, this paper provides evidence that workers' compensations programs do not generally remove the incentive to avoid injury. This is important for policymakers considering whether or not to worker's compensation systems.

4 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.

4.1 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.[2] According to this document, they are overtime non-exempt employees under the Fair Labor Standards Act (MOU, 28), meaning they are paid not less than 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

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

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 at least 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). According to the MOU, employees may choose to accumulate overtime pay in the form of additional paid time off rather than cash compensation (MOU, 29). Beyond the normal methods of gaining overtime pay, the MOU details that traffic officers may be assigned to work "special events" and would be paid at the overtime rate for these events (MOU, 29).

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). This is taken to mean that in theory, workers cannot add additional hours to their shift unless authorized. In my empirical approach, I use this to justify the assumptions that actual hours worked on a given day are exogenous.

The Memorandum also outlines payment guidelines surrounding minimum payments and "early report" pay. The city is required to pay a minimum of four 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).

The data do not contain information on how overtime shifts are assigned. We only have the statements form the MOU and some personal knowledge about common practices in public-safety overtime assignment. I believe that overtime is likely assigned using some form of rotating list, where it is offered to people at the top of the list first, and if rejected, the next person, etc. This is because overtime is often a desired commodity to supplement income. If no one takes the overtime, then the person on the top of the list is required to take the overtime. This is called being "forced." To achieve fairness, the list is likely rotated based on overtime taken in the past. The list may also be partly a function of seniority. I will assume this methodology in my modeling and discussion.

An attempt was made to reach out to the Los Angeles Department of Transportation for information about overtime assignment and shift structure. In particular, I am making an effort to verify the structure assumed in the last paragraph. At the time of writing there has been no response.

4.2 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[3], 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 1 below 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 associated number of hours, the amount of pay, the rate of pay, the division worked, and other descriptions of the type of pay, in particular *Variation Description.* 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.[4][5] This is because these employees have very irregular schedules. Next, I exclude officers who are injured with *Claim Cause* of criminal. I include only officer-days where the officer works or does not work, and exclude days where they take leave. The reason for this is

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

[4]The methodology for determining who is part-time is listed in the Appendix.

[5]I do include these employees in my measures of leave worked by others in division.

that I wish 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 and 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.

Among the working sample, the Tables 2 and 3 present the distribution by Claim Cause (reason for injury) and nature of injury (type of injury). Table 4 contains labor supply statistics on the intensive margin: hours worked daily. Table 5 contains labor supply statistics on the extensive margin: days worked in four-week periods.

From the labor supply tables two things are apparent. First, the extensive margin has much more variation than the intensive margin. 78% of shifts are 8 hours or less, but the probability of working 16 out of 28 days is about the same as working 22 out of 28 days (5 percent). Second, it seems to be that employees who experience injury tend to work less, not more, than those who do not. This turns out to be true even if I exclude all four week periods after injury and the final four weeks that includes 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 6 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 inline with the fact that most parking meters in Los Angeles allow free parking on Sunday, 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 8 contains aggregate pay statistics, including rates and typical weekly pay amounts, and what percentage of pay is overtime-related pay. Wages are quite compressed, with most individuals making 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 have 0 percent overtime pay, while 10 percent have more than a 33 percent overtime pay. Again these statistics indicate that much of the variation is occurring at the shift-level.

5 Model and Empirical Strategy

To help interpret the observed selection, I propose the following stylized model of the work decision, which is inspired heavily by Semykina and Wooldridge 2018. Denote Z_{it} as factors impacting the utility from work for individual i at time t. Denote X_{it} as factors impacting injury probability, which are a subset of Z_{it}. To be specific, X_{it} contains age, an indicator for federal holidays, the amount of precipitation, daily maximum temperature, seniority rank, the most current hourly wage, fixed effects for division, and fixed effects for day of the week and month of the year. Z_{it} includes all of these along with the number of other officers in the division on leave and seniority rank. I include the leave of others in utility because when more people in an officer's division go on leave, it becomes relatively more costly to choose not to work.

I normalize the utility from not working a shift to 0. An officer decides to work if expected utility from work exceeds 0, that is:

$$E[U_i(Z_{it}, Y_{it})|w_{it} = 1] \geq 0$$

For elements that are in both X_{it} and Z_{it}, there are two effects on the work decision. One is direct: these elements change the utility from work relative to not working by the amount β. The other is indirect: these elements change the expected probability of injury. I impose linearity of utility in the parameters and the unobserved taste shocks:

$$U_i(Z_{it}, Y_{it}) = Z_{it}\alpha + v_{it1}$$

I denote injury as y_{it} and model it as given by:

$$y_{it} = \begin{cases} 1 \text{ if } X_i'\beta + c_{i2} + u_{it2} \geq 0 \\ 0 \qquad \text{otherwise} \end{cases}$$

where note that y_{it} is assumed only to be observed if $w_{it} = 1$. That is, we have Heckman-style selection.

5.1 Identification

Prior to proceeding, it is worth commenting on identification. The above model, even with the assumed additive structure, is difficult to identify without parametric assumptions due to the following reasons:

1. It features non-random sample selection.

2. It features two sets of individual "fixed effects" which cannot be removed by differencing due to the non-linear (latent variable) structure of the outcome.

3. The primary outcome, injury, occurs infrequently, and as a result predicted probabilities should be close to 0.

The third issue implies that using a linear probability model is not a valid option, as the estimates will likely be inconsistent.[6] On the other hand, there are few constructive identification results for panel binary outcome sample selection models. However, if one views the unobserved term $c_{i1} + u_{it1}$ as the individual error, and instead consider an i.i.d. cross-sectional sample, there are many more identification results. In particular, if there is a *joint exclusion restriction*, that is one variable which only affects work and one which only affects injury, then Lee and Salanié 2018 show that non-parametric identification can be achieved even if the selection outcome (work) is not observed.

Unfortunately, we only have one exclusion restriction, but we do observe the selection decision. If I assume the following:

1. $(c_{i1} + u_{it1}, c_{i2} + u_{it2})$ is independent of (x_i, z_i)
2. $(c_{i1} + u_{it1}, c_{i2} + u_{it2})$ is symmetrically distributed around 0.
3. There exists one element of w_{it} that is excluded from x_{it}.

then Chen, Zhou, and Ji 2018 prove constructively that a more general panel data selection model (of which our model is a special case) is identified. Thus, our model is semi-parametrically identified given an excluded instrument. The authors suggest an estimation procedure, but because we wish to utilize the panel nature of our data, and injury is observed so infrequently, we choose to impose the following stronger parametric assumptions, with the understanding that identification does not rely on them.

The assumptions we make follow those outlined in Semykina and Wooldridge 2018. For the individual specific heterogeneity, we assume a Mundlak-Chamberlain device:

$$c_{i1} = \zeta_1 + \bar{z}_i'\gamma_1 + a_{i1} \tag{1}$$

$$c_{i2} = \zeta_2 + \bar{z}_i'\gamma_2 + a_{i2} \tag{2}$$

This yields the below set of equations to be estimated:

$$y_{it} = \begin{cases} 1 \text{ if } \zeta_2 + X_{it}'\beta + \bar{z}_i'\gamma_2 + a_{i2} + u_{it2} \geq 0 \text{ if } w_{it} = 1 \\ 0 \qquad \text{otherwise} \end{cases}$$

[6] The predicted probabilities will likely lie below 0, but consistent estimates from LPM require $0 < X_{it}'\beta < 1$ almost surely.

$$
w_{it} = \begin{cases} 1 \text{ if } Z'_{it}\alpha + \zeta_1 + \bar{z}'_i\gamma_1 + a_{i1} + u_{it1} \geq 0 \\ 0 \qquad \text{otherwise} \end{cases}
$$

Secondly, we invoke a joint normality assumption. Denote $v_{it1} = a_{i1} + u_{it1}$ and $v_{it2} = a_{i2} + u_{it2}$. Assuming v_{it1} and v_{it2} are independent of z_i and distributed as:

$$
\begin{pmatrix} v_{it1} \\ v_{it2} \end{pmatrix} \sim N\Bigg(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \Bigg)
$$

This assumption yields that $v_{it2}|v_{it1}, z_i \sim N(\rho v_{it1}, 1-\rho^2)$. With this in hand, I condition on v_{it1} and substitute ρv_{it1}, then integrate v_{it1} because it is unobserved. This process, outlined in Semykina and Wooldridge 2018, yields that the below probabilities which can be used to construct the partial likelihood:

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

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

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

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

The model can then be estimated using partial maximum likelihood, without specifying the dependence in the errors across periods. Fortunately, Semykina and Wooldridge 2018 points out this partial maximum likelihood estimator is essentially a pooled Heckman-Selection estimator for a binary outcome. As a result, the model can be fit using STATA's 'heckprobit' command with the addition of time means $\bar{z}_i$.

In our setting, x_{it} includes a federal holiday indicator, age, amount of rain in inches, the maximum daily temperature, the officer's wage,[7] division fixed effects (with small divisions grouped together), day of the week fixed effects and month fixed effects. z_{it} includes all elements of x_{it}, along with division leave of others (the count of other employees in the division on leave) and seniority rank in division. $\bar{z}_i$ includes officer-specific time averages of division leave of others and wage. Seniority rank was excluded from $\bar{z}_i$ as were all of the fixed effects because they did not vary enough across time, and thus cause co-linearity problems.

[7] 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.

The main assumptions of identification and estimation can be summarized as:

1. All structural equations presented in this section hold.

2. $(v_{it1}, v_{it2}) \perp\!\!\!\perp z_i$, with (v_{it1}, v_{it2}) jointly normal with unit variances conditional on z_i.

3. $dim(z_{it}) > dim(x_{it})$.

where, as discussed earlier, we can drop the normality portion of the second assumption and still achieve identification. As Semykina and Wooldridge 2018 point out, any variables which are time invariant are not identified unless they are conditionally independent of the individual heterogeneity. In my application, it is also true tenure effects cannot be distinguished from age effects, as tenure and age rise at the same rate over time.

Before proceeding, we take a moment to consider the interpretation of the structural parameters. To do so, examine the fully expanded expression for utility from work:

$$E[U_i(Z_{it}, Y_{it})|w_{it} = 1] = \zeta_1 + Z_{it}'\alpha + \bar{z}_i'\gamma_1 + a_{i1} + u_{it1}$$

$a_{i1} + u_{it1}$ conditional on z_i is correlated with injury, Y_{it}, and the strength of this correlation is captured by ρ. Because $a_{i1} + u_{it1}$ are assumed observed by the officer, we can think of ρ as measuring the total of two effects:

1. **Unobserved Type Correlation:** Time invariant characteristics that are unobserved that effect both injury and the decision to work. For example, perhaps officers with low amounts of savings have a higher desire to work, but also have less money and time to go in for preventative medical check-ups. This would manifest as correlation between a_{i1} and a_{i2}.

2. **The knowledge effect:** Officers may have additional information about their own propensity to be injured (beyond what is recorded in the data) on a given day that they account for in deciding whether to work. For example, perhaps their kids kept them up late into the night, and they are sleep deprived. This would manifest as correlation between u_{it1} and u_{it2}.

ρ captures the net effect of these two forces, and if it is positive, it means that observables constant, there is *selection on injury:* officers with a higher propensity to be injured are more likely to work on a given day. If it is negative, officers in a sense *internalize* their unobserved injury risk, perhaps because increased injury probability reduces expected utility. $\zeta_1 + \bar{z}_i'\gamma_1 + a_{i1}$ captures time invariant propensity to work, which in our static model include things like the value of leisure, the value of additional consumption. It can also be interpreted as similar to the fixed effects present in linear models.

5.2 Instrument Validity

It is important the main instrument we employ has significant variation. Table 7 contains summary statistics of the main instrument - the number of officers on leave by division. It provides summary statistics at the level of variation: division-day. The mean across divisions is quite different, indicating that there is significant spatial variation. The standard deviation relative to the mean is also quite large in each division, indicating that there is significant across-time variation.

The main assumption underlying identification without invoking normality is that leave of others in division is a valid instrument. In terms of the selection model, this requires that:

1. **Relevance:** Leave of others increases the probability that all officers work. In terms of the model, this manifests as the coefficient on leave in the work decision being positive and non-zero.

2. **Exclusion/Independence:** The leave of other officers does not directly increase injury risk. In terms of the model, this manifests as leave being independent of v_{i2} and not appearing in the injury equation.

I begin with the exclusion assumption. Conditional on X_{it} and $\bar{z}_i$, 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, we 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 we control for these holiday and seasonal 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 we 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.

We 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, we 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, we implement an instrument validity test that is meant for continuous outcomes. First, we implement a modified version of the test designed in Semykina 2012. The procedure uses a flexible control function method to correct for selection. In our implementation, we use the semi-parametric estimator proposed in Gallant and Nychka 1987 for the selection equation and then insert the selection correction into the outcome equation using a linear spline with 5 knots. We then test whether the instruments from the selection equation, in our 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 supports instrument validity. The test returns a J-statistic of 5.273 and a p-value of 0.0716. Therefore we fail to reject the null hypothesis at the 0.05 level.[8]

Another way to informally check instrument independence is to examine the balance of additional officer-day characteristics across values of the instruments. One such variable is *medical expenses paid*, which is an additional variable included in the workers' compensation data for each documented injury. Medical expenses are a loose proxy for the seriousness of injury: injuries with *Claim Cause* "Repetitive Motion - Other" had an average expense of $2,726, while those with "Collision or Sideswipe" had an average expense of $3,385. In theory, leave of others should increase the probability of injury occurring by inducing people to come into work. There is little reason to believe that leave of others should impact the magnitude of the injury. If leave of others does impact medical expenses among those injured, then there is reason to suspect the exclusion restriction. In Table 10, I regress medical expenses paid on the leave instrument with different sets of controls. In all specifications, the coefficient on leave is not statistically significant at the 0.05 level.

Next I discuss instrument relevance. Officers vary substantially in their number of shifts worked, as can be seen in Table 5. Since the Memorandum of Understanding requires equitable allocation of overtime, it is reasonable to attribute a good deal of this variation to officer choice. Given this, the question remains: does leave within a division induce officers to work?

Theoretically, if LADOT at least partially substitutes officers on leave for off-duty officers, then the answer is yes. Consider the list mechanism described early for assigning additional shifts. If more individuals call out sick or for bereavement, the supervisor will need to go farther down the list to fill empty positions. Even if an officer declines to work voluntarily, a higher number of positions to fill implies a higher probability he/she will be "forced." As a result, work probability should rise with the number of other officers on leave. To test this, we present F-statistics of linear probability model of work on the instruments in Table 9. All F-statistics are greater than 180. The coefficient on Division Leave (of others) is also highly significant in all specifications. Overall the table suggests instrument relevance is satisfied. This can also be seen graphically, in Figure 2. The scatter plot displays a clear positive association between the number of officers in a division on leave and the probability of working for non-leave officers.

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[8]The current test ignores the uncertainty and variance coming from the first-stage estimation of the selection correction. We plan to re-run the test and use a panel bootstrap to retrieve standard errors that account for the full procedure. It is highly likely that the current assumed asymptotic variance is underestimated, meaning our test will tend to over-reject the null hypothesis when it is true.

6 Model Estimation Results

The model parameter estimates are presented in Table 11. $\hat{\rho}$, the correlation between unobserved willingness to work and unobserved propensity to be injured (v_{i1}, v_{i2}) is negative. Monetary variables have a large positive coefficients: all else constant, a higher wage increases the probability of working on a given day. An indicator for whether a day was a holiday increases the probability of working on a given day, likely because there are premiums associated with working on these days. *Division leave*, which is adjusted to exclude own-leave, has a positive effect on the probability of working. The effect is also significant at the 5 percent level.

Table 12 displays the estimated probabilities of injury for under different conditions. These estimates are averaged across unobserved heterogeneity v_{it} and the observed values of the covariates. The first quantity, the model predicted injury rate conditional on working, is quite close to the observed injury rate (injuries divided by shifts worked): 0.0012 compared to 0.0013. The other estimates are counterfactual; they are never observed in the data. As a result, the standard errors are quite large, and they rely heavily on the normality of the unobserved v_i. The second statistic is the counterfactual probability of injury if it is assumed that everyone did not work. The injury rate is much higher, because of the negative correlation between the unobserved factors which influence injury and work. The third row is the injury probability conditional on observed work decision (that is, conditional on the work patterns we observe). The number quantifies the injury rate we would observe conditional on the v_i values implied by individual work decisions. The final statistic is the unconditional injury rate, and as expected it lies somewhere between the two prior numbers. This is the injury rate we would observe if we randomly selected an officer to work. Again, it is several times higher than the injury rate conditional on working.

Next we consider plots of the individual, time-constant heterogeneity along two dimensions: propensity to work and propensity to be injured. We specify individual heterogeneity using equations (1) and (2). Unfortunately, we cannot separate a_{i1}, a_{i2} from the individual time shocks u_{it1}, u_{it2}, and so only the relationship between $a_{i1} + u_{it1}$ and $a_{i2} + u_{it2}$ is known. We can still display the estimated portion of unobserved officer (time-constant) heterogeneity, which is given by the pair $\bar{z}_i'\gamma_1$ and $\bar{z}_i'\gamma_2$. These can be thought of as similar to individual fixed effects. A scatter plot of the estimates for all officers is displayed in Figure 3. The correlation coefficient of these estimates is -0.1546, meaning estimated heterogeneity is correlated in a similar way as unobserved heterogeneity: officers who tend to be injured also tend to be more reluctant to work.

In order to interpret the impact of various variables, I estimate probability elasticities. Table 13 displays the effect of a 1 percent change in wage, leave of others, and seniority rank on the probability of injury given the officer is already working. This metric removes the inducement effect (higher wages and more leave of others increases the probability of work) and focuses on the selection effect. Wage has the largest effect: a 1 percent increase in wage results in an estimated 12.42 percent increase in the conditional injury probability. The intuition is simple: as we increase the wage, officers with a lower unobserved willingness to work become willing to work. Since willingness to work (v_{i1}) is negatively correlated with unobserved propensity to be injured, the pool of people working increases in injury risk. Leave of others also has a positive effect, but it is smaller both in magnitude and significance. Table 14 accounts for the full effect of each variable on observed injury rates. As a result, all the elasticities are slightly larger, because each variable also increases the probability of working.

Negative $\hat{\rho}$ hints at our main result: officers select against injury risk, preferring to work when there is less injury risk. To be explicit, we graphically illustrate the probability of injury at various values of *Division Leave* in Figure 4. As the number of other employees on leave in division rises, the probability of injury conditional on working also increases. The positive slope of the line is indicative of positive selection: the more leave required to induce an officers to work, the more likely that officer is to be injured.

6.1 Marginal Probability of Injury

In this section, we formalize the idea of selection against risk by calculating an object we call the marginal probability of injury (MPI). Consider officer-days where officers are just indifferent between working and not working. That is, situations where $Z'_{it}\alpha + \zeta_1 + \bar{z}'_i\gamma_1 = v_{it1}$. Denote the left-hand-side as $\tilde{v}$. $\tilde{v}$ can be interpreted as unobserved resistance to work. We define the expected probability of injury among these individuals as *the marginal probability of injury*, or $MPI(x_{it}, \tilde{v}, i)$, which given our model can be expressed as:

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

Because $\hat{\rho} < 0$, the sample analogue of this function is increasing in $\tilde{v}$ for all x, i. This reflects the fact that officers with a higher resistance to work are more likely to be injured. The derivative of this function with respect to $\bar{v}$ can be calculate analytically as:

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

To summarize MPI across time and the population we construct the average MPI, defined as: $\bar{M}PI(\tilde{v}) = E_{x,i}[MPI(x, \tilde{v}, i)]$. Similarly we define the average derivative of MPI. We can approximate these by replacing the expectation with the sample analogue, and averaging across all officer-days. These functions are plotted for various resistances in Figures 7 and 8 respectively. The MPI plot is over the range $[-1, 0]$ because values outside this range either asymptote to 0 or have such wide error bands that they obscure the rest of the plot. The upward slope of the MPI function indicates the direction of selection: the higher an officer's resistance to working (or the lower their willingness to work) the higher their probability of injury. The derivative plot is zoomed in on the range $[-1, -0.6]$ to show the portion of resistance over which the marginal probability of injury is increasing in a statistically significant way.

We can get a sense of how much officer self-selection matters by comparing average MPI when $\bar{v} = -0.2533$ and $\bar{v} = -0.8416$. Intuitively, this is comparing an officer who is at the 60th percentile in terms of willingness to work with an officer at the 80th percentile. The less willing officer (60th percentile, $\bar{v} = -0.2533$) is 0.09473 (95% CI [0.00634,0.183]) percentage points more likely to be injured.[9] Injury probabilities on any given day are rather small, so it is important to put this gap into perspective. 0.0377 is equal to 260% of the predicted risk of the more willing officer. Put another way, the officer who is less willing to work has a 2.6 times higher probability of injury.

7 Robustness

We perform several versions of our analysis to test sensitivity to assumptions and address potential threats to identification. First, we construct a more conservative version oft he leave instrument, which excludes sick time. We do this because there may be a 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. Another concern might be increased sick leave makes the remaining pool of officers on average more healthy. This new instrument will have considerably less variation, because sick time represents a fourth to a third of leave.[10] Appendix Table A.2 displays the model parameters using this new instrument. Notably, $\hat{\rho}$ only changes by a few hundredths. The coefficient on leave actually rises, which is the opposite of what we would expect if any of the concerns mentioned earlier were valid.

We proxy injuries with workers' compensation claims, but employees may be falsely reporting injuries to gain worker's compensation benefits. Claims are verified by medical professionals, but for hard to verify

[9] These percentiles were chosen because they are places where the average structural function is estimated with better precision, so the standard errors are tighter. Similar percentiles, like 50 and 70, yield just as large point estimates but have very wide confidence intervals.

[10] See Table 7

injuries, like strains and psychological injuries, over-reporting can still be a concern. If this is true, the selection we observe could just be because officers who are more likely to file false claims also prefer to work less. To address this, we estimate our model again with claims described as "Strains" not considered injuries. We also perform the analysis not counting claims with medical expenses paid under various thresholds as injuries. The idea here is that more expensive claims are more serious injuries, and more serious injuries are less likely to be falsely reported. We present $\hat{\rho}$, the coefficient on leave, and the increase in probability between an officer at the 60th and 70th percentiles of willingness to work in Table A.2. We also include these same statistics for the version of the model which excludes sick time.

Across all specifications, the coefficient on leave remains stable near 0.02. Considering strains not injuries does reduce $\hat{\rho}$ substantially, but it remains negative and the increase in probability between the 60th and 80th percentile of willingness to work remains substantial. There are 30, 43 and 76 claims with medical expenses less than or equal to \$0, \$200, and \$400 respectively. When these are re-coded as not injuries, the model registers greater unobserved selection. This suggests if there is bias in our original analysis, it is in the conservative direction: the presence of hard to verify injuries actually dampens selection effects. When claims with no medical expenses are not considered injuries, the change in probability from the 60th to 80th percentile of willingness to work is 0.0841 percentage points. This is much larger than the change calculated using the main model. Again, this suggests easy to fake injuries are actually dampening selection.

In future versions of this paper, we plan to analyze the robustness of the findings to violations of the normality assumption. We also plan to estimate a version of the model which allows for the variance to depend on the covariates. We will do this by specifying an exponential function for the variance and including it in the partial likelihood.

8 Discussion

There is good reason to think that much of the information officers use in assessing risk is private. Factors like personal health and sleeping habits the night before are not things supervisors or schedules know when deciding who should work. This paper suggests officers have incentives to act on this information. In this section, we extend our results to address two policy relevant topics: the value of non-fatal injury risk and the design of injury-minimizing shift allocation mechanisms.

8.1 The Value of Non-Fatal Injury Risk

The *value of non-fatal injury* is a notion which is similar in spirit to the value of a statistical life. To get at this measure, I will consider equivalent variation in wages. Intuitively, whenever we observe an officer not working when there are many other officers on leave in their division, that officer is forgoing expected wages. Given the negative correlation between (v_{it1}, v_{it2}), and assuming substitution effects dominate, we expect officers that are paid higher wages will be more willing to accept more injury risk.

Formally, an officer who 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 an expected shift in the mean of v_{it2} of $\rho\alpha_w q$. Since wage is also in the injury equation, the wage increase also shifts the injury equation by $\beta_w q$ 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 wage-value of a p 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:

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

which is uniquely defined because the CDF is strictly increasing. Solving for q yields:

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

Using the q function above to derive the marginal value of injury risk requires specifying three parameters:

1. v, the unobserved level of resistance to work: For this, we specify v such that each employee is indifferent between work and not working, that is $v = \zeta_1 + z_{it}'\alpha + \bar{z}_i'\gamma_1$.

2. p, the probability change of injury we wish to evaluate: We specify several probably changes, which represent different multiples of the baseline risk of injury.

3. A multiplier which transforms q, which is denominated in hourly wage terms, into some measure of expected wealth: We assume that officers expected to work an 8 hour shift. We also present a scenario where officers expect to be paid the overtime rate (1.5 times the base rate) and a scenario where they expect to be paid the base rate. This gives a multiplier of either 12 or 8.

Definition 1 *The marginal value of injury risk, denoted q^*, for officer i on date t with covariates z_{it} is given by:*

$$q^*(z_{it}, p, m) := m \times q(x_{it}, V = z_{it}, p)$$

where m denotes the multiplier, and x_{it} is suppressed because it is a subset of z_{it}. The average structural function version of q^*, that is q^* averaged over the observed covariates with equal weights, is displayed for various probabilities and multipliers in Table 15. Using a multiplier of 1, We estimate that the average marginal value of a 1 percentage point increase in injury risk is \$31.42 with a 95% confidence interval of $[\$6.98, \$55.86]$. This is quite a small dollar value when one realizes 1 percentage point is equal to 9 times the average probability of injury conditional on working. A density plot of $q^*(z_{it}, p = 0.01, m = 8)$ is presented in Figure 5, which shows the marginal value of injury is quite heterogeneous across the officer-days, with the majority of values concentrated between \$20 and \$50.

8.2 The Case for Shift Auctions

The main finding, that all else equal, officers with higher unobserved injury risk prefer to work less, implies that there may be gains from allowing individuals more freedom over which shifts they work. We believe that currently, Los Angeles traffic officers are probably assigned to additional shifts using a *list mechanism*, which was 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, we discussed how officer labor supply is increasing in the wage. This means on average, 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, we 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 which 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.[11] In the below analysis, we explore the benefits of utilizing shift bidding.

Before providing simulation evidence, we consider the equilibria of the two mechanisms. For shift bidding, we 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

[11] 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.

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 we suppress the t subscript. Denote the non-monetary value of a shift to officer i as $\theta_i := (z_i'\alpha + \zeta_1 + \bar{z}_i'\gamma_1 - v_{i1})/\alpha_{wage}$ where we exclude the wage variable from z_{it} but do not introduce new notation for brevity. Our current specification assumes linearity in values and wages. The agent 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. We 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 period in division d as S_d. We assume that some number of the positions, denoted $r_{d,t}$ are filled by regular officers. The remainder, denoted $k_{d,t}$, are filled with additional officers. Because we do not observe how many shifts are regularly scheduled, we assume that, within each division, it can be approximated as the number of hours coded as "CURRENT ACTUAL HOURS WORKED ONLY" divided by 8.[12] Call this numbers R_d. We 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 we 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 the following.

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.

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

3. To simulate a shift auction, first randomly assign the 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 top $r_{d,t}$ 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.

We repeat this process 1,000 times. On average, shift auctions reduced the number of injuries by 38.54 percent. The effect was 35.86 percent and 42.13 percent at the 5th and 95th percentiles respectively. In terms of percentage point changes, shift auctions reduced the injury rate on average by 0.1583 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 we could assign the additional $k_{d,t}$ shifts directly to the employees with the lowest injury risk. To simulate it, we randomly assign regular shifts among officers who are willing to work, and then we 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, we give the shifts to those who we know will not be injured). The full information benchmark decreases injuries by 30.22 percent compared to shift auctions.

These simulation results are summarized in Figure 6. The figure displays the simulated injury rate distributions under all three regimes (assuming the number of shifts worked is constant). The distributions do not overlap at all, and shift bidding 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 to reduce the injury rate. Shift auctions are not the only mechanism which utilizes this selection effect, but they are a straight-forward way that is already implemented in several scheduling software packages.

9 Conclusion

This paper explores how individuals make shift-level labor supply decisions. Fundamentally, we ask the question of whether injury risk factors into their choices. Using a long panel consisting of over 500 Los Angeles traffic officers, and an identification strategy which uses the leave of coworkers as an instrument, we find that officers do indeed account for their own injury risk. Specifically, there is *positive selection:* officers prefer to work when they have lower injury risk. Although this result might be expected from a neoclassical, rational expectations perspective, it is more surprising when the context is considered. Injury on a given day is quite rare, and Los Angeles traffic officers have a worker's compensation system, which replaces some of the income lost from injury. In such a context, one might expect a rather small selection effect.

Yet the effect we find is large and economically significant. A 1 percent increase in wages increases average workplace injury among Los Angeles traffic officers by 12 percent. This is in part because higher wages incentivize more officers to trade risk for income. In effect, the relative value of injury decreases. Additionally, officers who work when 1 coworker is on leave as opposed to when 10 are on leave are, on average, 27 percent more likely to be injured. The story here is similar to that with wages: when the number of other employees out rises, the division eventually runs out of people who will take a shift voluntarily, and it must resort to forcing officers to work. This makes the pool of workers more injury-prone.

After establishing that selection plays a large role in observed injury rates, we use our model to investigate two policy relevant questions. First, we estimate the marginal value of non-fatal injury risk. These estimates are rare in the literature, and they provide a picture of how individuals in this specific context trade-off the dis-utility of injury and the benefits of additional wages. Importantly, we find rather small valuations, implying that although officers care about injury risk, concerns about earnings tend to dominate concerns about risk.

Second, we simulate the effect of shift auctions relative to a random list mechanism for shift assignment. We consider auctions where officers bid a wage for a shift, and the lowest k bidders receive the shift and are paid the wage bid by the $k+1$ bidder. In such auctions, it is well-known that the unique equilibrium is to bid your value, and as a result the winners of such an auction will be the k officers with the highest value of the shift. Given the negative correlation between values and injury risk, this mechanism should reduce injury risk even more than the random list mechanism. Simulation results confirm the theory, and we find that in this context, shift auctions significantly reduce injuries.

A major part of city budgets are the salaries of public safety workers, broadly defined as police, fire and other workers. This class of employees are characterized by two broad similarities: they work a large amount of overtime and they work in high-risk environments. As a result, it is in the interest of cities to understand how public safety officers, when allowed to make their own choices, trade-off injury risk for additional income. The findings of this paper support the hypothesis that officers generally do mitigate their own risk, even when there are workers' compensation systems present. However, this study also highlights the fact that the desire for more income tends to dominate the desire to not be injured. This may at first sound like bad news, but this desire for income is actually good news. It means that departments can harness alternative scheduling techniques, like shift auctions, to encourage officers to further mitigate injury risk. Implementing such a system can have benefits for both officer and cities, by lowering overtime costs and reducing injury rates.

Table 1: Basic Characteristics of Officers

	mean	sd	p5	p10	p25	p50	p75	p90	p95
Not Injured									
Age	44.56	10.09	28.27	30.18	37.31	44.12	52.11	58.64	60.18
Tenure (years)	13.18	8.60	1.95	2.86	7.20	12.41	17.98	26.49	28.20
Divisions Worked In	1.26	0.46	1.00	1.00	1.00	1.00	1.00	2.00	2.00
Injured									
Age	46.74	8.83	34.31	35.24	40.40	47.77	52.86	58.47	62.38
Tenure (years)	14.39	8.34	3.42	4.98	8.19	11.99	21.34	26.49	27.76
Divisions Worked In	1.24	0.45	1.00	1.00	1.00	1.00	1.00	2.00	2.00
Total									
Age	45.29	9.74	28.76	32.14	38.86	44.84	52.32	58.53	60.24
Tenure (years)	13.58	8.53	2.64	3.42	8.19	12.41	18.45	26.49	28.06
Divisions Worked In	1.25	0.46	1.00	1.00	1.00	1.00	1.00	2.00	2.00
Observations	540								

Age as of Jan. 1, 2015. Tenure as of first day observed.

Table 2: Injuries by "Claim Cause"

	freq	pct	cumpct
Strain or Injury By, NOC	53	21.81	21.81
Collision or Sideswipe w	40	16.46	38.27
Repetitive Motion - Other	24	9.88	48.15
Fall, Slip, Trip, NOC	18	7.41	55.56
Motor Vehicle, NOC	15	6.17	61.73
Other-Miscellaneous, NOC	12	4.94	66.67
Animal or Insect	10	4.12	70.78
Object Being Lifted or	8	3.29	74.07
Fellow Worker, Patient, or	7	2.88	76.95
Other Than Physical Cause	6	2.47	79.42
Cumulative, NOC	5	2.06	81.48
Dust, Gases, Fumes or	5	2.06	83.54
Exposure, Absorption,	4	1.65	85.19
Twisting	4	1.65	86.83
Foreign Matter in Eye(s)	3	1.23	88.07
Struck or Injured, NOC	3	1.23	89.30
Using Tool or Machinery	3	1.23	90.53
Bicycling	2	0.82	91.36
Broken Glass	2	0.82	92.18
Lifting	2	0.82	93.00
Pushing or Pulling	2	0.82	93.83
Repetitive Motion - Carpal	2	0.82	94.65
Temperature Extremes	2	0.82	95.47
Caught In, Under or	1	0.41	95.88
Contact With, NOC	1	0.41	96.30
Cut, Puncture, Scrape,	1	0.41	96.71
From Different Level	1	0.41	97.12
Hand Tool or Machine in	1	0.41	97.53
Holding or Carrying	1	0.41	97.94
Object Handled by Others	1	0.41	98.35
On Same Level	1	0.41	98.77
Running/Jogging/Walking	1	0.41	99.18
Stationary Object	1	0.41	99.59
Striking Against or Stepping	1	0.41	100.00
Total	243	100.00	

Among estimation sample: Full-time officers between Jan. 2015 and Sept. 2016.

Table 3: Injuries by "Nature of Injury"

	freq	pct	cumpct
Strain	118	48.56	48.56
Contusion	31	12.76	61.32
Sprain	30	12.35	73.66
No Physical Injury	11	4.53	78.19
Mental Stress	8	3.29	81.48
Inflammation	7	2.88	84.36
All Other Specific Injuries,	4	1.65	86.01
Bee Sting	4	1.65	87.65
Dermatitis	4	1.65	89.30
Foreign Body	4	1.65	90.95
Heat Prostration	4	1.65	92.59
Multiple Physical Injuries	4	1.65	94.24
Carpal Tunnel Syndrome	3	1.23	95.47
All Other Cumulative	2	0.82	96.30
Respiratory Disorders (e.g.,	2	0.82	97.12
Asbestosis	1	0.41	97.53
Bloodborne Pathogens	1	0.41	97.94
Hypertension	1	0.41	98.35
Infection	1	0.41	98.77
Laceration	1	0.41	99.18
Mult Injuries Incl Both	1	0.41	99.59
Stroke	1	0.41	100.00
Total	243	100.00	

Among estimation sample: Full-time officers between Jan. 2015 and Sept. 2016.

Table 4: Daily Hours Worked Summary Statistics

	mean	sd	p5	p10	p25	p50	p75	p90	p95
Not Injured	9.01	2.70	7.00	8.00	8.00	8.00	8.00	13.00	15.00
Injured	8.96	2.65	8.00	8.00	8.00	8.00	8.00	13.00	15.00
Total	8.99	2.68	8.00	8.00	8.00	8.00	8.00	13.00	15.00
N	181597								

Restricted to days with positive hours worked.

Table 5: Days Worked in 4 Week Periods

	mean	sd	p10	p25	p50	p75	p90
Not Injured	18.26	4.19	13.00	16.00	19.00	21.00	23.00
Injured	17.14	4.79	11.00	15.00	18.00	20.00	22.00
Total	17.88	4.44	13.00	16.00	19.00	20.00	22.00
N	10158						

Restricted to 4 week periods with at least one day with positive hours worked.

Table 6: Days Worked by Day of the Week

	freq	pct	cumpct
Tuesday	32014	17.63	17.63
Thursday	31356	17.27	34.90
Wednesday	30930	17.03	51.93
Monday	30551	16.82	68.75
Friday	29321	16.15	84.90
Saturday	16285	8.97	93.87
Sunday	11140	6.13	100.00
hline 54breakTotal	181597	100.00	

Officer-days with positive hours worked.

Table 7: Number of Officers on Leave By Division

	mean	sd	p10	p25	p50	p75	p90
811							
Officers with Positive Leave	4.56	3.70	1.00	2.00	4.00	6.00	8.00
Officers with Positive Sick	1.56	1.45	0.00	0.00	1.00	2.00	4.00
Total Leave Hours	37.53	23.79	2.00	18.00	40.00	56.00	66.00
812							
Officers with Positive Leave	11.18	7.43	1.00	3.00	12.00	17.00	20.00
Officers with Positive Sick	3.49	2.61	0.00	1.00	3.00	5.00	7.00
Total Leave Hours	84.40	56.82	4.00	24.00	95.50	129.00	154.00
814							
Officers with Positive Leave	16.72	10.10	1.00	5.00	21.00	25.00	28.00
Officers with Positive Sick	5.56	3.58	0.00	2.00	6.00	8.00	10.00
Total Leave Hours	126.98	77.43	8.00	32.50	154.50	187.00	210.00
816							
Officers with Positive Leave	9.32	5.79	0.00	3.00	11.00	14.00	16.00
Officers with Positive Sick	2.35	1.77	0.00	1.00	2.00	4.00	5.00
Total Leave Hours	71.64	45.08	0.00	24.00	84.00	108.00	123.00
818							
Officers with Positive Leave	4.72	3.29	0.00	1.00	5.00	7.00	9.00
Officers with Positive Sick	1.47	1.31	0.00	0.00	1.00	2.00	3.00
Total Leave Hours	35.80	24.97	0.00	8.00	40.00	55.00	68.00
819							
Officers with Positive Leave	16.95	10.39	1.00	4.00	21.00	24.00	28.00
Officers with Positive Sick	5.74	3.63	1.00	2.00	6.00	8.00	10.00
Total Leave Hours	128.17	79.62	8.00	32.00	152.00	186.00	220.00
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	11.22	10.90	0.00	0.00	8.00	16.00	24.00
Other							
Officers with Positive Leave	2.41	1.76	0.00	1.00	2.00	4.00	5.00
Officers with Positive Sick	0.67	0.82	0.00	0.00	0.00	1.00	2.00
Total Leave Hours	18.88	13.99	0.00	8.00	16.00	26.00	40.00
Total							
Officers with Positive Leave	8.42	8.59	0.00	2.00	5.00	14.00	22.00
Officers with Positive Sick	2.68	2.97	0.00	0.00	2.00	4.00	7.00
Total Leave Hours	64.33	65.14	0.00	10.00	40.00	108.00	171.00
Observations	4864						

Small division codes grouped as other.

Restricted to division-days observed in the analysis sample.

Table 8: Pay Statistics

	mean	sd	p10	p25	p50	p75	p90
Hourly Wage	30.11	2.31	26.64	30.54	30.54	30.54	32.22
Regular Pay	1231.06	705.90	0.00	976.00	1220.00	1564.00	2104.00
Overtime Pay	289.00	485.52	0.00	0.00	0.00	442.00	958.00
Proportion OT	0.12	0.14	0.00	0.00	0.00	0.25	0.33
Observations	42786						

Wage is maximum observed in week.

Overtime and straight time is classified based on Variation Description.

Table 9: F-Statistics of Linear Probability Models of Work Decision

	(1)	(2)	(3)	(4)
Division Leave (count)	0.0269***	0.0267***	0.0282***	0.00348***
	(0.000478)	(0.000459)	(0.000482)	(0.000644)
Seniority Rank	-0.000470	-0.000318	0.000291	0.000365
	(0.000241)	(0.000234)	(0.000197)	(0.000193)
Wage		0.0707***	0.0522***	0.0384***
		(0.00449)	(0.00476)	(0.00326)
Observations	256287	256287	256287	256287
First-Stage F.	738.2	690.6	185.0	266.6
Division FE	No	No	Yes	Yes
Day of Week FE	No	No	No	Yes
Month FE	No	No	No	No

Standard errors in parentheses

All specifications include person-averages of Division Leave and Wage.

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

Table 10: Balance Test: Regression of Medical Expenses Paid on Instruments

	(1)	(2)	(3)	(4)
Division Leave (count)	-8.949	32.83	79.34	98.18
	(27.33)	(36.60)	(55.23)	(61.88)
Seniority Rank	-6.811	0.604	-1.828	-1.542
	(9.682)	(9.863)	(10.35)	(10.44)
Observations	245	245	245	245
F.	0.364	.	.	.
Division FE	No	Yes	Yes	Yes
Day of Week FE	No	No	Yes	Yes
Month FE	No	No	No	Yes

Standard errors in parentheses

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

Table 11: Labor Supply Model: Select Parameter Estimates

	Injury	Work
Avg. Div. Leave	-0.0543***	0.0228***
	(0.00991)	(0.00676)
Avg. Wage	-0.0437	-0.154***
	(0.0656)	(0.0158)
Avg. Age	0.00200	0.0211*
	(0.0425)	(0.0105)
Age	0.00113	-0.0193
	(0.0422)	(0.0106)
Holiday	-0.697**	1.804***
	(0.260)	(0.148)
Amount Rain (in.)	-0.140	-0.0243
	(0.128)	(0.0224)
Max. Daily Temp.	-0.00112	-0.000183
	(0.00304)	(0.000457)
Wage	0.0519	0.152***
	(0.0659)	(0.0136)
Division Leave (count)		0.0194***
		(0.00247)
Seniority Rank		0.00142
		(0.000807)
Observations	256287	
Rho	-0.559	
Rho 95% CI	(-0.01, -0.848)	

Standard errors in parentheses

Specification includes division, month and day of the week fixed effects in both the work and injury equations.

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

Table 12: Conditional Probabilities

Statistic	Analytical Representation	Model Estimate	Observed
All Work	$E_{v,z_{it}}[Pr(y_{it=1} \| w_{it} = 1 \,\&\, z_{it} \& v)]$	.0012 (.0001)	0.0013
All Not	$E_{v,z_{it}}[Pr(y_{it=1} \| w_{it} = 0 \,\&\, z_{it} \,\&\, v)]$	.0289 (.0342)	–
Conditional on Observed	Varies	.0142 (.0190)	–
Unconditional	$E_{v,z_{it}}[Pr(y_{it=1} \| z_{it} \,\&\, v)]$	.0089 (.0108)	–

[1] Standard errors account for sampling of covariates.
[2] Averaged over all covariates and officer-days.
[3] Probability of injury conditional on working.

Table 13: Average Conditional Injury Probability Elasticities

Effect	Analytical Representation	Model Estimate
Wage	$E_{v,z_{it}}[\frac{wage_{it}}{Pr(y_{it}=1\|w_{it}=1,z_{it},v)}\frac{\partial Pr(y_{it}=1\|w_{it}=1,z_{it},v)}{\partial wage_{it}}]$	12.42 (6.073)
Leave in Div.	$E_{v,z_{it}}[\frac{leave_{it}}{Pr(y_{it}=1\|w_{it}=1,z_{it},v)}\frac{\partial Pr(y_{it}=1\|w_{it}=1,z_{it},v)}{\partial leave_{it}}]$	.2223 (.1407)
Seniority	$E_{v,z_{it}}[\frac{senior_{it}}{Pr(y_{it}=1\|w_{it}=1,z_{it},v)}\frac{\partial Pr(y_{it}=1\|w_{it}=1,z_{it},v)}{\partial senior_{it}}]$	.0618 (.0544)

[1] Standard errors account for sampling of covariates.
[2] Averaged over all covariates and officer-days.
[3] Probability of injury conditional on working.

Table 14: Average Joint Injury and Work Probability Elasticities

Effect	Analytical Representation	Model Estimate
Wage	$E_{v,z_{it}}[\frac{wage_{it}}{Pr(y_{it}=1,w_{it}=1\|z_{it},v)}\frac{\partial Pr(y_{it}=1,w_{it}=1\|z_{it},v)}{\partial wage_{it}}]$	14.71 (6.083)
Leave in Div.	$E_{v,z_{it}}[\frac{leave_{it}}{Pr(y_{it}=1,w_{it}=1\|z_{it},v)}\frac{\partial Pr(y_{it}=1,w_{it}=1\|z_{it},v)}{\partial leave_{it}}]$	.2657 (.1407)
Seniority	$E_{v,z_{it}}[\frac{senior_{it}}{Pr(y_{it}=1,w_{it}=1\|z_{it},v)}\frac{\partial Pr(y_{it}=1,w_{it}=1\|z_{it},v)}{\partial senior_{it}}]$	.0824 (.0634)

[1] Standard errors account for sampling of covariates.
[2] Averaged over all covariates and officer-days.
[3] Joint probability of work and injury.

Table 15: Marginal Value of Injury Risk

Multiplier of 1			Multiplier of 1.5		
+1%	+5%	+10%	+1%	+5%	+10%
31.42	51.97	66.65	47.13	77.96	99.97
(12.47)	(20.86)	(27.78)	(18.71)	(31.29)	(41.67)

Standard errors in parentheses
Averaged over realized covariate values.

Figure 1: Workers' Compensation Claims by Month

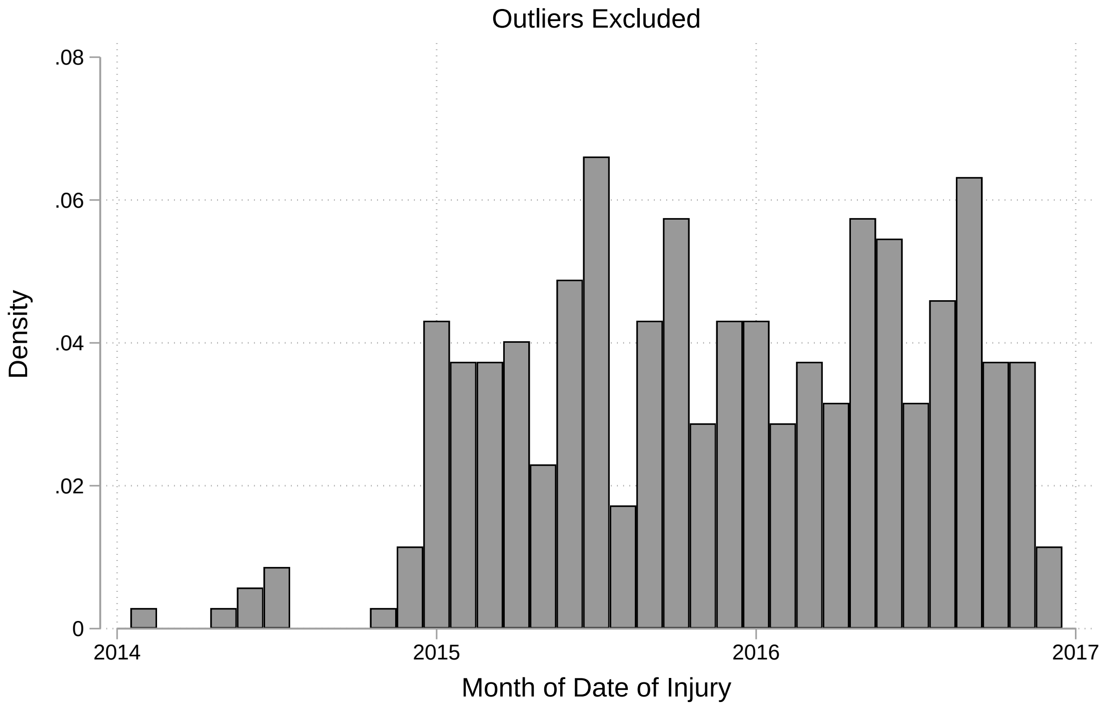


Figure 2: Instrumental Relevance: Division Leave and Probability of Working

Figure 3: Scatterplot of Estimated Time-Constant Heterogeneity

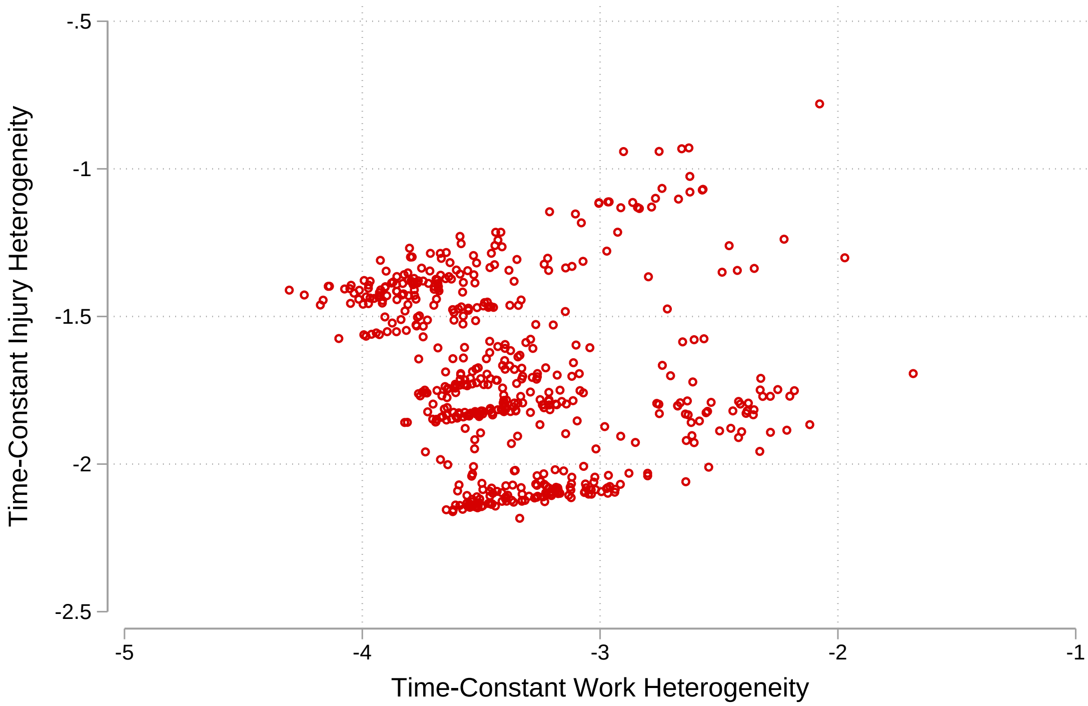


Figure 4: Average Probability of Injury at Various Values of Division Leave

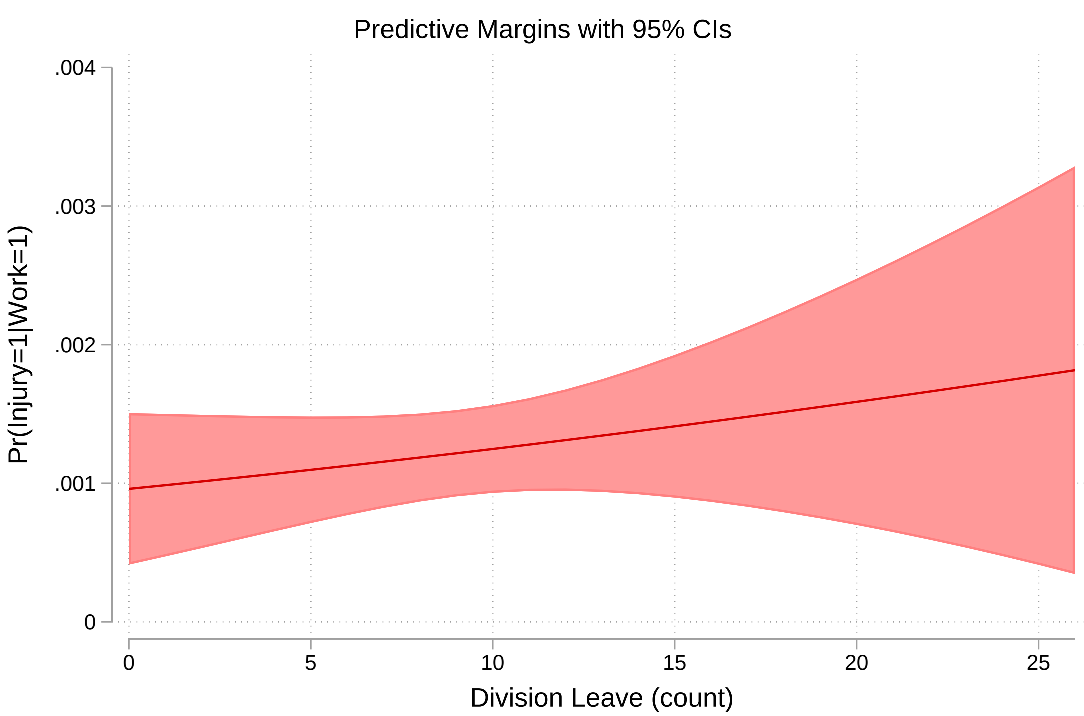


Figure 5: Distribution of Officer-Day Marginal Values of Injury

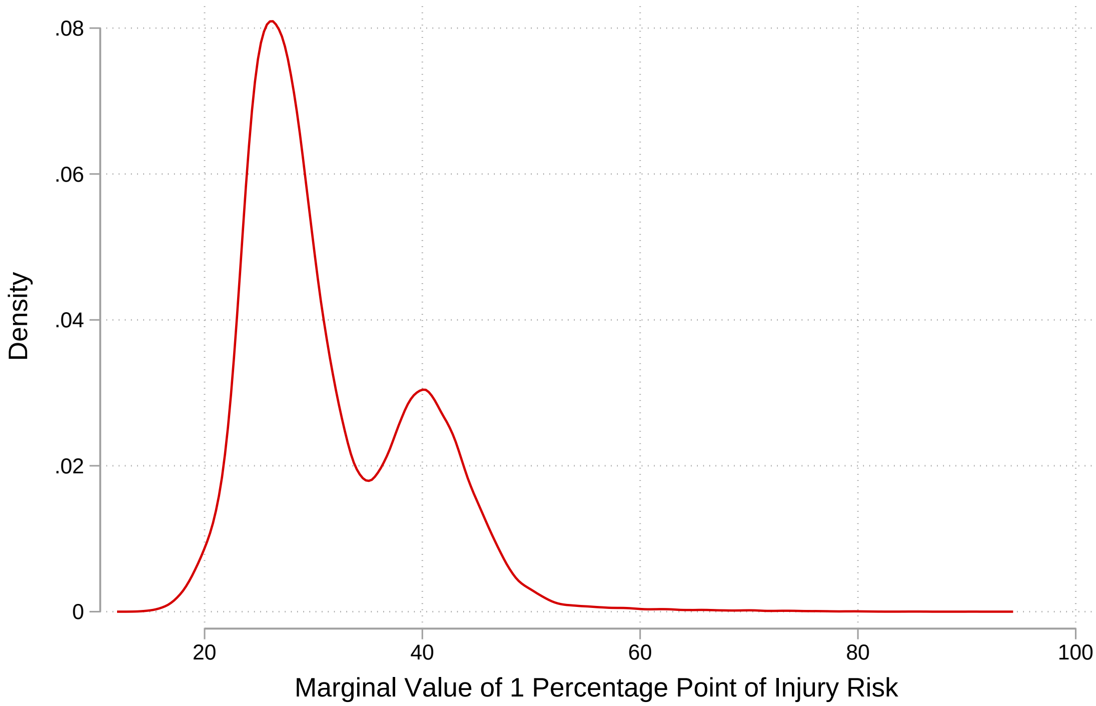
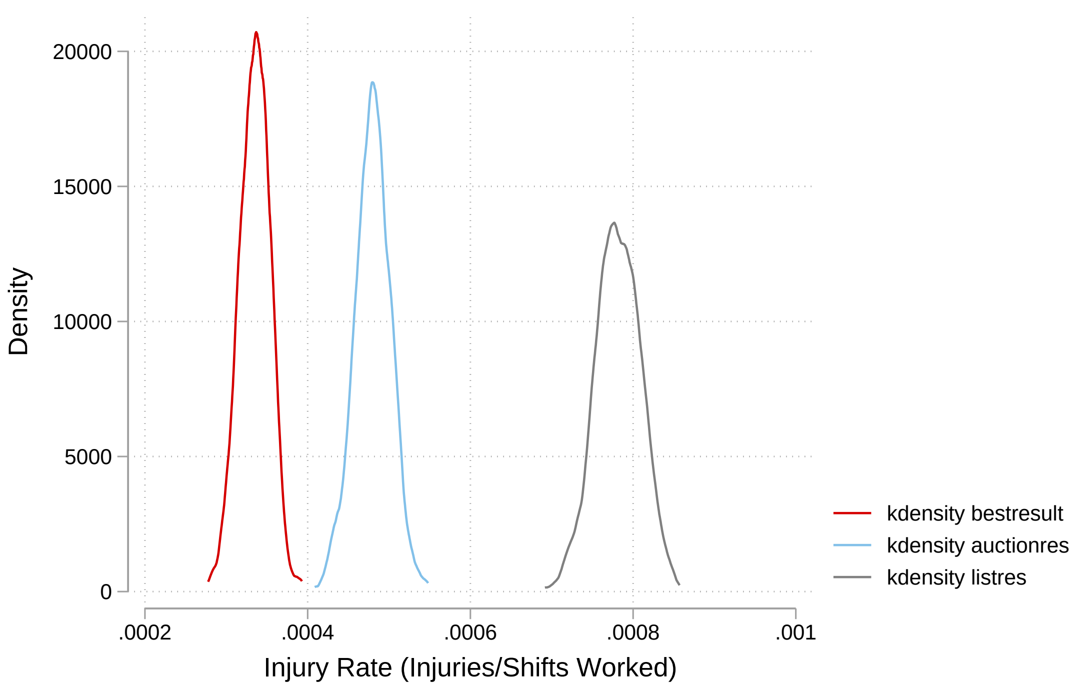


Figure 6: Simulated Injury Rate Distributions



Uses Epanechnikov kernel, with STATA's default bandwidth optimizer.

Figure 7: Average Marginal Probability of Injury

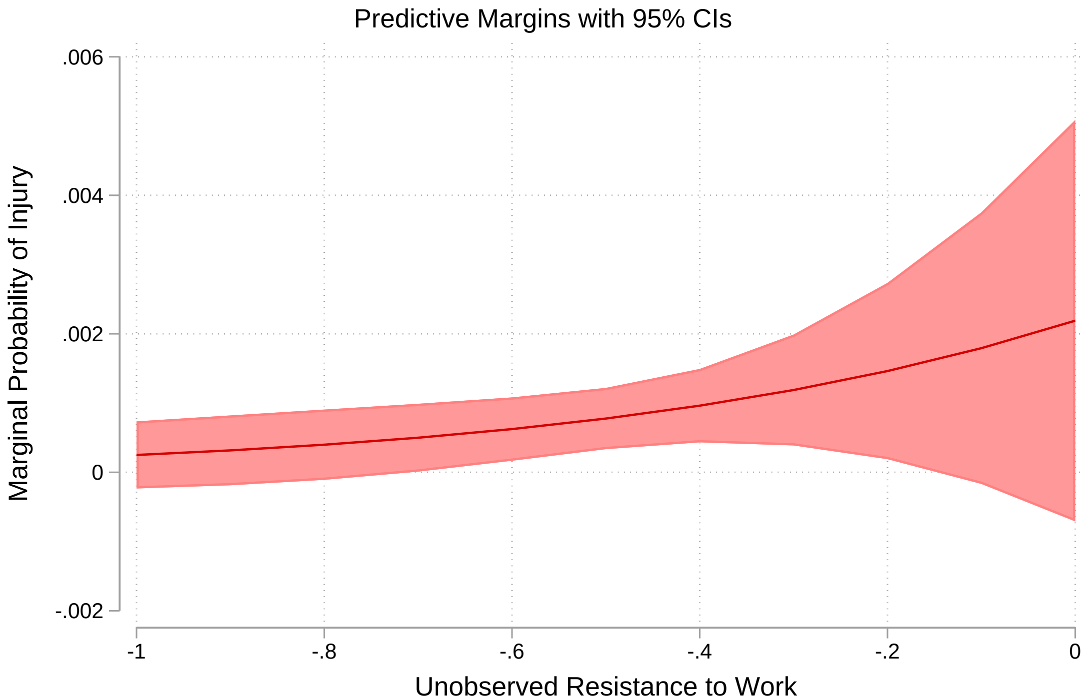
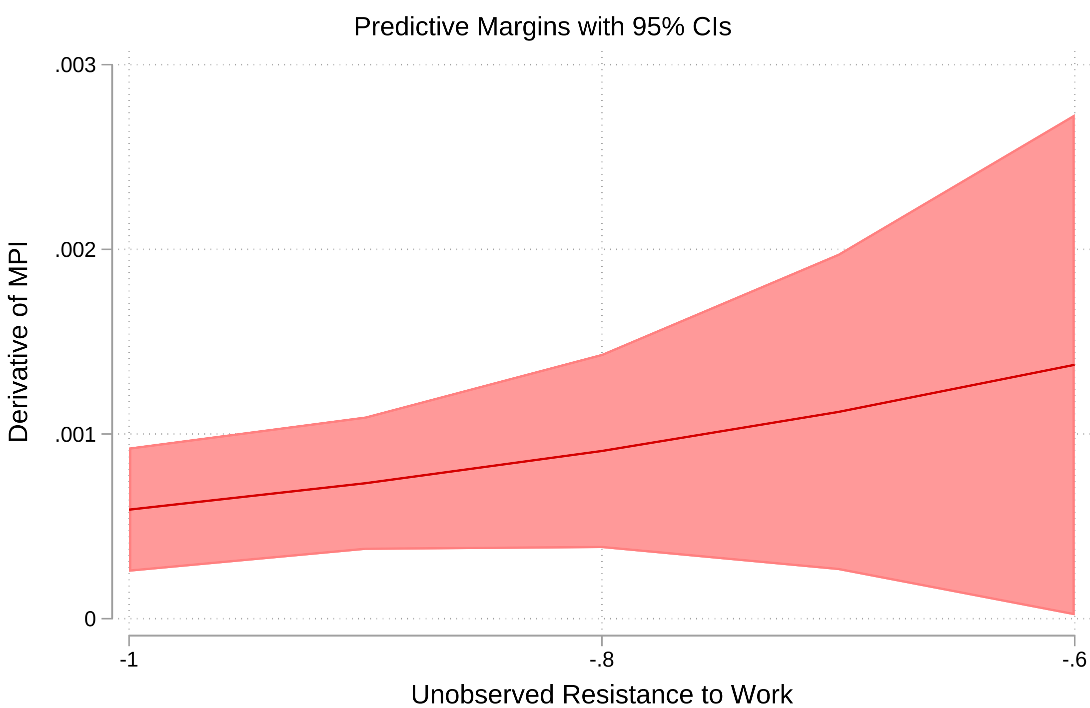


Figure 8: Average Derivative of Marginal Probability of Injury



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A Appendix

Table A.1: Model Parameters with Sick Time Excluded

	Injury	Work
Avg. Leave (No Sick)	-0.0824***	0.0335***
	(0.0145)	(0.00989)
Avg. Wage	-0.0392	-0.156***
	(0.0650)	(0.0158)
Avg. Age	0.00103	0.0113
	(0.0427)	(0.0107)
Age	0.00190	-0.00937
	(0.0424)	(0.0108)
Holiday	-0.694**	1.759***
	(0.256)	(0.148)
Amount Rain (in.)	-0.139	-0.00704
	(0.128)	(0.0220)
Max. Daily Temp.	-0.00116	-0.000131
	(0.00304)	(0.000456)
Wage	0.0488	0.154***
	(0.0652)	(0.0136)
Division Leave (No Sick)		0.0246***
		(0.00312)
Seniority Rank		0.00141
		(0.000809)
Observations	256287	
Rho	-0.555	
Rho 95% CI	(-0.02, -0.843)	

Standard errors in parentheses

Leave measure excludes sick time.

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

Table A.2: Robustness Analyses

	Leave Coef.	Coef SE	Rho	Rho SE	Prob. Incr.	Prob. SE
Sick Time Excluded from Leave	0.0246	0.0031	-0.5552	0.2133	0.0009	0.0005
Strains Not Considered Injuries	0.0194	0.0025	-0.3549	0.6526	0.0003	0.0003
Med Exp $\leq$0 Not Injury	0.0194	0.0025	-0.6804	0.1538	0.0008	0.0005
Med Exp $\leq$200 Not Injury	0.0194	0.0025	-0.7286	0.1275	0.0010	0.0006
Med Exp $\leq$400 Not Injury	0.0194	0.0025	-0.7691	0.1098	0.0011	0.0007

Table A.3: Variation Descriptions

Work	Leave	Other
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
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 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
	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
	OVERTIME TAKEN OFF (STRAIGHT)	SICK 100
	PREVENTIVE MEDICINE (POS OR NEG)	SICK 75
	SUSPENSION (POS OR NEG) / HOURS NO PAY	SICK 75
	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

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.