Workplace Injury and Labor Supply within an Organization

Jacob Kohlhepp*

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Abstract

In this paper, I study how voluntary labor supply decisions within an organization impact workplace injury using novel data on the payroll and workers' compensation claims of Los Angeles traffic officers. I use the leave taken by coworkers as an instrument to estimate the causal effect of daily labor supply decisions on workplace injury. Self-selection via voluntary labor supply reduces injuries by 48 percent compared to the underlying injury rate. The majority of the effect is driven by private factors, implying decentralized overtime assignment mechanisms like shift auctions can be used to reduce injury rates.

Keywords: overtime, workplace injury, labor supply, selection

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*UCLA Department of Economics. Contact: jkohlhepp@ucla.edu. I would like to specially acknowledge Michael Ludwig. His initiative and data assistance made this project possible. I am thankful for helpful comments from Maurizio Mazzocco, Till von Wachter, Johnny Huynh, Jaime Ramirez, Stepan Aleksenko, Sungwoo Cho, Felipe Goncalves, Adriana Lleras-Muney and Anastasia Semykina. I am grateful for support from the the Institute for Humane Studies' Hayek Fund.

1 Introduction

Workplace injury is a large economic burden. In the United States, injuries on the job cost $170.8 billion in 2018 alone. Such a cost is comparable to that of more well-known medical issues like heart disease.[1] However, much of the risk-relevant information is known only by the worker. A worker knows if they slept enough the night before. They know if they are feeling sick. They know if they drank too much alcohol at a party yesterday. They understand best their own physical capacity to safely work. At the same time, labor supply varies greatly across people (Blundell, Bozio, and Laroque 2011). Among Los Angeles traffic officers, a city report documents that in a single year, one worker earned $15 in overtime while another earned over $100,000 (Galperin 2015). How do such voluntary labor supply decisions impact workplace injury?

To answer this question, I develop a framework for understanding the connection between labor supply and workplace injury within an organization. I apply the framework to novel high-frequency panel data which details Los Angeles traffic officer work patterns, pay and workers' compensation claims. I use variation in the leave of coworkers to identify how labor supply varies with injury risk. I find daily labor supply is downward sloping in injury risk: officers are less likely to work when they are more likely to be injured. This self-selection generates an observed injury rate among Los Angeles traffic officers that is at least 48 percent lower than the underlying average injury rate. My framework allows me to decompose selection against injury into a part that could be deduced by an analyst (predictable component) and part known only by the worker (the private component). For traffic officers, 96 percent of selection is attributable to the private component. The vast majority of injury mitigation comes through unobservable selection that could not be replicated by a manager assigning shifts directly.

This paper has an important practical implication: carefully designed overtime assignment mechanisms can reduce injuries within organizations. Because so much of selection is due to private factors, mechanisms which encourage workers to act on risk-relevant private information will lower injury rates. An auction which awards extra shifts to the workers who bid the lowest wage is one such mechanism. I compare such shift auctions to a system where workers are put in a random list and given the option to accept or reject a shift. I show via simulation that shift auctions result in 11% fewer injuries than the list mechanism.

This paper has three primary contributions: one methodological and two substantive. Methodologically, it provides a framework which links intensive margin labor supply with

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

workplace injury risk. This framework formalizes the connection between the willingness to work and the propensity to be injured. Given a sufficiently strong instrument, it also allows the researcher to identify the average underlying injury rate: the probability of injury of a randomly drawn worker who is forced to work on a random day. I show the approach is numerically equivalent to a marginal treatment effects (MTE) strategy. MTE equivalence allows the researcher to leverage recent advances in the literature to decompose the link between injury and labor supply into a portion due to predictable willingness to work and private willingness to work. The relative importance of these components has an economic interpretation. When the predictable portion is large, a central planner or manager can greatly reduce the injury rate by assigning work using only observables. When the unpredictable portion is large, reducing the injury rate requires eliciting the private information of workers using an appropriate mechanism like an auction.

Substantively, this paper contributes to the large literature across economics, public health and epidemiology which studies the relationship between overtime and health. These papers use data covering a large number of diverse individuals to estimate the association between workplace injury and overtime (Dembe et al. 2005, Kim et al. 2016, Conway et al. 2017). My paper is complimentary: while it is less externally valid, it is more internally valid. I account for unobserved selection into overtime, and in so doing uncover the causal effect of an additional day of work on workplace injury. Importantly, my approach distinguishes between the observed injury rate and the counterfactual average underlying injury rate. I show that for Los Angeles traffic officers, the two are very different quantities. Most of the prior literature focuses on the observed injury rate. Although I cannot claim that my estimates hold for the general population, my results show it is dangerous to equate the observed injury rate with the average underlying injury rate. Estimating the average underlying injury rate requires accounting for labor supply-induced selection. Failing to do so biases estimates towards zero.

The second substantive contribution is to the labor supply literature in economics. Estimates of the intensive margin of labor supply abound in the labor economics literature (Liebman, Luttmer, and Seif 2009, Bargain, Orsini, and Peichl 2014, Blundell, Bozio, and Laroque 2011 , Chetty 2012). I complement this literature by demonstrating how injury risk can be an important unobserved confounder when estimating the elasticity of labor supply with respect to the wage. For a particular occupation, I show that labor supply is more elastic when injury is more likely. Because injury risk varies across jobs and also across the life cycle, this can help researchers interpret differences in labor supply elasticities by age and occupation. It is likely that some of the documented heterogeneity in elasticities is due not just to differences in preferences but also differences in injury risk.

Third, this paper contributes to the literature on compensating differentials (Moran and Monje 2016, Parada-Contzen, Riquelme-Won, and Vasquez-Lavin 2013, Kuhn and Ruf 2013, Viscusi and Aldy 2003). Only recently has the literature begun focusing on workplace safety as a firm specific amenity that can be adjusted (Lavetti 2020, J. M. Lee and Taylor 2019, Charles et al. 2019). I reinforce this finding by showing that the way overtime is assigned can greatly change the injury rate at a specific firm. On the worker side, Viscusi and Hersch 2001 and Guardado and Ziebarth 2019 make the important point that workers have some control of their own workplace safety. I affirm this, and suggest a specific pathway: workers can reduce risk by only working shifts when their injury risk is low.

The paper proceeds as follows. I begin by introducing a framework that links high-frequency labor supply decisions and injury risk. I then introduce the data and institutional details. Third, I present the main results of estimation. Fourth, I discuss the implications the results hold for shift assignment mechanisms and labor supply elasticities. For those interested, the Appendix documents how my results can be used to estimate the value of a statistical injury.

2 Conceptual Framework

In this section I develop a framework that links high-frequency labor supply decisions and individual injury risk. The framework allows the researcher to estimate whether labor supply decisions mitigate or propagate injury risk within an organization. Throughout, I refer to workers as "officers" because I will utilize my framework to study Los Angeles traffic officers. However, the framework is general and can be applied to other settings.

There are N officers indexed by i who make daily decisions to work on dates $t = 1, 2, .., T$. Denote the binary work decision W_{it} and the binary injury outcome Y_{it}^*. Y_{it}^* is the true underlying injury outcome, which is only observed when an individual works. When an officer does not work, Y_{it}^* is counterfactual. I specify that Y_{it}^* is determined by the following equation:

$$Y_{it}^* = \begin{cases} 1 \text{ if } X_{it}'\beta + C_{i2} + U_{it2} \geq 0 \\ 0 \qquad \text{otherwise} \end{cases} \tag{1}$$

X_{it} represents time-varying controls including date fixed effects. The sum $C_{i2}+U_{it2}$ represents what I call *private* injury risk. It is private because it is unknown to the analyst or the organization but may be partially known by the officer. C_{i2} represents time-invariant, person-specific injury risk. It captures factors like chronic health conditions (obesity, heart disease, diet, etc) and demographics. U_{it2} represents factors that make a particular officer more likely to be injured on a particular day. $X_{it}'\beta$ is predictable injury risk, because an organization can predict it given sufficient data.

If an officer does not work then Y_{it}^* is not observed (it is counterfactual). This induces a selection problem. The analyst only observes injury outcomes among individuals who work. Denote Y_{it} as the injury outcome that is observed. Then I have that observed injury is the product of the work decision and underlying injury outcome. Formally:

$$Y_{it} = Y_{it}^* \cdot W_{it} \tag{2}$$

Each officer decides to work if the expected utility of work is greater than not working. The utility of work relative to not working takes the linear form $Z_{it}'\alpha + C_{i1} + U_{it1}$. Thus the decision to work is given by:

$$W_{it} = \begin{cases} 1 \text{ if } Z_{it}'\alpha + C_{i1} + U_{it1} \geq 0 \\ 0 \qquad \text{otherwise} \end{cases} \tag{3}$$

Z_{it} includes all factors in X_{it} as well as at least one time-varying instrument. The sum $C_{i1} + U_{it1}$ represents *private* willingness to work. It is private because it is unknown to the analyst or the organization but is known by the officer. Similar to the injury unobservables, C_{i1} represents unobserved time invariant taste for work, due to things like a greater enjoyment from the job, or a lower value of leisure. U_{it1} represents unobserved time varying taste for work, driven by factors like wealth shocks, family events, or insufficient sleep the night before. $Z_{it}'\alpha$ is predictable willingness to work, because an organization can predict it given sufficient data.

In order to model the private component of selection in a way that is both simple and flexible. Thus, I specify that private willingness to work and private injury risk are jointly normally distributed, and are independent of all other variables conditional on person-specific means of all time-varying observables (denoted $\bar{Z}_i$).

Assumption 1 *Conditional on Z_i, X_i:*

$$\begin{pmatrix} C_{i1} + U_{it1} \\ C_{i2} + U_{it2} \end{pmatrix} \sim N\left(\begin{bmatrix} \bar{Z}_i\gamma_1 \\ \bar{Z}_i\gamma_2 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right)$$

where $-1 \leq \rho \leq 1$ and throughout $\Phi(\cdot)$ is the standard normal CDF.

This approach allows within-worker mean dependence between the unobserved components and the components of Z_{it}. For the rest of the paper I implicitly include $\bar{Z}_i$ in Z_{it} and X_{it}.[2] I will often plot and refer to the demeaned quantiles of the two private components as V_{i1}, V_{i2}:

$$V_{i1} := \phi^{-1}(C_{i1} + U_{it1} - \bar{Z}_i\gamma_1) \qquad V_{i2} := \phi^{-1}(C_{i2} + U_{it2} - \bar{Z}_i\gamma_2)$$

These have a more natural scale and they connect directly to percentiles and to the well-known idea of treatment resistance.

2.1 Parameters of Interest

This framework is useful because it allows me to formally define and estimate the following three important quantities:

1. **Observed Injury Rate:** This is the probability of injury conditional on working. It is defined as:
$$\mathbb{E}[Y|W = 1] = \mathbb{E}[Y^*|W = 1]$$
It can be estimated as the number of injuries divided by the number of shifts worked.

2. **Average Underlying Injury Rate:** This is the expected probability of injury of a random officer forced to work on a random date. It is defined as:
$$\mathbb{E}[Y^*] = \mathbb{E}_X[\Phi(X'\beta)]$$

3. **Labor supply as a function of private injury risk:** This quantifies how labor supply varies with private injury risk. I denote this function as $L(v)$ throughout and it is defined and can be estimated as:
$$L(v) = \Phi\left(\frac{z'\alpha + \rho\Phi^{-1}(v)}{(1-\rho^2)^{1/2}}\right)$$

The framework allows me to speak precisely about selection and the connection between labor supply and injury risk. If there is selection against injury the average underlying injury rate should be higher than the observed injury rate, that is:

$$\mathbb{E}[Y^*] > \mathbb{E}[Y|W = 1] \tag{4}$$

To understand how private injury risk enters the labor supply function, we can analyze $L(v)$.

[2]This vastly simplifies notation.

Lemma 1 *$L(v)$ is strictly decreasing if and only if $\rho < 0$.*

Lemma 1, which is proved in Appendix Section A.1, establishes that whether $L(v)$ is upward or downward sloping depends only on the sign of ρ, an estimated parameter. If $\rho < 0$, labor supply is downward sloping in private injury risk, and the data is consistent with officers using labor supply decisions to avoid injury. If $\rho > 0$, labor supply is upward sloping in private injury risk, and the data is consistent with officers using labor supply decisions to induce injury.

Sleep is a good way to illustrate these ideas. Recent work suggests that people are aware they are too sleepy to drive (Williamson et al. 2014), and driving is a major part of traffic officer's jobs. However, most supervisors do not know how well-rested a given employee is on a given day. Therefore the number of hours of sleep the night prior to a shift is private information about an employee's ability to work safely. If officers avoid working shifts on days when they are sleep deprived, we would expect ρ to be negative.

The direction of the inequality in equation 4 determines the overall direction of selection. However, we can decompose overall selection into predictable and private components. The private component is captured by the correlation between private injury risk ($C_{i2} + U_{it2}$) and private willingness to work ($C_{i1} + U_{it1}$). Under the normal specification, this correlation is fully captured by ρ. A negative correlation between these components is consistent with an officer possessing private risk-relevant information and using this information to *mitigate injury.* A positive correlation is consistent with officers possessing private information and using it to *exacerbate injury.* Predictable selection is captured by the correlation between $Z_{it}'\alpha$ and $X_{it}'\beta$.

2.2 A Connection to the Marginal Treatment Effect

My framework connects naturally to the marginal treatment effect, as introduced in Heckman and Vytlacil 1999. Work is the treatment, and officers are induced to take the treatment by an instrument, in my case leave of coworkers. The outcome of interest is workplace injury. Because a worker cannot be injured if they do not work, we have that $Y_{it}(0) = 0$. Thus the treatment effect is exactly $Y_{it}(1) - Y_{it}(0) = Y_{it}(1)$, that is the probability of injury conditional on work. The *marginal treatment effect* of work on workplace injury, is then given by:

$$MTE(\tilde{u}, x) = \Phi\left(\frac{X_{it}'\beta - \rho\Phi^{-1}(\tilde{u})}{(1 - \rho^2)^{1/2}}\right) \tag{5}$$

where $\tilde{u}$ is unobserved resistance to treatment (work). It connects directly to the quantiles introduced earlier: $\tilde{u} = 1 - V_{i2}$. It follows directly from Lemma 1 that the MTE is increasing in $\tilde{u}$ if ρ is positive, just like labor supply as a function of unobserved injury propensity. In this way, the MTE approach is the dual of the labor supply approach. One perspective asks how additional injury risk impacts average labor supply. The other asks how inducing additional labor supply changes the injury rate among marginal workers.

The duality clarifies that my empirical strategy is a marginal treatment effects approach in a panel data setting. The main differences from typical applications of the marginal treatment effect are that I explicitly account for the binary outcome and I relax the usual exclusion restriction. These two adjustments are crucial because workplace injury is quite rare and very little demographic information is available.

Given this equivalence, I can leverage recent developments in the marginal treatment effects literature. In particular, I follow X. Zhou and Xie 2019 and express the marginal treatment effect as a function of the propensity to be treated rather than covariates (X_{it}):

$$M\tilde{T}E(\tilde{u}, p) = \mathbb{E}_{X_{it}}[MT\mathbb{E}(\tilde{u}, X_{it})|\Phi(Z_{it}'\alpha) = p] = \mathbb{E}_{X_{it}}[\Phi\left(\frac{X_{it}'\beta - \rho\Phi^{-1}(\tilde{u})}{(1-\rho^2)^{1/2}}\right)|\Phi(Z_{it}'\alpha) = p]$$

Now the marginal treatment effect is a function of two scalars with straightforward interpretations. $\tilde{u}$ is unobserved resistance to work. This maps directly to private willingness to work:, specifically $\tilde{u} = \Phi^{-1}(-C_{i1} - U_{it1})$. p is propensity to work. This maps directly to predictable willingness to work, specifically $p = \Phi(Z_{it}'\alpha)$. Thus we can project selection into a private and predictable dimension.

Intuitively, a savvy manager could use historical data and institutional knowledge to derive the predictable component, p. This manager could then use these predictions to assign work to minimize injury. Not so with the private component. Even the most savvy manager can only derive the average relationship, and will never know the exact $\tilde{u}$ for a particular officer on a particular day. This private component captures many things, most prominently private health information, like how much an officer slept or drank the night before. A key element of this paper is estimating the relative importance of the private and public components. If the private component dominates, then an organization which wants to reduce its injury rate will need to design mechanisms which essentially elicit private information from workers. In the language of the mechanism design literature, incentive compatibility will be important.

3 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.

3.1 Institutional Details

The population of workers studied in this analysis are Los Angeles traffic officers. The city of Los Angeles is divided into 18 divisions, and work assignments, including overtime, are controlled at the division level. Throughout this study, I will refer to officers who work in the same division (work location) as "coworkers."

Los Angeles traffic officers control their labor supply mainly by working additional overtime shifts. Traffic officers are union employees covered by the Memorandum of Understanding 18 (MOU) between the City of Los Angeles and Service Employees International Union Local 721.[3] According to the MOU, traffic officers are non-exempt employees eligible for overtime pay under the Fair Labor Standards Act (Department of Labor 2017). The MOU describes the manner in which officers are paid for regular as well as overtime and "early report" hours. 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).

Over 150,867 hours were billed to overtime pay codes in calendar year 2015. This overtime comes from three sources. First, there is overtime arising from excess demand for traffic control due to something like an emergency (i.e. a pipe burst or a broken traffic light). Second, there is overtime generated by the absence of a scheduled officer during a normal shift. The data reveals that officers take leave for all sorts of reasons, including bereavement, sickness, vacation, jury duty, etc. For a full list of the various types of leave see Appendix Table B.12. Finally, there is *special events* overtime, which based on city reports is likely the main source of overtime. Special events include the Los Angeles Marathon, Dodger games, the Oscars, parades, and protests.

The MOU describes the general policy for the assignment of overtime amongst traffic officers. "Management will attempt to assign overtime work as equitably as possible among all qualified employees in the same classification, in the same organizational unit and work location" (MOU, 27). Employees must also be notified 48 hours in advance for non-emergency overtime and unofficial overtime that is not sanctioned by a supervisor is "absolutely prohibited" (MOU, 28). Workers cannot add additional hours to their shift unless authorized.

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

For this reason my paper focuses on the decision to work additional shifts rather than the decision to work additional hours.

The specifics on overtime is assigned to individual officers are not spelled out in the MOU. However, a report by the City Controller's office (Galperin 2015) gives more details about special events overtime. Special events overtime is assigned using a mechanism officers call "spinning the wheel." The generation and assignment of overtime is summarized in Figure 1.

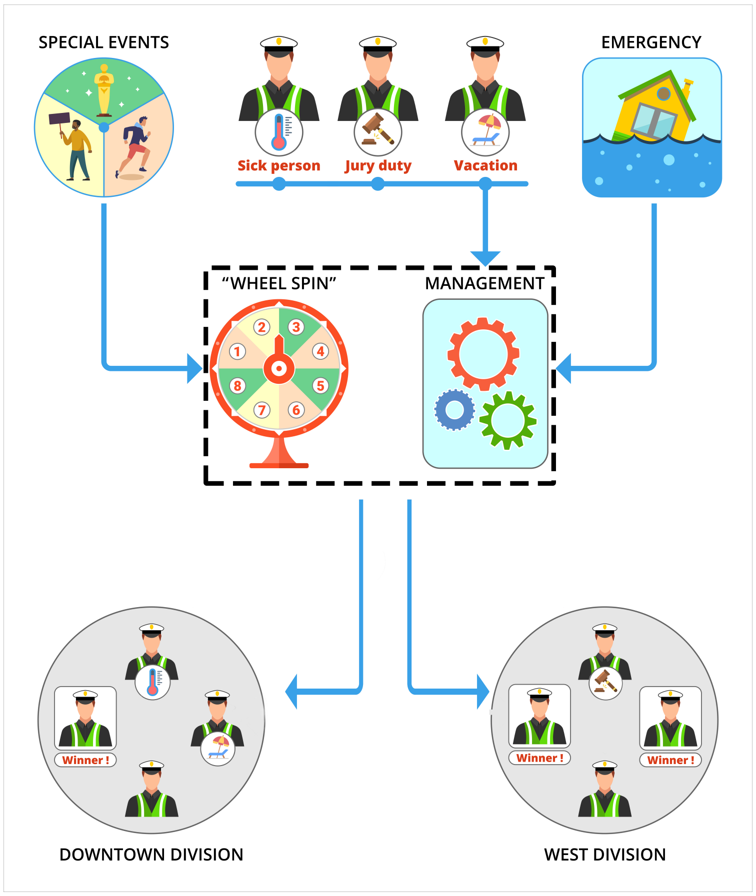


Figure 1: The Overtime Assignment Process

Under the wheel spin system, officers first volunteer to be on an overtime list. Each month, the list is sorted according to seniority. As special events become available they are offered sequentially to officers in the order they appear on the list. Once offered a shift, an officer may work it or find a substitute. As more shifts become available it is necessary to request officers from further down the list.

This institutional setting allows me to use leave of coworkers as an instrumental variable to achieve identification. Consider how a coworker (j) going on leave impacts an officer (i). If j goes on leave, two things occur. First, when j goes out sick, the department must "find replacements to perform the individual's regular job duties." Thus the absence generates overtime. Second, j's absence means there is one less person in the division (work location) who can take on additional overtime. Both forces lead to an increase in the probability that i will work. It is this variation that I will exploit in order to identify the underlying injury rate.

A reader may be concerned that officers which do not volunteer never have to work overtime. If there are always sufficient volunteers to fill any need, this issue could threaten identification. However, Galperin 2015 states that while only 192 officers signed up to volunteer in FY 2013-2014[4], 471 officers worked overtime. This is evidence that management occasionally exhausts the volunteer list and has to force force non-volunteers to work overtime.

Finally, traffic officers are an ideal population for exploring how injury risk affects labor supply decisions. They receive frequent opportunities to choose to work additional shifts. At the same time, traffic officers represent a middle ground among public safety occupations. The closest occupation with statistics on the BLS website for 2019 was crossing guards and flaggers.[5] In 2019, the nonfatal injury incidence rate was 128.6 injuries per 10,000 workers (*Incidence rates for nonfatal occupational injuries and illnesses* 2020). This was above the incidence rate for firefighters (56.2) and below the incidence rate for police officers (733.8). Traffic officers are representative of occupations where hazards are present (e.g. fast-moving traffic, hot weather) but not pervasive (e.g. carrying a gun, investigating violent crimes).

3.2 Data

The analysis population is limited to full-time officers with at least one work-related pay record between January 1, 2015 and September 1, 2016. Additional details regarding how the sample is constructed are listed in the Appendix A.4. The result of the data construction process is an unbalanced daily panel of 553 traffic officers. Table 1 reports descriptive statistics at the officer and officer-date level. The typical officer is around 45 years old and is observed working 332 days.

[4]This is the year prior to my analysis period which spans part of FY 2014-2015 and FY 2015-2016.

[5]Traffic officers are not exactly crossing guards but are also not exactly police officers.

Table 1: Descriptive Statistics

Panel A: Officer Statistics					
	Mean	Std. Dev.	p10	p50	p90
Days Observed	469.91	155.31	194.00	544.00	573.00
Days Worked	332.11	127.88	100.00	379.00	447.00
Injuries Observed	0.46	0.76	0.00	0.00	1.00
Divisions Worked	1.25	0.46	1.00	1.00	2.00
Age	45.14	9.73	32.03	44.65	58.31
Observations	553				

Panel B: Officer-Date Statistics					
	Mean	Std. Dev.	p10	p50	p90
Worked	0.71	0.46	0.00	1.00	1.00
Hours Worked	6.35	4.67	0.00	8.00	12.00
Overtime Pay Hours	1.08	2.74	0.00	0.00	5.00
On Leave	0.02	0.13	0.00	0.00	0.00
Hours on Leave	0.08	0.78	0.00	0.00	0.00
Injured	0.00	0.03	0.00	0.00	0.00
Coworkers on Leave	8.36	8.36	0.00	5.00	21.00
Wage	30.10	2.30	26.64	30.54	32.22
Seniority Rank	30.44	25.36	3.00	22.00	71.00
Observations	259,861				

[1] Age as of January 1, 2015.
[2] Wage is maximum base rate observed on the date.
[3] Worked, On Leave and Injured are indicator variables.

Table 1 also includes summary statistics on injuries. I define an "injury" as the submission of a workers' compensation claim. The vast majority of claims list medical expenses paid out, implying that the claim was approved and a real injury occurred. The probability that an injury will occur on any given day is quite low. However, 34 percent of officers are injured at least once in the period studied and 10 percent of officers are injured multiple times. The cause and nature of injuries are tabulated in Appendix Table B.3. Most injuries are related to the fact that traffic officers work outside in heavy traffic: officers can be sideswiped, get into car accidents, or suffer heat-induced injuries. Injuries span the gamut from superficial to serious.

Table 2 describes variation in time worked across officers. Panel A presents statistics for the distribution of the hours worked in a day. Panel B presents statistics for days worked in four-week periods. Because an injury causes officers to subsequently miss work, Panel B excludes data after the first observed injury.

From these tabulations of work patterns two things are apparent. First, there is much more variation in the days per shift than the hours per day. The inter-quartile range of shift length is 0, while the inter-quartile range of days worked in four weeks is 5. For this reason I focus on the variability in the number of days rather than the number of hours. Second, employees who experience injury tend to work fewer days per month than those who do not. This fact suggests more injury-prone officers work less.

Table 2: Distribution of Time Worked

(a) Daily Hours Worked

	Mean	Std. Dev.	p10	p50	p90
Not Injured	9.00	2.70	8.00	8.00	13.00
Injured	8.94	2.62	8.00	8.00	13.00
Total	8.98	2.67	8.00	8.00	13.00
N	183659				

(b) Days Worked in Four Week Period

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

Table 2 displays the distribution of work at the hourly and daily margins. It should be noted that in Panel A, the sample is restricted to days with positive hours worked. In Panel B, the sample is restricted to 4 week periods with at least one day with positive hours worked.

Table 3 describes officer compensation. Most individuals earn a wage that is a little less or a little more than $30 per hour. This is consistent with a common wage schedule which is set during negotiations between the union and the city. Overtime on average represents 12 percent of pay, but this masks a highly skewed distribution. At least 50 percent of officer-weeks do not have overtime pay, while 10 percent are comprised of more than 33 percent overtime pay. Again these statistics indicate that schedules vary most in terms of number of days worked rather than number of hours worked per day.

Table 3: Pay Composition Statistics

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

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

3.3 Descriptive Evidence of Self Selection

The purpose of this section is to show selection against injury is a robust pattern observed in the data, and not an artifact of the framework introduced earlier. If individuals incorporate their own private information about injury risk into their labor supply decisions, and we assume individuals dislike being injured, we should observe positive selection in the data. That is, the probability of injury among officers who work on any given day should be lower than the probability that would result from randomly forcing an officer to work. Mathematically, it should be true that:

$$\mathbb{E}[Y^*] > \mathbb{E}[Y|W = 1]$$

To trace out how unobserved selection influences injury, I use variation in the leave of coworkers as an instrument. When more coworkers go on leave in a division, management is left with more open shifts and fewer officers to fill those shifts. This should increase the probability that any given officer who is not on leave works without impacting that officer's injury risk directly. We can visually check for selection by graphing a binned scatter plot of injury against the number of hours of leave taken by coworkers. I do this in Figure 2.

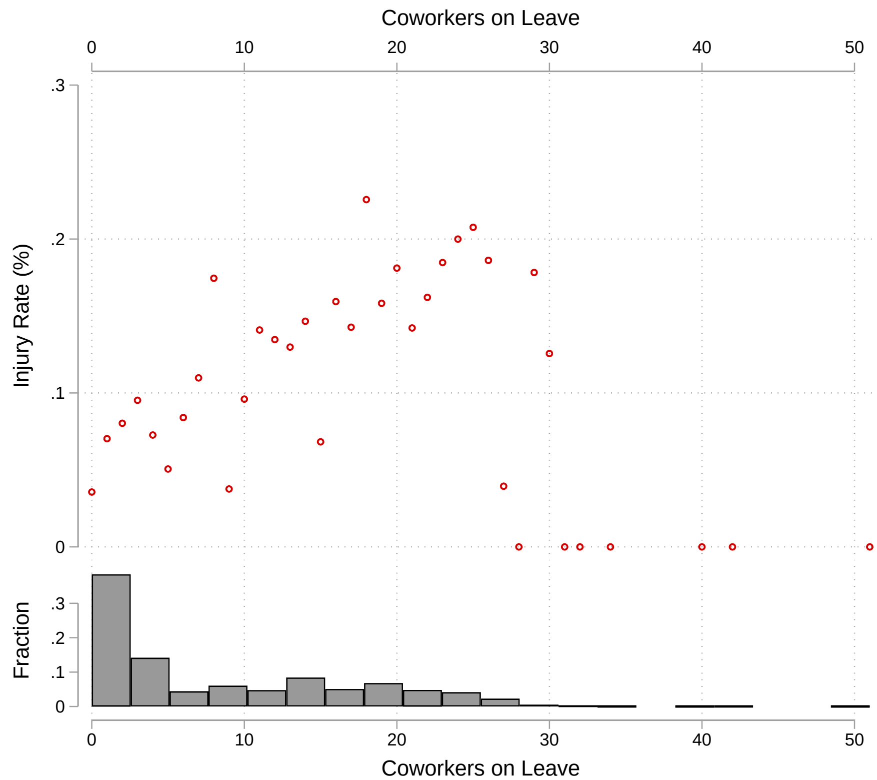


Figure 2: Evidence of Selection Against Injury. This figure plots the average probability of injury conditional on different values of coworker leave. The probability rises with coworker leave, evidence that the officers select against injury.

Figure 2 demonstrates that as leave of coworkers increase, the injury probability also rises. This is consistent with self-selection against injury. When officers are given the choice to work, they prefer not to work when their injury risk is elevated. When more coworkers go on leave management must force other officers to work, making the pool less selected thus bringing the injury rate closer to the underlying injury rate.

Comparing regression coefficients makes the same point. In Appendix Table B.6 I regress injury on work. The coefficient on work is exactly the average underlying injury rate if selection is random. In Table B.13, I perform several fixed-effects instrumental variable regressions. Comparing any two columns in the tables, we see that the naive estimate is much lower than the instrumental variables estimate. Just as in Figure 2, this result suggests that voluntary labor supply decisions result in selection against injury.

Although these arguments are helpful to establish the presence of selection, quantifying the magnitude and computing the average underlying injury rate requires the framework introduced earlier. I now turn to identification and estimation of the key parameters in the framework.

4 Empirical Strategy

The main threat to identification of the average underlying injury rate is that injury risk is likely correlated with the decision to work. Indeed, the entire premise of this paper is to understand the nature of this dependence. To identify and adjust for unobserved selection, I exploit variation in the number of coworkers who are out on leave. When more coworkers go on leave in a division, management is left with more open shifts and fewer officers to fill those shifts. This should increase the probability that any given officer who is not on leave works without impacting that officer's injury risk directly.

My identification strategy is best described as an instrumental variables approach in a binary panel data setting using leave of coworkers as the instrument. Estimation is performed using partial maximum likelihood, with expressions for the likelihood given in Appendix Section A.3. As noted in Semykina and Wooldridge 2018, models of this type camn be estimated as pooled Heckman selection probit models. As a result, I estimate the parameters using Stata's built-in 'heckprobit' command with the addition of person-specific means ($\bar{Z}_i$) in the selection and outcome equations. Standard errors are clustered at the officer level to account for within officer serial-correlation.

The main assumptions required for identification in my model involve the excluded instrument. Leave of coworkers must be properly excluded from the injury equation, it must be sufficiently relevant to the work decision, and it must generate sufficient variation in the support of the propensity to work. I provide evidence that these assumptions are satisfied in Section 4.2. The panel structure of the data allows me to relax the exclusion restriction to allow for individual-specific mean dependence between the instrument and the unobserved components.

The reader may wonder why I impose parametric structure on the estimated model, given that the underlying strategy is essentially an instrumental variable approach. This is because injury is a rare outcome and the data is not large enough to accommodate more flexible approaches. This appears to be without loss: my main qualitative findings exist without the structure.[6] Other readers may wonder why I do not use a linear probability model. I do not do this because injury is a rare event and I am concerned with computing the injury rate across the distribution of willingness to work. A linear probability model will result in estimates that are outside the unit interval.

[6] See the descriptive evidence section.

4.1 Variable Construction

On date t for officer i "leave of coworkers" is constructed as the number of officers in the same division as i on date t that are out on leave for eight or more hours. The majority of variation is therefore at the division-date level. I exclude leave taken by officers who are observed to have worked that day, since such leave might be correlated with injury risk on that specific date and thus violate the exclusion restriction.

In the estimation of the probability of injury, the X_{it}'s includes age, the officer's wage, the officer's seniority rank within the division on date t, division indicators (with small divisions grouped together), and a full set of date fixed effects. Because injury is rare and binary, including date fixed effects comes at the cost of lower statistical power. It weakens the assumptions for identification but it means dates which do not have injuries will not be used during estimation because their log-likelihood estimate is undefined. The effective estimation sample therefore reduces from 259,861 to 80,898 officer-days. All 553 officers remain in the effective sample.

The Z_{it} variables in the probability of working equation include everything contained in X_{it}'s as well as leave of coworkers to satisfy the exclusion restriction. $\bar{Z}_i$ includes officer-specific time averages of leave of coworkers and wage. Seniority rank, division, date indicators and age are excluded from $\bar{Z}_i$ because they are highly co-linear with time. For example, age can be perfectly predicted from average age and date indicators.[7]

4.2 Instrument Validity

Identification of the model requires leave of coworkers to be a valid instrument: it must be properly *excluded* from the injury equation and *relevant* to the work decision. I provide statistical and then theoretical arguments that these assumptions are satisfied. Fortunately, the requirements for identification are weaker than the typical exclusion restriction. The panel nature of the data allows the mean of the leave of coworkers to directly impact the injury outcome. Formally, this is reflected by the fact that $\bar{Z}_i$ enters the injury equation.

To statistically test the exclusion restriction I conduct a balance test using medical expenses of an injury as a proxy for injury severity. I first restrict the data to the officer-dates with an injury outcome. I then sum the medical expenses paid in the associated workers' compensation claim. Intuitively the exclusion restriction requires that leave of coworkers only impact the binary injury outcome by inducing officers to work. If leave of coworkers is correlated with the severity of an injury this suggests some sort of direct effect. I find no

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

evidence that the exclusion restriction is violated. The results are presented in Appendix Table B.14. There seems to be no correlation between the severity of an injury and the leave taken by coworkers.

Figure 3 presents graphical evidence that leave of coworkers is relevant to the work decision. The figure displays a binned scatter plot of work probability and coworkers on leave, with equally spaced bins by number of coworkers on leave. The relationship is generally upward sloping, indicating a positive link between the instrument and work probability.[8] As a statistical test, I present F-statistics of an analogous linear probability model of work on the leave of coworkers in Table B.7. All F-statistics are greater than 99. The coefficient on coworker leave is also highly significant in all specifications. Overall the table suggests instrument relevance is satisfied. Additional formal tests of weak instruments are documented in Appendix Section A.6. All tests support the assumption that leave of coworkers is relevant to the work decision and not a weak instrument.

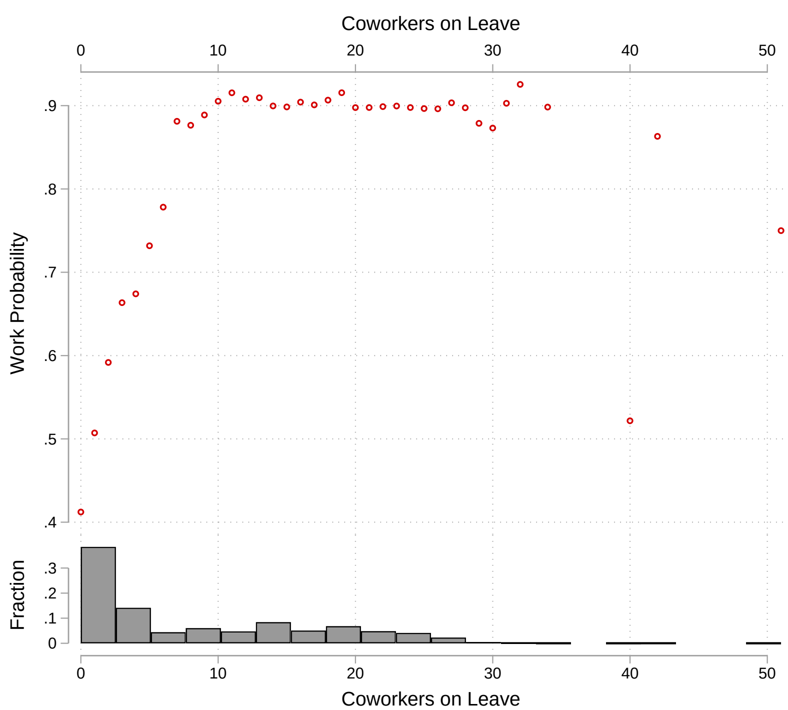


Figure 3: Instrumental Relevance. The figure visualizes the relationship between coworkers on leave and probability of working overtime, with relative frequencies underneath. Each circular dot represents each of the values taken on by coworker leave on the x-axis and the corresponding average probability of work for those observations. As the number of coworkers on leave increases, the probability an officer works rises.

[8]In the Appendix I provide a binned scatter plot which does not interpolate between bins. This plot also supports relevance.

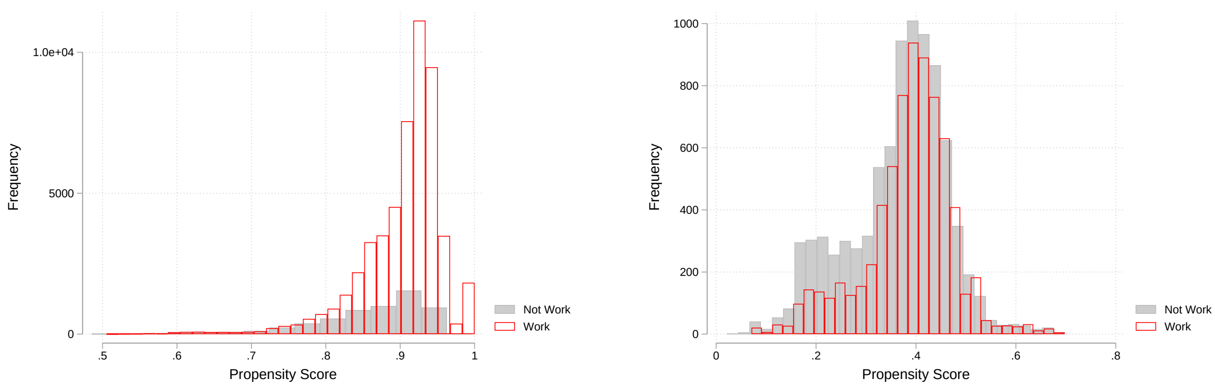
These results appear consistent with our theoretical intuition. Conditional on X_{it} and $\bar{Z}_i$, "coworker leave" must only impact injury through the decision to work. For many forms of leave, like bereavement and jury duty, this seems likely to be satisfied. The death of a coworker's relative is unlikely to affect own work conditions or own health status. For other forms of leave, such as vacations or floating holidays, this requirement is conditionally satisfied. That is, people may tend to take vacations during times of the year when weather conditions contributing to injury risk prevail. For example, more vacation may be taken during the summer when heat exhaustion is a factor. But I control for date fixed-effects, and conditional on these, there is likely no dependence. Use of sick leave might violate the exclusion restriction if coworkers are likely to infect each other. To address this concern I estimate the main parameters using a leave instrument that does not include sick time. These estimates are in Appendix Table B.8 and are discussed in more detail in the robustness section.

Leave of coworkers must also be relevant. Recall that the LADOT uses a "spin the wheel" system to assign overtime. As discussed at length earlier, if more individuals go on leave, the supervisor will need to select a larger number of volunteers and the pool of people available to work will shrink. Thus, conditional on volunteering, the probability of working an extra shift rises. Even if an officer does not volunteer, there is nothing in the memorandum of understanding preventing supervisors from forcing officers to work if the volunteer pool is exhausted. In fact, the MOU describes some overtime as "required," implying that management can force officers to work in certain situations. The MOU also states that many rules are suspended during emergencies. Thus, it is reasonable to assume that the city can force officers to work during incidents such as water main breaks, earthquakes, etc. The probability of any individual officer working in such circumstances will, once again, depend on the size of the pool of available workers. As a result, the probability of working for non-volunteers should also be increasing in the number of other officers on leave.

4.3 Identifying the Average Underlying Injury Rate

As mentioned earlier my empirical strategy is equivalent to a marginal treatment effects approach. The average underlying injury rate is then the analogue of the average treatment effect (ATE). Like the ATE, the average injury rate is counterfactual and requires strong conditions on the instrument to be identified and estimated. Fortunately, because workplace injury never occurs when someone does not work, I do not need to satisfy all of the typical marginal treatment effect propensity support conditions. However, identification still requires that the instrument bring the propensity score arbitrarily close to 1 for those who work (Heckman and Vytlacil 1999). If the instrument does not do this, estimating the average population injury rate will rely entirely on the parametric assumption to extrapolate beyond the support.[9]

Figure 4 plots propensity scores for the weekends (Saturday and Sunday) and Monday through Thursday.[10] We see from this diagram that while the propensity score comes close to 1 for Monday through Thursday, it never rises above 0.6 for Saturday and Sunday. Therefore I do not claim to identify the unconditional average underlying injury rate. I only claim identification of the injury rate conditional on work being performed on a weekday (Monday through Thursday). Unless otherwise noted, all estimates and plots in the results section average only over the weekday observations. As a result they should be interpreted as objects that are conditional on being a weekday (Monday through Thursday).



(a) Monday through Thursday

(b) Saturday and Sunday

Figure 4: The figures display the support of the propensity score for weekdays (Mon through Thursday) and weekends (Saturday and Sunday).

Even for weekdays, some readers may still be concerned the support is sparse near 1. To alleviate this concern, I implement a bounding method proposed by Heckman and Vytlacil 1999 in the robustness section.

5 Results

This section presents the results. I start with the parameter estimates, then the impact of injury risk on labor supply, followed by the impact of labor supply on injury, and end with

[9]This is often referred to identification at infinity. I thank an anonymous referee for pointing this out.

[10]Friday is excluded because it is a hybrid between a weekday and a weekend. It has a higher average work probability then the weekdays but a lower probability then the other weekdays.

a decomposition of selection into predictable and private components. All results support the conclusion that officers use their labor supply decisions to avoid injury. The majority of this selection comes through private rather then predictable factors. Although the model is estimated using all days of the week, most of the results are conditional on the date being a weekday (Monday through Thursday) because of the identification issue discussed earlier. For more discussion, see Section 4.3.

5.1 Parameter Estimates

Estimates of the most important coefficients in Equations 3 and 1, as well as ρ (the unobserved correlation between injury propensity and work utility), are presented in Table 4. Recall that selection effects as well as decompositions hinge crucially on the estimate of ρ. When ρ is negative there is evidence that officers are utilizing private information about injury risk to avoid working risky shifts.

Table 4: Workplace Injury and Labor Supply Model: Select Parameter Estimates

	Injury	Work
Avg. Coworkers on Leave	-0.0638***	0.0143**
	(0.0120)	(0.00611)
Avg. Wage	-0.0590	-0.101***
	(0.0584)	(0.0183)
Wage	0.0756	0.107***
	(0.0610)	(0.0157)
Seniority Rank	0.00165	0.000900
	(0.00142)	(0.000787)
Coworkers on Leave		0.0150***
		(0.00267)
Observations	80898	
Rho	-0.658	
Rho 95% CI	(-0.19, -0.882)	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table displays the main coefficient estimates of the injury and work equations. "Avg." variables are time averages for each person across time periods.

Due to the non-linear nature of the model, I also report average elasticities of the work probability with respect to several variables in Appendix Table B.10. I find large wage elasticities: a 1 percent increase in the wage increases the probability a worker takes a shift by 2.27 percent. Leave of coworkers has the expected positive effect. Appendix Table B.11 reports average elasticities of injury conditional on work. That is, how the observed injury rate responds to changes in the main covariates conditional on the officer having worked. A one percent increase in the number of coworkers on leave results in a 0.23 percent increase in the probability of injury given work.

5.2 Impact of Injury Risk on Labor Supply

The most important takeaway from Table 4 is the estimate of ρ. Since $\hat{\rho} = -0.66$ and the estimate is significant, I can reject the null hypothesis that $\rho = 0$ at the 0.05 level. Recall by Lemma 1, a negative value for ρ leads to a labor supply $(L(v))$ which is downward sloping in private injury risk. Thus, the estimated value for ρ indicates that officers are less likely to work when they are more likely to be injured. Intuitively, this suggests officers are acting on private injury risk information in order to avoid injury. Figure 5 plots labor supply as a function of private injury risk. We can compare different points along the graph to understand how officers with different private injury risk make labor supply decisions. An officer at the 80th percentile of unobserved injury risk is 21 percentage points less likely to work on a particular date than an officer at the 20th percentile.

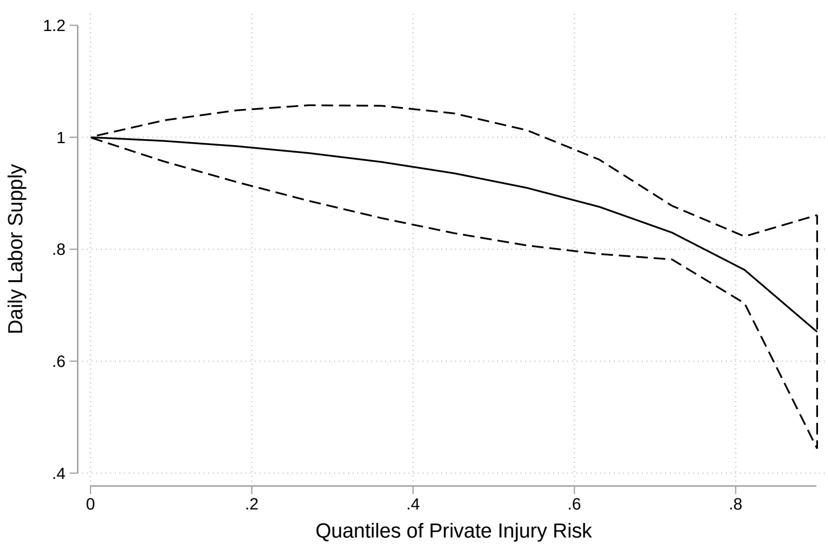


Figure 5: Average Daily Labor Supply and Private Injury Risk. This figure plots daily labor supply (in terms of probability of working) at different levels of private injury risk. Injury risk is in terms of v a quantile-based measure of private injury risk. Higher v indicates higher private injury risk. Dotted lines represent 95 percent confidence intervals with a Bonferroni correction for multiple hypothesis testing. The x-axis is truncated on the right for better visualization.

5.3 Impact of Labor Supply on Injury Risk

The last section illustrated how injury impacts labor supply. We can also ask how labor supply impacts injury rates. When more coworkers are on leave, an officer is less able to self-select out of work. This should increase the probability of injury. This is exactly what we observe in Figure 6. As the department has to dig deeper into the pool to fill open slots, it has to rely on officers who are less willing to work and thus more likely to be injured.

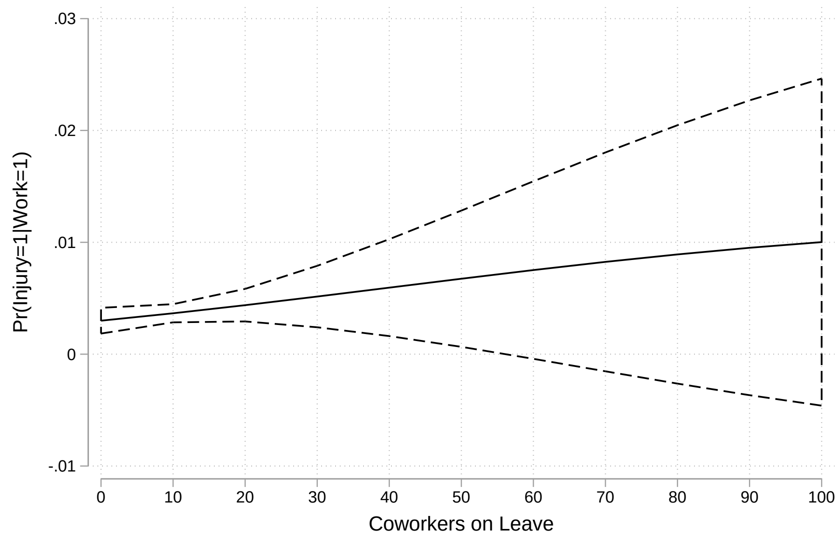


Figure 6: Expected Injury Rate Conditional on Different Instrument Values. Point estimates are averages of both unobserved heterogeneity and covariates. Dotted lines represent 95 percent confidence intervals with a Bonferroni correction for multiple hypothesis testing. The x-axis is truncated on the right for better visualization.

As I show in section 2.2, the effect of voluntary labor supply decisions on workplace injury within an organization is fully captured by the well-known marginal treatment effect function. My framework yields an explicit expression for the marginal treatment effect given by Equation 5. I use this expression averaged over the observed covariates values X_{it} to plot the marginal treatment effect in Figure 7. The upward slope of the MTE indicates that officers which are more resistant to work are more likely to be injured. If we think of workplace injury as a negative outcome, this represents positive selection. The most risky officers are the least likely to undergo the treatment which is working a shift.

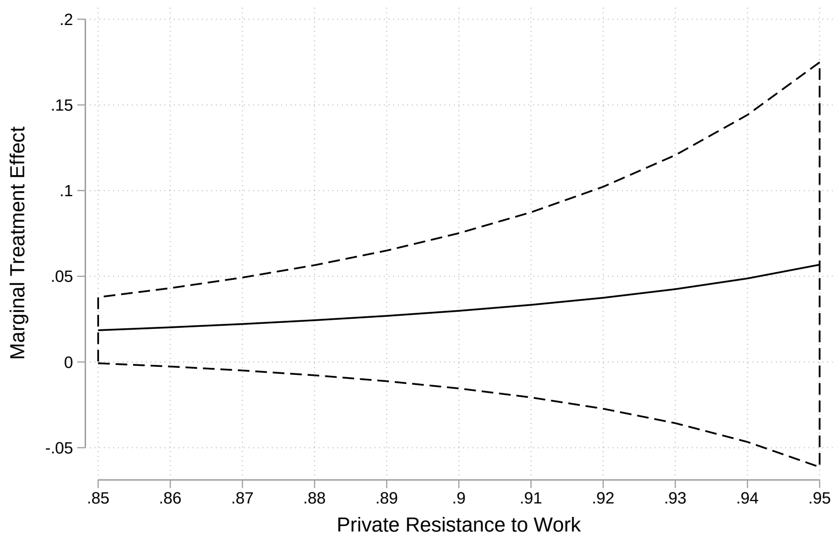


Figure 7: Marginal Treatment Effect of Work on Workplace Injury. This figure visualizes selection against injury: officers who are more resistant to work are more likely to be injured. Dotted lines represent 95 percent confidence intervals with a Bonferroni correction for multiple hypothesis testing.

To measure the magnitude of selection, we can compare the observed injury rate (injuries divided by days worked) with the average underlying injury rate. Recall that this is the expected injury rate of a random officer forced to work on a random date. It is the average treatment effect of work on workplace injury, and a counterfactual quantity. Comparing the observed and underlying rates demonstrates that selection effects are large: the average underlying injury rate is 1.2 percent while the observed injury rate is 0.38 percent. This means that selection via voluntary labor supply decisions greatly mitigates injury risk among Los Angeles traffic officers. It also means that an officer who is forced to work will generally have a much higher injury risk than an officer who volunteers. In the robustness section I provide a lower bound on the average underlying injury rate which accounts for potential violations of the propensity score requirements. This lower bound is 0.71 percent.

5.4 Decomposing Selection

Recall that the work decision is based on two pieces: a predictable component, $Z_{it}'\alpha$, and a private component $C_{i1} + U_{it1}$. When the sum of the two components is positive, the officer works. In this section we establish how much of selection comes through each component. If we assume $Z_{it}'\alpha, X_{it}'\beta$ are jointly normal, the fraction of selection due to the private component is given by:

$$\lambda := \frac{\rho^2}{\rho^2 + Corr(Z_{it}'\alpha, X_{it}'\beta)}$$

I can estimate λ by replacing all the variables on the right hand side with their empirical counterparts from the estimated model. The only additional step is to compute the correlation between the linear predictions. I find that $\hat{\lambda} = 0.96$, meaning 96 percent of selection is due to private factors while the remaining 4 percent is due to predictable factors. We can also follow X. Zhou and Xie 2019 and express the marginal treatment effect as a function of just the propensity score (another measure of the predictable component) and resistance to work (another measure of the private component). Because we have an exact expression for the MTE, I can create a grid of the average MTE for various values and see how much variation is explained by each component. Using this method, I find 82 percent of variation in the marginal treatment effect is attributable to private factors while 18 percent is attributable to predictable factors. Both methods confirm that the majority of selection is due to private factors: things like private health information and demographics that a manager either could not predict or could not legally use to assign work. I explore in the discussion section how this finding implies that carefully designed overtime assignment mechanisms can help reduce injury rates.

Motivated by a similar diagram in X. Zhou and Xie 2019, I visualize the patterns of selection across the private and predictable components in Figure 8.

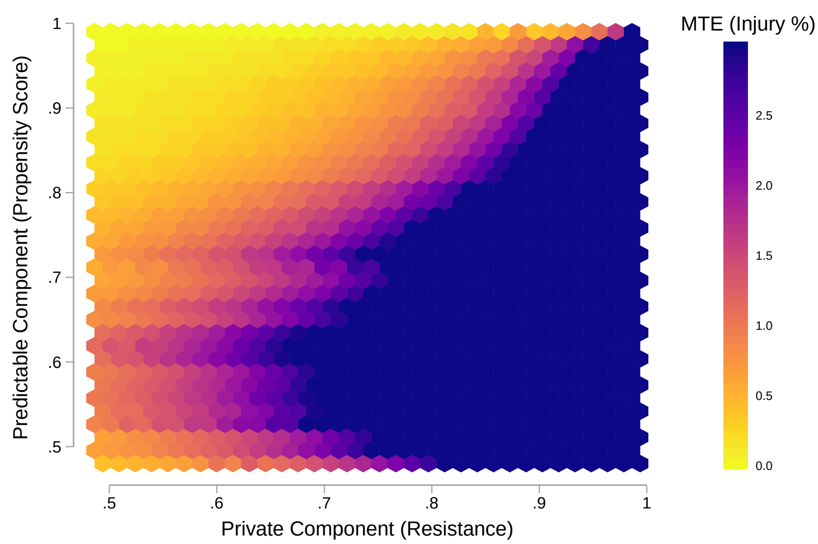


Figure 8: Decomposition of Selection. This figure plots the marginal treatment effect for different values of the predictable component (expected labor supply given observables) and the private component (unobserved resistance or willingness to work).

In the diagram we can think of each point as representing a different type of officer. As we move along the x-axis from left to right, officers become less willing to work along the private component. The unobserved parts of their net utility from work become lower. As we move from bottom to top along the y-axis, officers become more willing to work along the predictable component. The shading represents the expected injury rate of each type of officer. Darker shading indicates a higher injury rate while light shading indicates a lower injury rate.

Figure 8 paints a fuller picture of the two dimensions of selection. The fact that the darkest portions of the diagram are in the right bottom corner indicates that private and predictable selection move in the same direction. Officers who we expect to work (higher propensity score) generally have a lower marginal treatment effect (average injury rate) for all values of resistance. Officers who have a higher unobserved resistance tend to have a lower marginal treatment effect for all values of the propensity score.

Figure 8 can be used to think about the problem of a central planner trying to minimize the injury rate of an organization subject to some labor supply constraint. Suppose the planner can choose who to assign a shift, but can only base their decision on observable factors. Such a planner will only be able to exploit selection along the y-axis (predictable component). This is quite limiting: the planner could greatly reduce injury rates if it is able to use the x-axis as well (private factors).

The mechanism design literature tells us that there exist mechanisms, like shift auctions, which will induce officers to reveal their private willingness to work. Because the private components are highly correlated, the social planner can design mechanisms which also extract officer's private injury risk. Section 7.1 provides a concrete example of these ideas.

6 Robustness

I estimate several variations of the model to test the sensitivity of the main results and detect any potential threats to identification. A summary of parameter estimates under each specification is provided in Appendix Table B.9. For each specification, I report the coefficient on leave of coworkers as well as $\hat{\rho}$ and the average underlying injury rate.

First, I construct a more conservative version of the leave instrument, which excludes sick time. I do this out of concern that sick leave violates the exclusion restriction. For example, diseases may be contagious and thus there could be a direct effect of the sick days taken by others on own injury risk. Alternatively, increased sick leave might make the remaining pool of officers on average more healthy. This conservative instrument has considerably less variation, because sick time represents a fourth to a third of leave.[11] For this analysis only I additionally provide all main coefficient estimates in Appendix Table B.8. All estimates

[11] See Appendix Table B.5.

remain relatively stable,

Second, I test the sensitivity of my results to changes in the definition of injury. Because I measure injuries as workers' compensation claims, there is a concern that false reporting of injuries might be biasing my results. Claims are verified by medical professionals, but for hard-to-verify injuries, like strains and mental stress, over-reporting might still be a concern. If this is true, the selection I observe could be generated by correlation between an officer's propensity to file false claims and their unwillingness to work. To address this, I estimate my model again with claims described as "Strain" not considered injuries. Out of 243 injuries, 118 are classified as a "Strain." This removes almost 50 percent of the injuries, so it is not surprising that my estimates fall in magnitude and statistical significance. However, it is reassuring that all estimates remain qualitatively similar: $\hat{\rho}$ remains negative and the average underlying injury rate remains of a similar magnitude.

Third, I run the analysis reclassifying injuries based on a thresholds for medical expenses. We can assume that more expensive claims are more serious injuries, and more serious injuries are less likely to be falsely reported. I re-estimate the model with low value claim–those more likely to be fraudulent–reclassified as non-injuries. First I estimate the model reclassifying claims incurring \$0, then reclassifying those incurring less than \$200, and finally, those less than \$400. Surprisingly, $\hat{\rho}$ actually rises as I raise the minimum expense threshold. Similarly, the average underlying injury rate also rises as more claims fall below the minim threshold. This result suggests that if there is fraudulent reporting of workplace injury, it is likely causing me to underestimate selection against risk.

Lastly, I address concerns about the support of the propensity score. As mentioned previously, I only claim to identify the weekday average underlying injury rate. This is mainly because my instrument does not generate sufficient support of the propensity score for weekend dates. Still, even among weekdays there are very few observations where an individual works and the propensity score is above 0.98. This might leave some concerned that the support condition is still not fully satisfied, and that the resulting estimates rely on extrapolation and identification at infinity.

To account for this I estimate bounds on the average injury probability. Appealing to the fact that the average underlying injury rate is the average treatment effect of work on injury, I use the results derived in Heckman and Vytlacil 1999. Define $\bar{p}(x)$ as the maximum observed propensity score for covariate pattern x among individual-days with $W = 1$. Then we have:

$$\mathbb{E}[Y^*|X = x] = \int_0^{\bar{p}(x)} \mathbb{E}[Y^*|X = x, U = \tilde{u}]d\tilde{u} + \int_{\bar{p}(x)}^1 \mathbb{E}[Y^*|X = x, U = \tilde{u}]d\tilde{u}$$

The first integral is always observed. Because injury is a binary event, the second integral is bounded between $[0, 1 - \bar{p}(x)]$ which implies that the average underlying injury rate for covariate pattern x is bounded in the following way:

$$\int_0^{\bar{p}(x)} \mathbb{E}[Y^*|X = x, U = \tilde{u}]d\tilde{u} \leq \mathbb{E}[Y^*|X = x] \leq \int_0^{\bar{p}(x)} \mathbb{E}[Y^*|X = x, U = \tilde{u}]d\tilde{u} + 1 - \bar{p}(x)$$

Note the interval collapses to a point when the maximum observed propensity score is 1. Because workplace injury is a rare event, the upper bound is not informative. However because I am generally concerned about whether the average underlying injury rate is higher than the observed injury rate, the lower bound is my focus. I set $\bar{p} = 0.98$ based on the plots of the propensity score. I then approximate the first integral using the midpoint method. The procedure generates a lower bound for the weekday average underlying injury rate of 0.71 percent. This is lower than the main estimate of 1.2 percent I report but still nearly double the observed weekday injury rate of 0.37 percent. This is evidence that the main qualitative result does not rest on identification at infinity or functional form extrapolation.

7 Discussion

The traffic officers I analyze are assigned overtime through a relatively simple system: extra shifts are given to volunteers based on seniority and whether or not the person has already worked overtime during the relevant period. This system is not designed to reduce injury rates. It is designed to maximize ex-ante fairness. Strikingly, however, it still generates a large amount of positive selection which drives the observed injury rate to be much lower than the underlying injury rate. This is because it gives officers opportunities to self-select out either by not volunteering or declining a shift.

This result lends some nuance to news stories about overtime among public safety professionals. Many articles are alarmed by the massive amount of overtime worked by certain fire fighters and police officers (Ashton and Reese n.d., Steinbach 2019). My analysis suggests such massive overtime is not necessarily a problem for workplace injury. I analyze 553 officers over 609 days. The median number of days worked is 379, but the top 10 percent of officers work more than 447 days. One officer worked 601 of the 609 days. The data cannot speak to the quality of the work performed by an officer who works almost everyday. However, my results indicate this overtime inequality reflects a process which is helping to reduce injury.

To see this, notice what I call the average underlying injury rate is also the counterfactual injury rate we would observe if work assignments were determined mechanically by a random number generator, and all officer choice was removed. Such a system assures equality in overtime outcome: all officers can expect to work the same number of shifts. The observed injury rate is the rate which arises under the spin the wheel mechanism, which assures equal overtime opportunity but not equal overtime outcomes. The fact that the observed rate is so much lower than the underlying rate implies that achieving overtime equality will come at the cost of more injuries.

Thus, inequality in the distribution of overtime ex-post is not necessarily bad in terms of injury rates, as long as the inequality is generated by a voluntary process. Indeed, my results highlight that the distinction between mandatory and voluntary work is of first-order concern when it comes to injury. Many descriptive analyses have shown a positive relationship between excessive work and workplace injury. These include studies using the NLSY (Dembe et al. 2005), a survey of fire fighters in Korea (Kim et al. 2016) and an analysis using the PSID (Conway et al. 2017). Importantly, these studies do not distinguish between mandatory and voluntary overtime. Under my framework, we can think of mandatory overtime as shifts worked when willingness to work is low. I have shown both private and predictable willingness to work is negatively correlated with injury risk. This implies mandatory overtime is more dangerous than voluntary overtime. Because of this, analyses which lump mandatory and voluntary overtime together will always be estimating a weighted average of the mandatory and voluntary effect. Additionally, two identical companies employing identical populations of employees could still have completely different observed injury rates if they allocate work differently. Organizations which rely on voluntary mechanisms will tend to have lower injury rates, while organizations which force employees will tend to have higher rates.

Because I have variation in wages, I am able to estimate the value of a statistical injury for different traffic officers. Because this is not the main focus of the paper, the calculations and estimates are provided in Appendix Section A.8. One observation worth noting is that even within a single occupation and a single organization, the value of a statistical injury can be heterogeneous. This is illustrated in Appendix Figure 12.

7.1 Shift Auctions

The decomposition of selection into a private and predictable component revealed that the majority of selection is private. I have shown in this paper that the current mechanism used to assign traffic officers to shifts leverages *some* of this private selection. In this section, I demonstrate both theoretically and via simulation that organizations can reduce the injury rate further by using a better mechanism, specifically an auction.

First, recall a few results from auction theory. In a second-price auction with private values, it is weakly dominant to bid one's true value. As a result, the auction will generally assign the object to whoever values it most. When officers are the bidders and shifts are the objects, net utility from work is the value. Suppose officers bid by posting a wage, and the winning officer is the one who posts the lowest wage. Suppose it is a second-price auction, so the winning officer works the shift at the second-lowest wage bid. From auction theory we know that in equilibrium, the winning officer will be the one with the highest net utility.

We can use the earlier estimated results to analyze the efficacy of such a mechanism. I have shown net utility is negatively correlated with injury risk (through both the private and predictable component). The coefficient on wages in the work decision is also positive, indicating officers value wages. This means officers will trade-off wages and injury risk, and the winning officer will have one of the lowest expected injury risks. In theory this should increase selection against injury, because we no longer assign shifts sequentially but rather let officers compete for the shift. Intuitively, shift auctions induce officers to truthfully reveal their injury risk.[12] In this way a shift auction should theoretically improve upon the status quo. Revisiting Figure 8, a shift auction would free a manager to use variation along both dimensions to minimize injury rates.

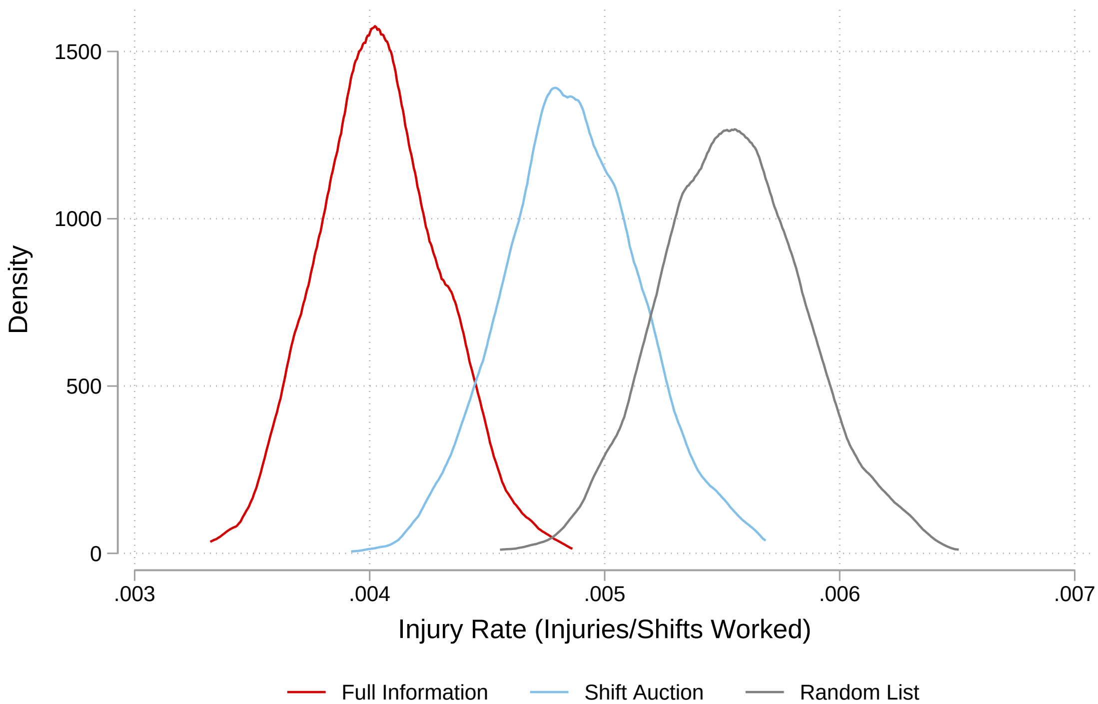
I now show via simulation that auctions reduce injury rates. I compare a shift auction like the one described previously to a random list mechanism. I employ a simple random list mechanism similar in spirit to the status quo spin the wheel system. A full description of the simulation of the list and shift auction mechanisms is given in Appendix Section A.7. I perform 1,000 simulations. On average, the shift auction mechanism generates an average daily injury rate of 0.49 percent, while the random list mechanism generates an average daily injury rate of 0.55 percent. This means the shift auction results in a 12 percent decrease in the injury rate.

I also compare shift auctions to what I call the *full information benchmark*. The full information benchmark is the injury rate that would be observed if a manager could assign additional shifts directly to the employees with the lowest injury risk. To simulate it, I randomly assign regular shifts among officers who are willing to work, and then I assign the additional shifts to the officers with the lowest injury risk. The full information benchmark results in an average daily injury rate of 0.40 percent.

The simulation results are summarized in Figure 9. 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 injury rate distribution when officers bid for shifts approaches the full information benchmark, and yields much lower injury rates than the random list. This exercise highlights the practical implication of my results: because so much of selection

[12] This intuition comes via the revelation principle.

is driven by private, unobserved factors, carefully designed mechanisms which induce officers to act on their private information can reduce an organization's injury rate. The shift auction is one such mechanism: because officers value wages but dislike injury, the winning bidder will have low injury risk.



	mean	p5	p95
Random List	0.0055	0.0051	0.0061
Shift Auction	0.0049	0.0044	0.0054
Full Information	0.0040	0.0036	0.0045
Simulations	1000		

Figure 9: Simulated Injury Rates Under Three Mechanisms. The figure plots the simulated distribution of the injury rate under three different overtime assignment mechanisms. The full information mechanism is the ideal case, when a planner assigns shifts to the officers with the lowest risk. The random list mechanism is similar to the mechanism currently used by the City of Los Angeles, where shifts are given randomly to everyone who volunteers. The shift auction assigns extra shifts to the officers who bid the lowest wage.

In the simulated shift auction, a manager posts the available shifts, and officers may place a wage bid for each. The shift is then assigned to the officer who bids the lowest wage. Although shift auctions may seem unorthodox, many scheduling software companies already include such a system as a built-in option.[13]

7.2 Labor Supply Elasticity

So far I have established that, all else being equal, officers will work less when they have elevated injury risk. That is, the labor supply curve slopes downward in injury risk. In this section, I quantify how injury risk impacts labor supply elasticities with respect to the wage. My model allows me to estimate the elasticity of the probability of working a shift with respect to the wage conditional on different unobserved propensities to be injured. This allows me to see how elasticities vary at different levels of risk. Formally, I calculate the quantity:

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

and average over observed Z_{it}. This yields an average labor supply elasticity for each value of v. I plot this relationship in Figure 10 and see that the elasticity is increasing in private injury risk.

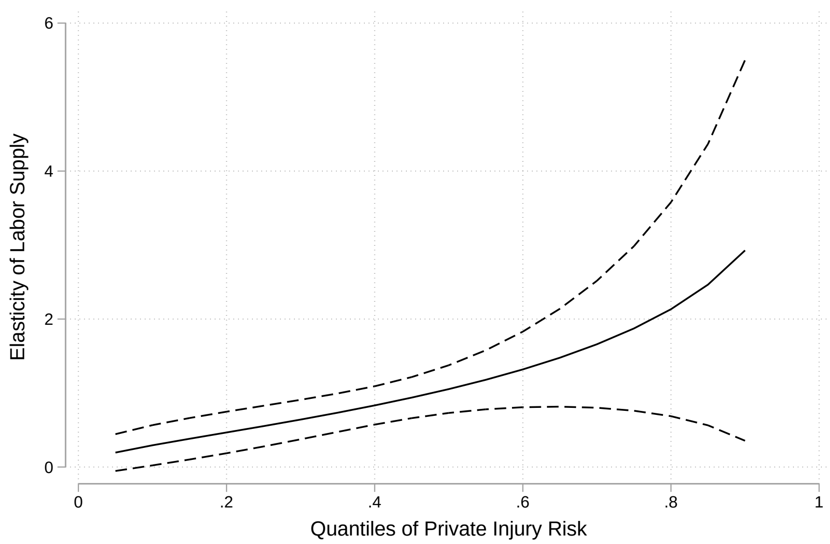


Figure 10: Average Labor Supply Elasticity by Injury Risk Propensities. The figure displays the average work probability (labor supply) elasticity conditional on different values of unobserved injury propensity. The dotted lines represent a 95 confidence interval with a Bonferroni correction for multiple hypothesis testing.

Appendix Table B.15 contains the point estimates from Figure 10. Individuals with a private injury risk at the 30th percentile have an expected elasticity of 0.642, while those

[13] 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.

with an injury propensity around the 60th percentile will have an elasticity of around 1.32. As injury risk rises, labor supply becomes more sensitive to wage changes. This illustrates that heterogeneity in injury risk can be an important confounder when estimating intensive margin labor supply elasticities.

8 Conclusion

This paper provides evidence traffic officers consider their individual injury risk when deciding whether to work. I identify and estimate a labor supply model utilizing the unique structure of overtime assignment employed by the Los Angeles Department of Transportation. I establish that daily labor supply is downward sloping in unobserved injury risk, implying officers work less when they are more likely to be injured. This behavior implies the population of officers working on any given day is positively selected (less injury prone) compared to the underlying workforce. I then show this plays a significant role in mitigating observed injury rates.

I also illustrate the practical implications of the main result. I propose shift auctions with workers bidding the wage at which they are willing to work as a mechanism which can leverage self-selection to reduce injury even more than traditional overtime assignment schemes. I show by simulation that a shift auction reduces the observed injury rate compared to a typical assignment mechanism.

To my knowledge, this paper is the first to explore how workers within a single organization working the same job incorporate private injury risk into high-frequency labor supply decisions. The fact that idiosyncratic injury risk plays such a large role in labor supply decisions raises a number of questions across both economics and public health. Across both disciplines, it suggests current estimates of injury rates are biased downwards. This is because the estimates use observational data, and the observed injury rate will tend to overweight low-risk workers who choose to take on additional shifts. Within economics, it implies injury risk within some jobs is a choice variable, which workers can control through their labor supply. Within public health, the fact that some public safety professionals work massive amounts of overtime may not be bad for injury rates. If it is the result of voluntary labor supply decisions, ex-post inequality in days worked can be evidence of self-selection acting to mitigate injury.

It has long been established that workers sort across occupations based on injury risk concerns. Future work should explore how such extensive margin sorting interacts with the intensive margin sorting within an organization established here. It is not clear how such sorting shapes and is shaped by labor market equilibrium.

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A Appendix

A.1 Labor supply as a function of unobserved injury propensity

The following lemma establishes that whether $L(v)$ is increasing or decreasing depends only on ρ.

Lemma 2 *$L(v)$ is strictly decreasing if and only if $\rho < 0$.*

Proof. Note that:

$$\frac{\partial}{\partial v}\Phi\left(\frac{\zeta_1 + Z'_{i,t}\alpha + \bar{Z}'_i\gamma_1 + \rho\Phi^{-1}(v)}{(1-\rho^2)^{1/2}}\right) < 0 \qquad \forall v$$

for any value of $\zeta_1 + Z'_{i,t}\alpha + \bar{Z}'_i\gamma_1$ if and only if $\rho < 0$. Then the expectation is just an integral over values of $\zeta_1 + Z'_{i,t}\alpha + \bar{Z}'_i\gamma_1$, and I can invoke dominated convergence to say that:

$$\frac{\partial L(v)}{\partial v} = \mathbb{E}_{Z_{i,t},\bar{Z}_i}\left[\frac{\partial}{\partial v}\Phi\left(\frac{\zeta_1 + Z'_{i,t}\alpha + \bar{Z}'_i\gamma_1 + \rho\Phi^{-1}(v)}{(1-\rho^2)^{1/2}}\right)\right] < 0 \qquad \forall v \qquad Q.E.D.$$

A.2 Additional Traffic Officer Details from the Memorandum of Understanding

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

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

A.3 The Partial Likelihoods

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

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

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

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

A.4 Data Cleaning and Population Definition

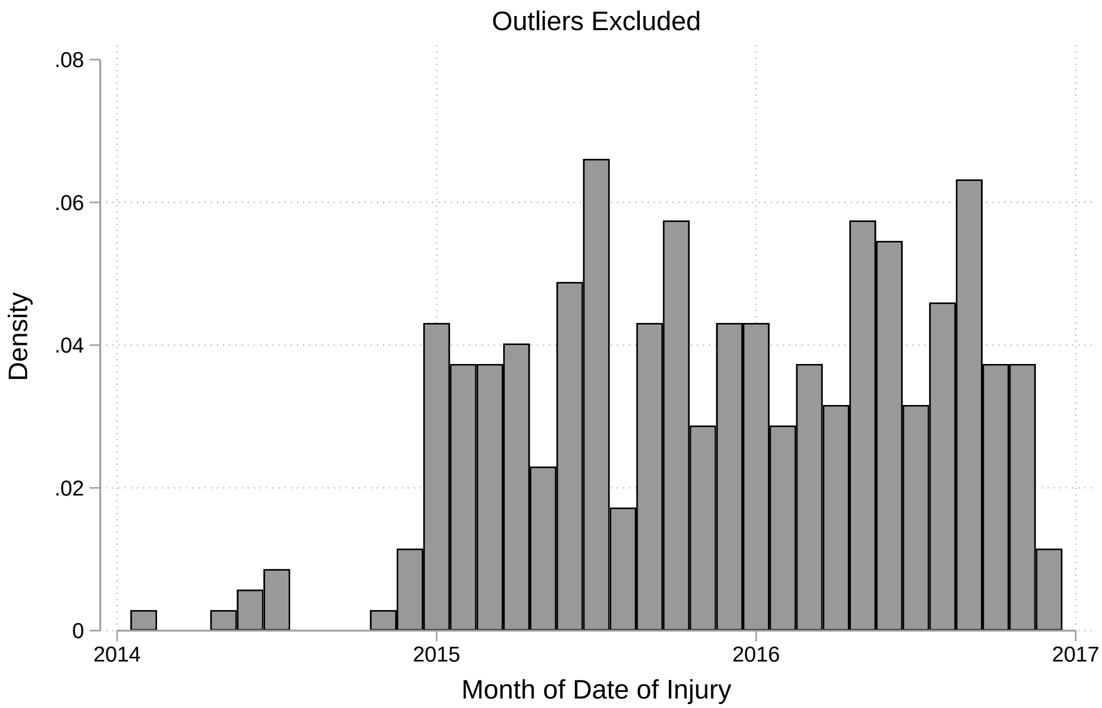
The worker's compensation and payroll data was provided by the City of Los Angeles. The data was de-identified, and spans from 2014 to 2016. It was first provided to a city employee, who performed the de-identification and merged together the two sources. Originally, only the worker's compensation files 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,[14] 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

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

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 11 displays the distribution of claims across the period. The claim counts appear abnormally low prior to January 2015 and after September 2016.

Figure 11: Workers' Compensation Claims by Month



Note: The figure plots the number of workers' compensation by month. Unlike subsequent months, there are almost no claims prior to January 2015. To avoid confounding the results with observations from a different data generating or reporting system, I limit the analysis window to January 1, 2015 to September 1, 2016.

The pay data includes records for each type of pay received on each day. It also includes the number of hours, amount of pay, rate of pay, division worked, and *Variation Description*. Variation Description is a pay code which describes the reason for a payment. I use Variation Description to classify records as work-related, leave-related, or neither. Table B.12 displays the classification process.

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 study period to workdays and injuries between January 1, 2015 for the reason described above. Second, I exclude all part-time employees (defined as officers having more than three four week periods with less than 60 hours of leave and work) due to their highly irregular schedules.

I include only officer-days where the officer works or does not work, and exclude days where they are on leave. I exclude non-work officer-days that occur after an injury but before the first day worked after injury. I also exclude the first day worked after injury. The decision to return to work after an injury follows a different process than the normal decision to work a shift. The days off work may be medically required. The first day returned also is part of the workers' compensation process and not subject to the normal labor supply decision. Omitting these days allows me to focus on the decision to work a shift, rather than the decision to use a sick or vacation day. Finally, ten injuries occurred on dates without positive work hours. Four of these injuries are associated with the day prior (it appears that the work may have crossed over midnight). Six injuries are assumed to have happened immediately, and the date is considered worked.

A.5 Justifying Identification

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

A.6 Statistical Tests of the Instrument Validity

Several authors have proposed tests of instrument validity in traditional sample selection models where the outcome is continuous and the data is cross-sectional. However, at the time of writing, I could not find any tests for instrument validity when the outcome is binary (i.e. when the link function is not the identity function). As a result, I implement an instrument validity test that is meant for continuous outcomes. First, I implement a modified version of the test designed in Semykina 2012. The procedure uses a flexible control function method to correct for selection. In my implementation, I use the semi-parametric estimator proposed in Gallant and Nychka 1987 with a fourth-degree polynomial for the selection equation and then insert the selection correction into the outcome equation using a linear spline with 5 knots. I then test whether the instruments from the selection equation, in my case *seniority rank* and *leave of others in division* satisfy over-identifying moment restrictions. The null hypothesis is the variables do satisfy the restrictions, and thus are uncorrelated with the injury outcome errors. Failing to reject the null hypothesis provides evidence that the variables satisfy the exclusion restriction. The test returns a J-statistic of 1.40 and a p-value of 0.496. Therefore I fail to reject the null hypothesis at the 0.05 level.[15]

Another test of instrument independence examines the balance of other officer-day characteristics across values of the instruments. One such variable is *medical expenses paid*, which is included in the workers' compensation data for each documented injury. Medical expenses are a proxy for the seriousness of injury. For example, injuries with *Claim Cause* "Repetitive Motion - Other" had an average expense of $2,726, while those with "Collision or Sideswipe" had an average expense of $3,385. In theory, leave of others and cumulative potential contacts should only impact injury by inducing more people to go into work. Both instruments should not impact the severity of the injury. If they do, then there is reason to suspect that the exclusion restriction does not hold. In Table B.14, I regress medical expenses paid on the leave instrument with different sets of controls.

For linear models, there are many formal under-identification, over-identification, and weak instrument tests. Unfortunately, my model is nonlinear. In Appendix Table B.13, I report results from what I call a "proxy" model. It is a fixed effects 2SLS specification (the model I would fit if y_{it} were continuous). Across all specifications, using the Kleinbergen-Paap rK LM test, I reject the null hypothesis of under-identification. Using the Kleinberg-Paap rk Wald F test, I reject the null hypothesis that the instruments are weak. Overall I find no evidence the identifying assumptions are violated in the proxy model.

I can use the proxy model to see how instrument strength impacts the coefficients. Using the tables presented in Stock and Yogo 2002, for my preferred specification (the third model in Table B.13) the maximum relative bias of the IV estimator is less than 10% (relative to OLS). The Cragg-Donald F-Statistic of my preferred specification is 230. According to D. L. Lee et al. 2020, this means I can safely use the 1.96 critical-value for testing hypotheses while maintaining a Type 1 error of 5 percent. This means I have sufficient instrument strength to reject the null hypothesis of random selection into work at the 0.05 level.

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

A.7 Description of Shift Auction Simulation

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

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

There are a number of complexities related to how overtime shifts can be assigned. I abstract from these complexities, and consider a simple situation where each division on each date requires $s_{d,t}$ officers, where $s_{d,t}$ is determined as the number of people observed working. Denote total shifts in the the entire analysis period in division d as S_d. I assume that some number of the positions, denoted $r_{d,t}$ are filled by regular officers. The remainder, denoted $k_{d,t}$, are filled with additional officers. Because I do not observe how many shifts are regularly scheduled, I assume that, within each division, it can be approximated as the number of hours coded as "CURRENT ACTUAL HOURS WORKED ONLY" divided by 8.[16] Call this numbers R_d. I also assume the fraction of shifts which are regular is time invariant. This allows us to approximate $r_{d,t}$ as $R_d/S_d \times s_{d,t}$ rounded to the nearest whole number. $k_{d,t}$ is then $s_{d,t} - r_{d,t}$. With these in hand, the simulation procedure I use to obtain injury rates under the random list and shift auctions is as follows:

[16] 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 steps 2-4.

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

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

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

A.8 The Value of a Statistical Injury

I use an approach similar to that observed in 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 decrease the probability of injury on a work day by $1/n$ multiplied by n. I set n to be 259,861. This is the number of officer-days in my analysis population. Thus the VSI I present has the usual interpretation: it is the amount of money a large number of officers are willing to collectively pay to avoid one additional injury in the 609-day period.

In my setting, variation in wages allows us to back out the value of a statistical injury using a willingness to pay approach. 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. The methodology I use to calculate the value of statistical injury is listed in Appendix Section A.9. I estimate that on average, the implied value of a statistical injury for Los Angeles traffic officers is between \$125,445 and \$250,891.[17]

[17] Dollars are as of 2015 and unadjusted for inflation.

Table A.1: Value of a Statistical Injury

Lower Bound (M = 1)	
Willingness to Pay	VSI
1.151	67195.5
(1.971)	(115136.0)

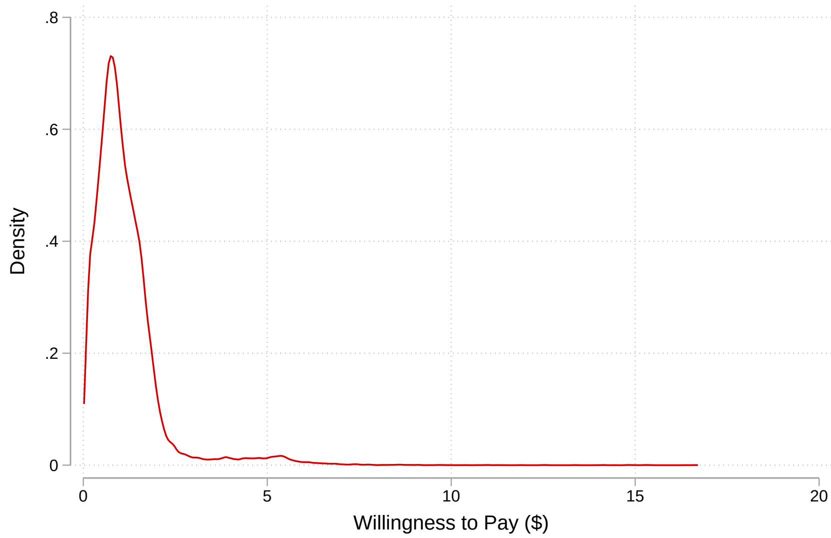
Standard errors in parentheses

Upper Bound (M = 2)	
Willingness to Pay	VSI
2.301	134391.0
(3.943)	(230272.0)

Note: This table displays the willingness to pay for an injury risk reduction, which is the average amount an officer who is indifferent between working and not would pay to reduce injury risk by $1/259,861$. The value of a statistical injury (VSI) is the willingness to pay multiplied by $259,861$.

These aggregate figures mask significant individual and temporal heterogeneity. Figure 12 displays a density plot of willingness to pay estimates across officer-days. The distribution is bimodal, with a peak near $0.1 and another near $0.5. This is a cautionary tale: even though the analysis is restricted to a single occupation in a specific city, willingness to pay for injury risk reduction varies greatly from person to person. My results also suggest that as working arrangements become more flexible and under the worker's control (through gig-economy growth and the transition to contractor employment), workplace injury should fall.

Figure 12: Distribution of Willingness to Pay Across Officer-Days



Note: The figure plots the distribution of willingness to pay for a $1/259,861$ reduction in risk. The unit of observation is officer-day. The Epanechnikov kernel is used to estimate the density. Values above $2 (less than 3% of the data) are removed for better visualization.

Viscusi and Aldy 2003, which surveyed VSI estimates as of 2003, report developed country VSI estimates ranging from $8,148 to $242,671 (using year 2000 US dollars). Most of the estimates they report are between $20,000 and $50,000. My estimates adjusted to 2000 dollars[18] yield an estimated VSI range of $90,606 to $181,212. It is hard to compare VSI estimates, because they depend heavily on the severity of injuries faced as well as the risk tolerance of the population analyzed. Individuals sort into occupations partly based on risk tolerance. Therefore, because I analyze a specific occupation, my estimates are not representative of the average working population's value of a statistical injury.

There are several potential reasons why my estimates are higher than past estimates. First, the VSI estimates in the Viscusi and Aldy 2003 survey use the coefficients from hedonic wage regressions. This approach implicitly assumes that risk within occupations is exogenous. In the case of traffic officers at least, individuals can control their own risk through daily labor supply decisions. The fact that our VSI estimates are high relative to others suggests this endogeneity causes a downward bias. Second, a good portion of the injuries I analyze are severe and related to vehicle accidents. Such injuries have the potential to be fatal, and are much more likely to have long term consequences for quality of life.

[18]using the U.S. Bureau of Labor Statistics' CPI Inflation Calculator.

A.9 Description of Value of Statistical Injury Calculations

For the purposes of these calculations, I assume that all officers are indifferent between working and not working *prior to the probability change.* Mathematically, this means that $\zeta_2 + x'\beta + \bar{Z}_i'\gamma_2 = v_{it1}$. Such officers are willing to accept an increase of $\alpha_w q$ in v_{it1} in exchange for a \$$q$ increase in the wage. This increase in v_{it1} translates into injury probability because it is correlated with v_{it2}. Thus an increase in v_{it1} (unobserved willingness to work) shifts the conditional distribution of v_{it2} (unobserved injury resistance). Specifically, it decreases the mean of injury resistance by $\rho\alpha_w q$. The proportional change in the probability of injury for an officer with covariates x_{it} and initial value of unobserved work utility v_{it1} 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 $1/n$ 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:

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

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

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

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

$$VSI = M \cdot n \cdot 8 \cdot \mathbb{E}_{x,v}[q(x, v)]$$

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

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

B Additional Tables

Table B.1: Number of Unique Injuries

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

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

Table B.2: Types of Injuries

	Count	Percent
Strain or Injury By, NOC	53	20.95
Collision or Sideswipe w	40	15.81
Repetitive Motion - Other	24	9.49
Fall, Slip, Trip, NOC	18	7.11
Motor Vehicle, NOC	16	6.32
Other-Miscellaneous, NOC	12	4.74
Animal or Insect	10	3.95
Object Being Lifted or	8	3.16
Other Than Physical Cause	8	3.16
Fellow Worker, Patient, or	7	2.77
Person in Act of a Crime	7	2.77
Cumulative, NOC	5	1.98
Dust, Gases, Fumes or	5	1.98
Exposure, Absorption,	4	1.58
Twisting	4	1.58
Foreign Matter in Eye(s)	3	1.19
Struck or Injured, NOC	3	1.19
Using Tool or Machinery	3	1.19
Bicycling	2	0.79
Broken Glass	2	0.79
Lifting	2	0.79
Pushing or Pulling	2	0.79
Repetitive Motion	2	0.79
Temperature Extremes	2	0.79
Other (Catch-all)	11	4.40
Total	253	100.00

(a) Injuries by "Claim Cause"

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

(b) Injuries by "Nature of Injury"

Table B.3: The table displays the distribution of injuries across two injury classification variables.

Table B.4: Days Worked by Day of the Week

	Count	Percent	Cum. Pct.
Tuesday	32364	17.62	17.62
Wednesday	31548	17.18	34.80
Thursday	31329	17.06	51.86
Monday	30933	16.84	68.70
Friday	29757	16.20	84.90
Saturday	16478	8.97	93.87
Sunday	11250	6.13	100.00
Total	183659	100.00	

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

Table B.5: Number of Officers on Leave By Division

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

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

Table B.6: Regressions of Injury on Work

	(1)	(2)	(3)	(4)
Work	0.00140***	0.00141***	0.00113***	0.00116***
	(0.000100)	(0.000103)	(0.000106)	(0.000109)
Age	0.0000108	0.0000116	0.0000119	0.0000117
	(0.00000769)	(0.00000982)	(0.00000981)	(0.00000987)
Observations	259861	259861	259861	259861
F-Stat.	97.78	9.668	5.509	.
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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

Table B.7: Linear Probability Models of Work Decision

	(1)	(2)	(3)	(4)	(5)
Coworkers on Leave	0.0191***	0.0192***	0.0218***	0.00148***	0.00380***
	(0.000474)	(0.000437)	(0.000461)	(0.000523)	(0.000669)
Age		0.000322	0.000312	0.000385	0.000366
		(0.000424)	(0.000290)	(0.000285)	(0.000283)
Wage		0.0577***	0.0448***	0.0281***	0.0267***
		(0.00487)	(0.00464)	(0.00357)	(0.00363)
Seniority Rank		-0.0000898	0.000160	0.000223	0.000221
		(0.000187)	(0.000164)	(0.000164)	(0.000163)
Observations	80898	80898	80898	80898	80898
First-Stage F.	583.7	390.8	114.0	112.1	99.45
Division FE	No	No	Yes	Yes	Yes
Month/Day of Week FE	No	No	No	Yes	No
Date FE	No	No	No	No	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents estimates of a linear probability model of the work decision. Time averages of age, leave of coworkers, seniority rank and wage are included in all specifications. The table suggests that the instruments are relevant to the work decision. The sample is limited to dates where an injury is observed. Standard errors are clustered at the officer level.

Table B.8: Model Parameters with Sick Time Excluded

	Injury	Work
Avg. Leave of Coworkers	-0.0360***	0.00520
	(0.00972)	(0.00493)
Avg. Wage	-0.0694	-0.104***
	(0.0627)	(0.0182)
Age	0.00308	0.00173
	(0.00285)	(0.00137)
Wage	0.0870	0.111***
	(0.0652)	(0.0155)
Seniority Rank	0.00138	0.000949
	(0.00143)	(0.000794)
Leave of Coworkers		0.0150***
		(0.00264)
Observations	80898	
Rho	-0.653	
Rho 95% CI	(-0.18, -0.880)	

Standard errors in parentheses

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

Parameter estimates when sick time is excluded from the leave instrument. $\hat{\rho}$ remains negative and significantly different from 0.

Table B.9: Robustness Analyses

	Leave Coef.	Coef SE	Rho	Rho SE	Avg. Pop. Inj. Rate	Avg. Pop. Inj. Rate SE
Base Model	0.0150	0.0027	-0.6583	0.1722	0.0117	0.0069
Sick Time Excluded from Leave	0.0150	0.0026	-0.6534	0.1736	0.0115	0.0068
Broader Date FE	0.0116	0.0025	-0.5800	0.3364	0.0093	0.0090
Strains Not Considered Injuries	0.0152	0.0026	-0.5697	0.4996	0.0026	0.0046
Med Exp $\leq$0 Not Injury	0.0116	0.0025	-0.8013	0.1710	0.0194	0.0164
Med Exp $\leq$200 Not Injury	0.0116	0.0025	-0.7915	0.1752	0.0177	0.0152
Med Exp $\leq$400 Not Injury	0.0116	0.0025	-0.8264	0.1404	0.0191	0.0152

The table displays results of a number of robustness analyses. The first row provides the reference values from the primary specification. The second row removes sick time from the leave instrument. The third row (and all following rows) utilizes week and day of the week fixed effects rather than date fixed effects. The fourth row excludes strains as injuries. The fifth through sixth rows recode injuries with medical expenditures less than different amounts as non-injuries.

Table B.10: Average Labor Supply Elasticities

Effect	Analytical Representation	Model Estimate
Leave of Coworkers	$\mathbb{E}_{z_{it}}[\frac{leave_{it}}{Pr(w_{it}=1\|z_{it})}\frac{\partial Pr(w_{it}=1\|z_{it})}{\partial leave_{it}}]$	.0327 (.00583)
Wage	$\mathbb{E}_{z_{it}}[\frac{wage_{it}}{Pr(w_{it}=1\|z_{it})}\frac{\partial Pr(w_{it}=1\|z_{it})}{\partial wage_{it}}]$	.6253 (.09263)
Seniority	$\mathbb{E}_{z_{it}}[\frac{senior_{it}}{Pr(w_{it}=1\|z_{it})}\frac{\partial Pr(w_{it}=1\|z_{it})}{\partial senior_{it}}]$	.0049 (.00425)

This table reports averages elasticities of the work outcome. Estimates are averages over all covariates and officer-days, with standard errors accounting for sampling of covariates. The values can be interpreted as a 1% increase in the variable changes the probability of working by x%.

Table B.11: Average Elasticities: Injury Conditional on Working

Effect	Analytical Representation	Model Estimate
Wage	$\mathbb{E}_{z_{it}}[\frac{wage_{it}}{Pr(y_{it}=1\|w_{it}=1,z_{it})}\frac{\partial Pr(y_{it}=1\|w_{it}=1,z_{it})}{\partial wage_{it}}]$	12.37 (5.3440)
Leave of Coworkers	$\mathbb{E}_{z_{it}}[\frac{leave_{it}}{Pr(y_{it}=1\|w_{it}=1,z_{it})}\frac{\partial Pr(y_{it}=1\|w_{it}=1,z_{it})}{\partial leave_{it}}]$	.2347 (.12577)
Seniority	$\mathbb{E}_{z_{it}}[\frac{senior_{it}}{Pr(y_{it}=1\|w_{it}=1,z_{it})}\frac{\partial Pr(y_{it}=1\|w_{it}=1,z_{it})}{\partial senior_{it}}]$	.2165 (.13800)

This table reports averages elasticities of the injury outcome conditional on working. The elasticities are averages over all covariates and officer-days, with standard errors accounting for sampling of covariates. The values can be interpreted as a 1% increase in the variable changes the conditional probability of injury by x%.

Table B.12: Variation Descriptions

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

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

Table B.13: Fixed Effects IV: Testing Instrument Validity

	(1)	(2)	(3)	(4)
Work	0.00263***	0.00233***	0.00740*	0.00265
	(0.000336)	(0.000299)	(0.00379)	(0.00224)
N	259861	259861	259861	259861
Underid K-P LM-stat	336.7	342.5	28.20	57.41
C-G F-Stat	60651.3	67321.7	497.8	1377.4
Weak id. K-P F-stat	3394.3	3470.9	29.66	67.40
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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

Table B.14: Balance Test: Regression of Medical Expenses Paid on Instruments

	(1)	(2)	(3)	(4)	(5)
Coworkers on Leave	-34.17	-34.17	-15.19	3.865	-112.8
	(33.82)	(33.82)	(51.04)	(49.36)	(136.4)
Age	34.85	34.85	24.94	12.21	110.6
	(33.77)	(33.77)	(26.41)	(27.25)	(128.2)
Wage	69.89	69.89	25.04	8.804	-62.47
	(107.4)	(107.4)	(116.4)	(123.3)	(330.8)
Seniority Rank	4.654	4.654	8.538	5.421	23.74
	(11.28)	(11.28)	(12.80)	(12.87)	(32.36)
Observations	257	257	257	257	257
First-Stage F.	0.447	0.447	.	.	.
Division FE	No	No	Yes	Yes	Yes
Month FE	No	No	No	Yes	No
Date FE	No	No	No	No	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

Table B.15: Labor Supply Elasticities

Private Injury Risk Quantile	Elasticity
0.15	0.382
	(0.143)
0.30	0.642
	(0.133)
0.45	0.939
	(0.164)
0.60	1.319
	(0.337)
0.75	1.873
	(0.738)
0.90	2.928
	(1.312)

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