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

Jacob Kohlhepp and Michael Ludwig

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Abstract

We employ a novel data set of 219,000 workers' compensation claims and pay records to determine whether individuals consider workplace injury risk when making daily labor supply decisions. Using the leave of coworkers

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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. This estimate 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 sick and probably should have stayed home, and which used controlled substances. In the age of a global pandemic, this private information about lifestyle and health becomes all the more important.

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 injury-reducing 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, giving individuals more freedom to make labor supply decisions will reduce organizational injury rates.

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

In this paper, we show that, in our setting, individuals make injury-conscious labor supply decisions. We focus on Los Angeles traffic officers and use administrative records detailing work hours and workers' compensation claims. In order to trace out selection patterns, we use variation in the number of coworkers on leave. As more coworkers go out on leave, less willing officers are forced to work. We show that there is selection against injury: officer-days with higher injury risk are less likely to be worked. Given number here.

Our approach allows us to go beyond the core selection story. First, we are able to estimate the implied value of a statistical injury using a willingness to pay approach. We find that in our population, the value of a statistical injury is between \$10,000 and \$20,000. These estimates allow us to 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.

We contribute to this literature by providing VSI estimates for individuals working in a particularly important and hazardous occupation: public safety. Because we examine a single group of people working the same job in the same location, and each officer makes multiple labor supply decisions, we can comment on the level of heterogeneity in willingness to pay for risk reductions.

Second, we 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 point 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). We 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

Third, we simulate the injury risk reduction under several counterfactual assignment mechanisms. In particular, we show that assigning shifts using an auction, where officers bid a wage they are willing to work for an open shift, results in a 38 percent reduction in the injury rate compared to the mechanism we believe is being used by LADOT.

Our results 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 our 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. Our 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.

Los Angeles traffic officers are ideal for exploring how injury risk enters labor supply decisions. This is because they receive frequent opportunities to work additional shifts which are not part of their normal schedule. They staff special events (Oscars, large sporting events, presidential visits) and also provide support to police and fire departments during traffic-disrupting emergencies like water main breaks. They work in relatively dangerous conditions: they drive, stand and walk on streets with large amounts of fasting moving traffic. This increases the prevalence of injury (stat here), making it more likely they are consciously considering it when making decisions. At the same time, their job is less risky than that of other public safety workers, like police officers and fire fighters. As a result, our results are a lower bound on the selection effects we would expect in the general population of public safety workers.

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.[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 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).

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

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).

This paper considers all shifts worked by traffic officers. However, officers mainly control their labor supply by taking on "special events." Special events are paid at 1.5 times the normal rate (similar to typical overtime). Special events include things like the Los Angeles Marathon, Dodger Games, and block parties. When the event is not hosted by the city itself, he bill for traffic officer overtime incurred during the events is paid by the host organization. In FY 2013-2014, special events accounted for $5.9 million in overtime paid to LADOT officers. To put this in perspective, if we divide this by $45 (officers earn around $30 an hour), we see that this implies over 100,000 overtime hours were worked on special events alone.

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 technically cannot add additional hours to their shift unless authorized. For this reason our 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 assigned. 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.

Although this 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 internally 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 is ex-ante fair, officers with enough determination can bargain with the winners of the wheel spin to work even more overtime.

These two features of overtime assignment are an essential part of our 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.[3]

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[4], 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

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

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

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.[5][6] 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 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). The distribution of Claim Cause helps paint a picture of the hazards faced by the traffic officers. The hazards do not seem to reach the level of a coal miner or police officer, but they are much larger than the injuries faced by typical white collar workers. Most of this is due to the simple fact that traffic officers work outside in heavy traffic: they can be sideswiped, get into car accidents, or suffer from 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. Beyond these broad categories, the data also contains individual text descriptions of each industry. We summarize these descriptions using a word cloud ins Figure...

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 these 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

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

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

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.

3 Preliminary Evidence of Selection Against Injury

In the next section, we will introduce a formal model of daily labor supply. However, before adding any structure, we think it is helpful to see the selection effect in a very simple way. We can summarize our empirical approach and the fundamental idea behind our identification this way: we 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 other officers are out on leave, even extremely unwilling officers will need to work, or else they risk their relationship with their supervisors and potentially their job. Similarly, as officers come into contact with more other officers outside their division, they build a network. The more expansive their network, the easier it is to find overtime trading partners.

Even without a formal model, we can see evidence of this selection by comparing the OLS regression of injury on work to the two-stage least squares regression of injury on work with leave of others and cumulative contacts as instruments. We 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).

The results of this exercise are in Table ¡cite table after it is generated¿. As predicted, the 2SLS estimate is 21% higher.[7] The intuition is that the observed injury rate (OLS estimate) is much lower than the injury rate we would observe if officers came into work at random (2SLS estimate). This is evidence of positive

[7]A better identified FE-2SLS version of this result is presented in the Appendix. It too shows similar patterns.

selection: officers avoid work on days they are more likely to be injured, and go to work on days they are more less likely to be injured. The following section only serves to quantify this selection result and more rigorously demonstrate identification.

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:

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

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. We 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 (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: we only observe injury outcomes among individuals who go to work. Denote y_{it} as the injury outcome we observe. Then we have that:

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

We 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 $U_{it} = Z'_{it}\alpha + \zeta_1 + c_{i1} + \epsilon_{it1}$. Then the decision to work is given by:

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

c_{i1} and ϵ_{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. ϵ_{it1} represents unobserved time varying taste for work, driven by factors like wealth shocks, wanting to watch your child's soccer game, or not getting enough sleep the night beforehand.

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, this would enter as a negative correlation between ϵ_{it2} and ϵ_{it1}. This could be because the officer dislikes injury risk, and then ϵ_{it1} is a private signal of potential higher injury risk. It could also be because it is just 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 reduced form model capturing the general way 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, our model would be a special case of the switching model described in Chen, Zhou, and Ji 2018. Then we could achieve non-parametric and estimation identification with a single exclusion restriction and a symmetry condition on the unobservables.

But we are 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 $Pr(y_{it}) \approx 0$. This implies that $X'_{it}\beta$ is unlikely to be bounded between $[0, 1]$ almost surely, which makes the linear probability model rather implausible (Horrace and Oaxaca 2006).

Given these circumstances, we 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:*

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

Notice that this assumption is *weaker* than assuming full independence. 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, our specification will still deliver consistent estimates of all parameters. Further, we 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 our model.[8] Intuitively, identification of the unobserved correlation, ρ, is driven by the excluded instrument effectively tracing out the patterns of selection. In our case we use both the number of coworkers on leave currently and a proxy for the size of an officer's network as the excluded instruments. We will argue in the next few sections that these two instruments are both relevant to the work decision and do not directly impact injury risk.

4.3 Model Comments

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

1. $Cov(a_{i1} + u_{it1}, a_{i2} + u_{it2})$: 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. We can compare this variance to 1, which is the variance of $a_{i1} + u_{it1}$.

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

[8] Indeed our model is motivated by Semykina and Wooldridge 2018.

propensity captured by individual effects. We can compare this variance to 1, which is the variance of $a_{i1} + u_{it1}$.

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, we take a moment to introduce an important object.

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 selection occuring due to voluntary overtime using a single concept. In terms of our model, 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 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:

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

The key question we answer in this paper is whether MPI 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 this function is increasing in $\tilde{v}$ for all x.*

The lemma follows directly from the fact that the CDF of the normal distribution is strictly increasing and the denominator is always positive. From the lemma, we can test whether MPI is increasing by testing the null hypothesis that $\rho = 0$. If $\rho < 0$ we say there is selection against injury. If $\rho > 0$ we say there is selection into injury.

4.4 Estimation

In our setting, X_{it} includes a federal holiday indicator, age, amount of rain in inches, the maximum daily temperature, the officer's wage,[9] division indicators (with small divisions grouped together), day of the week indicators and month indicators.

[9] 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 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 other officers an officer has worked in the same division as on the same day in the past. This is a measure of the potential size of an officer's network.
- **Seniority Rank:** The rank of officer i in terms of number of years since hire among all officers in the department.

Z_{it} includes these instruments as well as all the variables in X_{it}. $\bar{Z}_i$ includes officer-specific time averages of division leave of coworkers and the wage. Seniority rank, division, day of the week, month, age and weather variables were excluded from $\bar{Z}_i$ because they did not vary enough (either temporally or across officers).[10]

Estimation proceeds using partial maximum likelihood, with the expressions of the likelihood presented in the Appendix. As astutely pointed out in Semykina 2012, models of the type we have specified are essentially pooled Heckman-selection probit models. As a result, we can be 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.

4.5 Instrument Validity

Identification of our model requires leave of coworkers to be a valid instrument. Validity requires that leave of coworkers and cumulative potential contacts is both properly excluded from the injury equation and relevant to the decision to work. We support these assumptions both statistically and theoretically in this section.

4.5.1 Exclusion Restrictions

Conditional on x_{it} and $\bar{z}_i$[11], 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

[10] Trying to include these variables causes convergence problems.

[11] 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 divsion may be correlated with injury probability. This is dealt with by conditioning on $\bar{z}_i$

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.

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 contacts will come through extra special events, where officers from all divisions interact to direct something like the LA marathon. Since special events are often voluntary, there may be a concern that less injury prone officers have greater more cumulative contacts. However, because we condition on average cumulative contacts, we allow for this dependence. All that is necessary is that idiosyncratic variation in cumulative contacts satisfy exclusion. This idiosyncratic variation likely comes through division changes as well as other officers leaving or being hired. Because the main part of the job is not cooperative (patrolling parking meters and directing traffic) there is little reason to think this variation is correlated with injury propensity.

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.[12]

Another way to check instrument independence is to examine the balance of additional officer-day charac-

[12]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

teristics 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.

4.5.2 Relevance

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 earlier, where shifts are offered sequentially to officers on a list. 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, both because an officer has a greater chance of being offered the slot and because an officer has a higher chance of being forced. To test this, we present F-statistics of a linear probability model of work on the leave of others 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.

For linear models, there are many formal under-identification, over-identification, and weak instrument tests that can be used to test the identifying assumptions. Unfortunately, our model is nonlinear. In the appendix Table A.4, we report results from what we call the "proxy" model. It is a fixed effects 2SLS specification (the model we would fit if y_{it} was not binary). Across all specifications, we reject the

hypothesis when it is true.

null hypothesis that our instruments are under-identified. We fail to reject the null hypothesis that our instruments are correctly excluded from the injury equation. We also reject the null hypothesis that our instruments are weak. Overall we find no evidence that our identifying assumptions are violated in the proxy model. We can use the proxy model to see how instrument strength impacts the coefficients. Using the tables presented in Stock and Yogo 2002, for our preferred specification (the third model in Table A.4) the maximum relative bias of the IV estimator is 15% (relative to OLS). We also perform the tF procedure described in Lee et al. 2020. The adjusted critical value for the coefficient on work based on Lee et al. 2020 Table 3 is 2.33. This implies that the coefficient on work remains statistically significantly different from 0 at the 0.05 level.

5 Model Estimation Results

6 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.[13] 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 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

[13] See Table 7

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.

7 Discussion

The main result of this paper is that our population of officers selects against injury. This main result has implications for labor supply elasticities, the value of statistical injury and the optimal assignment of overtime. We discuss these implications in turn.

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. Our 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 us to trace out how elasticities vary at different levels of risk. Formally, we 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. We plot this relationship in Figure and see that the elasticity is declining in unobserved injury propensity.

7.2 The Value of a Statistical Injury

We 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 1/540 risk of injury, multiplied by 540.[14] In our 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, we briefly state our methodology for calculating willingness to pay using our model.

In our 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 1/540 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:

$$\Delta(x_{it}, q(x_{it}, v, p), v) = \frac{1}{540}$$

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

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

To calculate VSI, we assume that officers expect to work 8 hours ex-ante (so our VSI will be multiplied by 8). Finally, the value of a statistical injury is given by:

$$VSI = M \cdot 540 \cdot 8 \cdot E_{x,v}[q(x, v)]$$

where note that we have integrated out v, the unobserved utility from work.[15] M represents a multiplier on

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

[15] For our estimates, we integrate out v using Gauss-Hermite quadrature with 5 nodes.

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, we 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 15. We estimate that on average, the implied value of a statistical injury for Los Angeles traffic officers is between \$10,206 and \$20,412.

Even the upper VSI bound we compute

These aggregate figures mask significant individual and temporal heterogeneity. To visualize the heterogeneity, we calculate the willingness to pay using each individual officer-day (rather than averaging over all officer-days). Figure 5 displays a density plot of the lower bound of VSI calculated using each officer-day. The distribution has most mass concentrated between \$150,000 and \$250,000. Interestingly, there are two peaks to the distribution. This suggests there are two "types" of officer-days: those with a lower willingness to pay which results (represented in the peak around \$200,000) and those with a higher willingness to pay (represented by a peak around \$250,000).

7.3 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.[16] In the below analysis, we explore the benefits of utilizing

[16]Some examples: Stay Staffed, which produces a nurse scheduling software; Celayix Software, a multi-industry workforce

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 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.[17] 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:

management software company; EPay Software, a human capital management provider.

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

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.

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 under all three regimes plotted for 1,000 simulations (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 by an organization to reduce the injury rate. Shift auctions offer a simple implementation that is already available in several scheduling software packages.

8 Conclusion

Our paper explores how individuals make shift-level labor supply decisions. Fundamentally, we ask the question of whether injury risk factors into their choices. We bring a long panel consisting of over 500 Los Angeles traffic officers to bear on these questions. Leave of coworkers and cumulative potential contacts serve as instruments which make it easier for officers to acquire additional shifts. We 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. 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 three policy relevant questions. First, we compute how labor supply elasticities change when risk varies. We find intensive labor supply is less elastic with respect to wages when injury risk is elevated.

Second, we estimate the marginal value of non-fatal injury risk. These estimates provide a picture of how individuals trade-off the dis-utility of injury and the benefits of additional wages. Importantly, we find rather small valuations, implying officers care about injury risk but concerns about earnings tend to dominate concerns about risk.

Finally, 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. These employees all share two important characteristics: 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.

Our analysis population is Los Angeles traffic officers. Although these employees are technically public safety officers, they do not face the same level of risk as fire fighters and police officers, since they do not usually fight fires or perform arrests. At first glance, this might seem to mean that our results are not general. But we would argue the opposite: if traffic officers self-mitigate their risk, and they experience lower baseline risk than police officers, it is likely police officers and other high-risk public safety workers also self-mitigate.

In some ways, this dissimilarity between police officers and traffic officers makes our findings more externally valid. Because traffic officers do not directly fight crime or fight fires, their jobs are similar to a broad class of outdoor service occupations, where the main tasks involve driving and walking between locations. Some prominent examples include postal workers, delivery drivers, and taxi/ridesharing drivers. These sorts of jobs compose a decent fraction of the US labor market, and their proportion is likely to increase with the current rise of food delivery apps.[18] Workers in these similar occupations face similar risks, and at least in the case of delivery apps, they have the choice of whether to take on deliveries. Companies can use mechanisms like shift auctions to minimize worker injury and delivery disruption.

[18] https://thespoon.tech/report-food-delivery-apps-will-have-44m-u-s-users-by-2020/

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)
Leave of Coworkers (count)	0.0269***	0.0267***	0.0282***	0.00347***
	(0.000480)	(0.000462)	(0.000482)	(0.000644)
Cumulative Officer Potential Contacts	0.0000388	-0.000228	0.000397	0.000335
	(0.000373)	(0.000328)	(0.000235)	(0.000201)
Seniority Rank	-0.000472	-0.000313	0.000327	0.000405*
	(0.000246)	(0.000240)	(0.000197)	(0.000192)
Wage		0.0710***	0.0517***	0.0379***
		(0.00450)	(0.00480)	(0.00328)
Observations	256287	256287	256287	256287
First-Stage F.	543.7	532.8	173.1	251.9
Division FE	No	No	Yes	Yes
Day of Week FE	No	No	No	Yes
Month FE	No	No	No	No

Standard errors in parentheses

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

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

	(1)	(2)	(3)	(4)
Leave of Coworkers (count)	7.247	33.50	80.16	101.2
	(25.75)	(35.84)	(55.40)	(61.90)
Cumulative Officer Potential Contacts	-6.251	-1.637	-1.598	-5.088
	(6.712)	(7.355)	(7.495)	(8.223)
Seniority Rank	-7.571	0.0623	-2.385	-3.353
	(9.581)	(9.449)	(9.941)	(9.822)
Observations	245	245	245	245
F.	0.516	.	.	.
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. Coworker Leave	-0.0553***	0.0218**
	(0.00940)	(0.00684)
Avg. Wage	-0.0350	-0.153***
	(0.0622)	(0.0158)
Avg. Age	0.000138	0.0315**
	(0.0415)	(0.0101)
Avg. Cum. Potential Contacts	0.00155*	-0.00118
	(0.000708)	(0.000894)
Age	0.00295	-0.0296**
	(0.0412)	(0.0102)
Holiday	-0.744**	1.803***
	(0.247)	(0.148)
Amount Rain (in.)	-0.137	-0.0233
	(0.124)	(0.0224)
Max. Daily Temp.	-0.00102	-0.000167
	(0.00295)	(0.000457)
Wage	0.0418	0.151***
	(0.0622)	(0.0136)
Leave of Coworkers (count)		0.0194***
		(0.00247)
Cumulative Officer Potential Contacts		0.00193*
		(0.000818)
Seniority Rank		0.00157
		(0.000804)
Observations	256287	
Rho	-0.605	
Rho 95% CI	(-0.12, -0.858)	

Standard errors in parentheses

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

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

Lower Bound (M = 1)		Upper Bound (M = 2)	
Willingness to Pay	VSI	Willingness to Pay	VSI
21.21	11455.6	42.43	22911.2
(11.67)	(6303.8)	(23.35)	(12607.6)

Standard errors in parentheses

Figure 1: Workers' Compensation Claims by Month

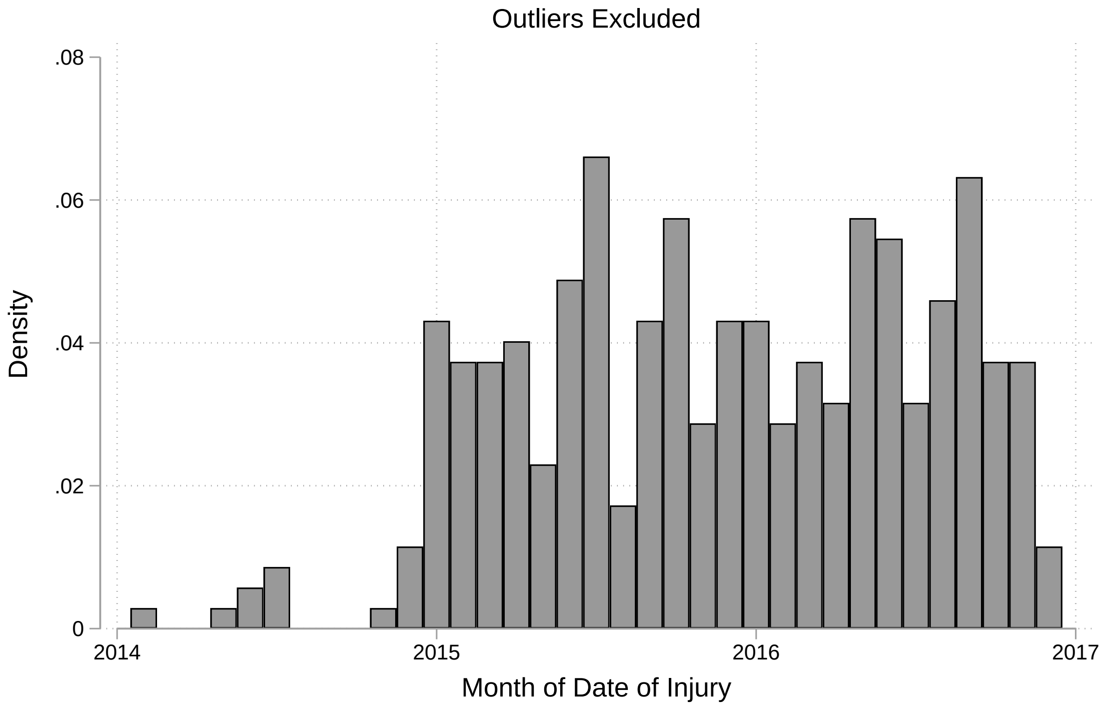


Figure 2: Instrumental Relevance: Division Leave and Probability of Working

Figure 3: Scatterplot of Estimated Time-Constant Heterogeneity

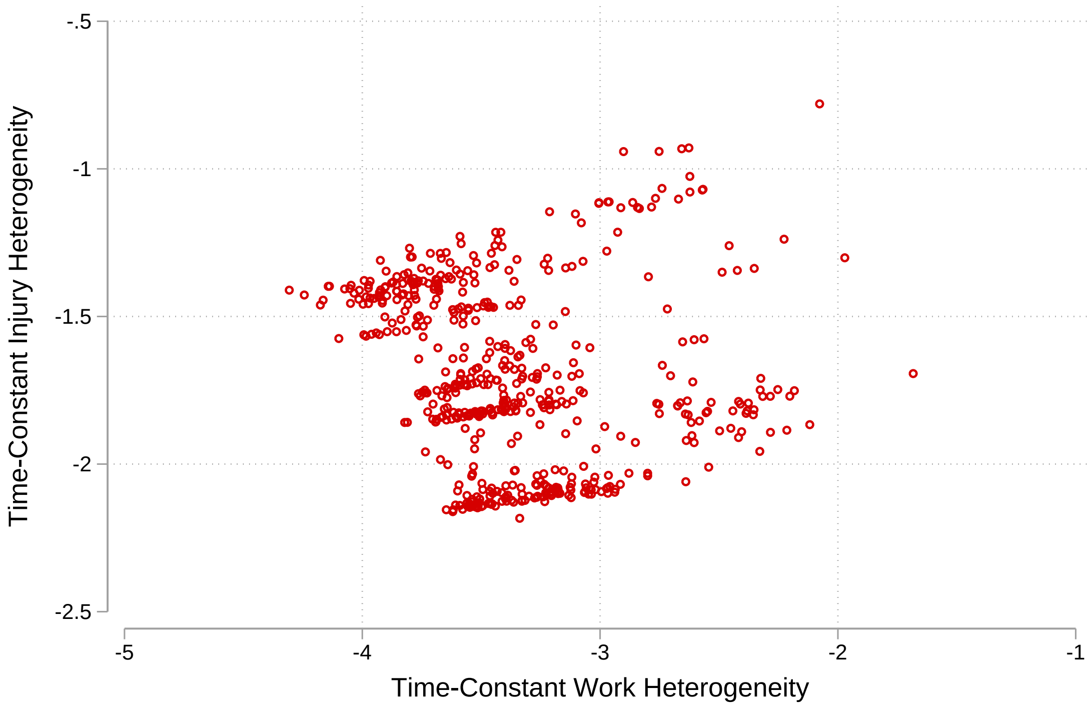


Figure 4: Average Probability of Injury at Various Values of Division Leave

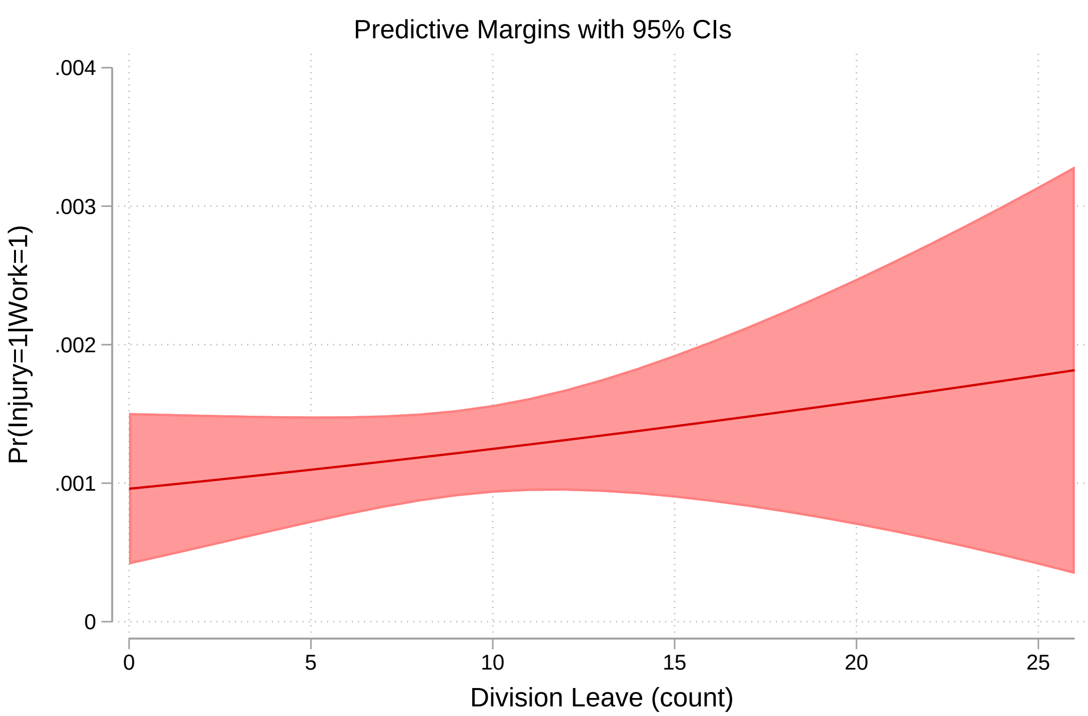


Figure 5: Distribution of Officer-Day Marginal Values of Injury

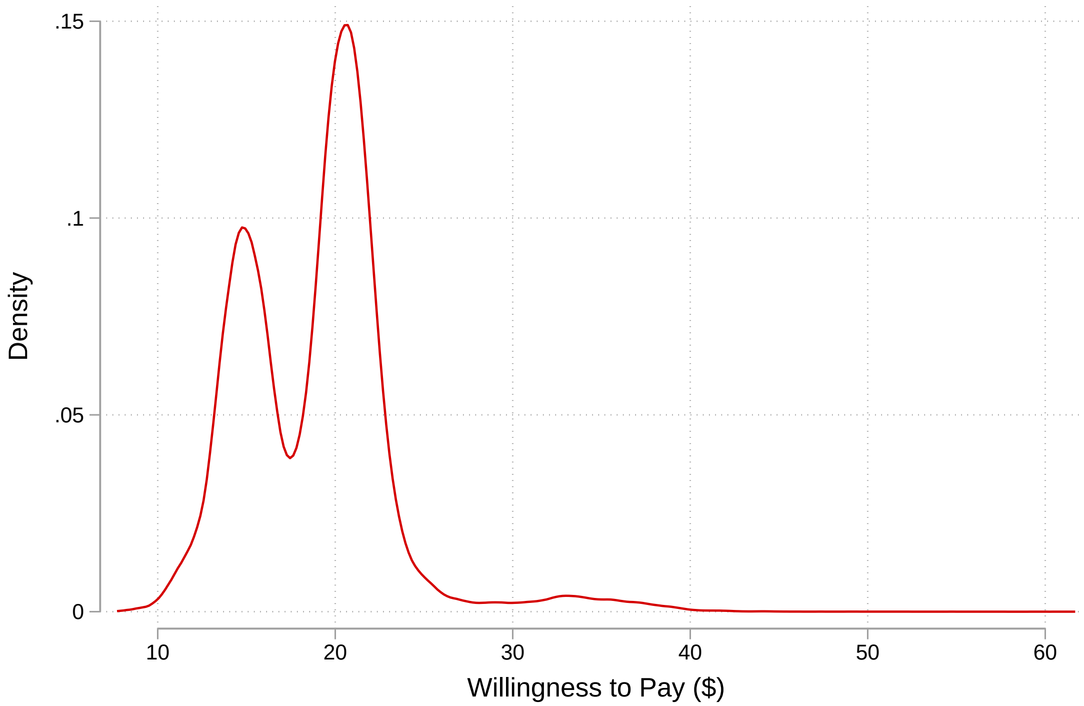


Figure 6: Simulated Injury Rate Distributions

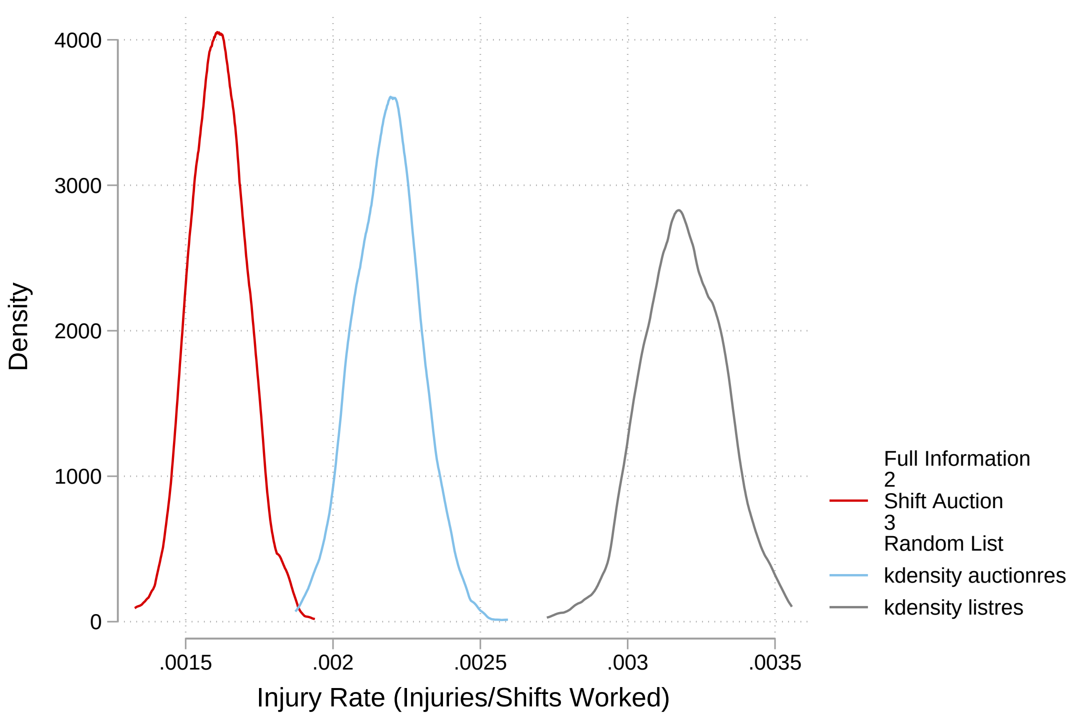


Figure 7: Average Marginal Probability of Injury

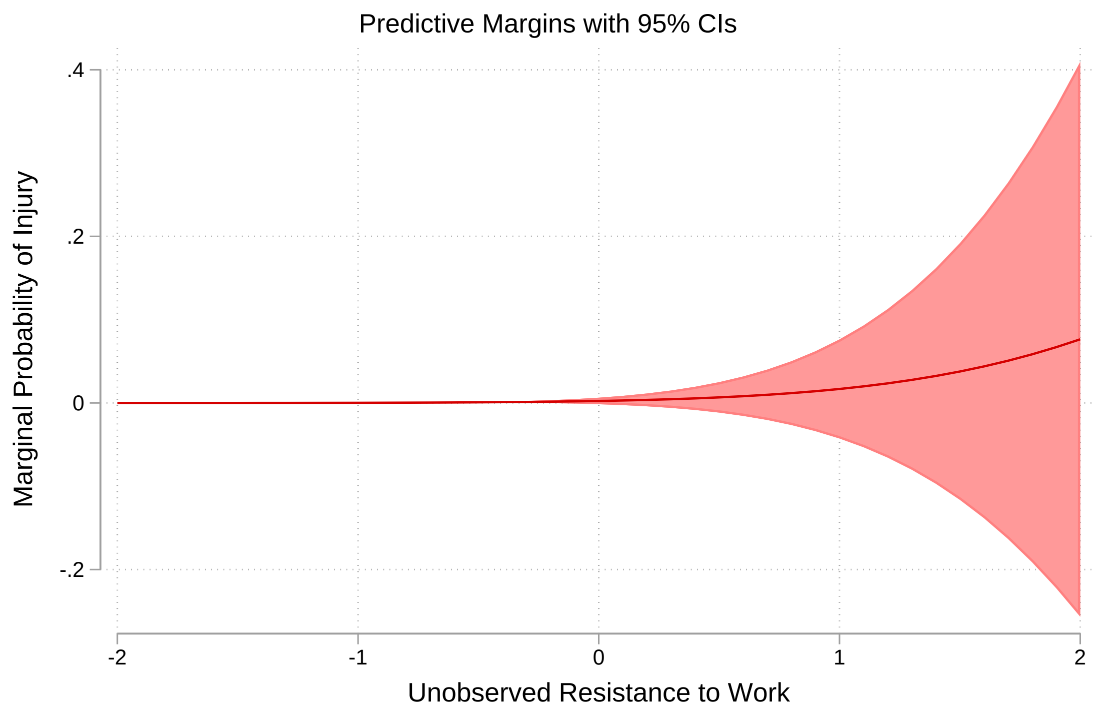
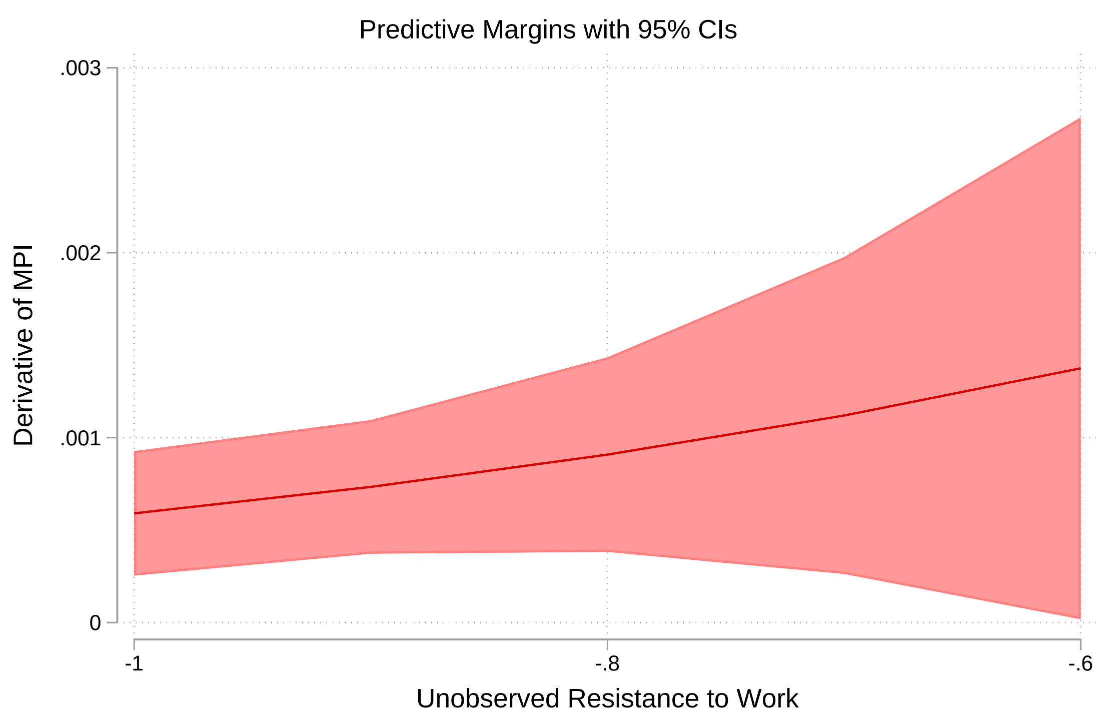


Figure 8: Average Derivative of Marginal Probability of Injury



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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	-0.0344	-0.155***
	(0.0635)	(0.0157)
Avg. Age	0.000461	0.0220*
	(0.0418)	(0.0103)
Avg. Cum. Potential Contacts	0.00158*	-0.00126
	(0.000718)	(0.000903)
Avg. Leave (No Sick)	-0.0804***	0.0316**
	(0.0139)	(0.0101)
Age	0.00249	-0.0200
	(0.0415)	(0.0104)
Holiday	-0.736**	1.759***
	(0.247)	(0.148)
Amount Rain (in.)	-0.137	-0.00598
	(0.125)	(0.0220)
Max. Daily Temp.	-0.00106	-0.000115
	(0.00296)	(0.000457)
Wage	0.0427	0.153***
	(0.0635)	(0.0136)
Division Leave (No Sick)		0.0246***
		(0.00312)
Cumulative Officer Potential Contacts		0.00201*
		(0.000825)
Seniority Rank		0.00157
		(0.000807)
Observations	256287	
Rho	-0.596	
Rho 95% CI	(-0.10, -0.854)	

Standard errors in parentheses

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

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
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

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	0.00260***	0.00231***	0.00829*	0.00287
	(0.000333)	(0.000293)	(0.00349)	(0.00219)
N	256287	256287	256287	256287
Underid K-P F-stat	334.9	339.7	32.07	58.86
Weak id. K-P F-stat	1702.6	1717.3	17.14	35.44
Hansen J	1.890	1.042	0.298	.
Hansen J p	0.169	0.307	0.585	
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

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