Workplace Injury and the Labor Supply of Traffic Officers

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Abstract

This paper investigates the relationship between individual workplace injury risk and labor supply. I utilize a novel panel data set of traffic officers. Unique aspects of overtime assignment, including randomization, leave of coworkers, and informal trading enable identification. 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 leads to an observed injury rate which is 8.5 times smaller than the underlying average injury rate. I show this has wide-ranging implications for labor supply elasticities, the value of statistical injuries, and overtime assignment.

Keywords: overtime, workplace injury, workers' compensation

JEL codes: I18, J8, J32

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1 Introduction

Workplace injury represents 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] Yet, 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 slightly sick. They know if they drank too much alcohol at a party yesterday. They understand best their own physical capacity to safely work shifts above and beyond their normal schedule. At the same time, intensive labor supply varies significantly across people and across the life-cycle (Blundell, Bozio, and Laroque 2011). A natural question at the intersection of labor economics and public health is how workplace injury risk enters individual labor supply decisions.

In this paper, I establish individual injury risk as a major factor in the labor supply decisions of traffic officers. 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 significantly reduces injuries. I estimate the underlying average injury rate is 8.5 times larger than the observed injury rate.[2] I show these results using a daily panel data set of Los Angeles traffic officers. I exploit unique aspects of overtime assignment within the department, including randomization, leave of coworkers (sick, bereavement, vacation), and informal shift trading to identify the correlation between individual utility and individual injury propensity.

Beyond illustrating the negative relationship between injury risk and labor supply, this paper has three secondary contributions. First, it provides estimates of the average injury

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

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

rate of a population accounting for selection induced by daily labor supply decisions. Many papers across epidemiology and public health provide representative or large sample size estimates of the observed injury rate (Dembe et al. 2005, Kim et al. 2016, Conway et al. 2017). However, my results suggest it is dangerous to equate this injury rate with the *underlying average injury rate.* If researchers want the underlying average injury rate, they need to account for labor supply decisions. Failing to do so will cause downward bias.

Second, the paper estimates daily labor supply elasticities at different thresholds of injury risk. 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 impact labor supply elasticities with respect to the wage. When injury is more likely, labor supply is less elastic. When injury is less likely, it is more elastic. This can help researchers interpret differences in labor supply elasticity estimates over time and across occupations. It is likely that some of the documented differences are due not just to differences in preferences but also differences in injury risk.

Third, it follows from the main result that organizations which want to minimize injury rates can do so by changing the way they assign additional shifts. Because officers with lower injury risk are more willing to work a shift, mechanisms which assign shifts to those who value them most will tend to reduce injury rates. I show via simulation that *shift auctions*, where workers bid a wage for overtime shifts, are one way to leverage selection to reduce injury rates. Specifically, auctions result in a 34 percent reduction in the injury rate compared to a benchmark random list mechanism.

Fourth, my model allows me to compute the implied value of a statistical injury (VSI) using a willingness to pay approach. Many papers estimate the value of a statistical injury, but most use a hedonic wage regression which identify the VSI using wage differentials across occupations with different risk (Moran and Monje 2016,Parada-Contzen, Riquelme-Won, and Vasquez-Lavin 2013,Kuhn and Ruf 2013,Viscusi and Aldy 2003). This approach implicitly assumes that risk within occupations is exogenous. As this paper makes clear, workers can often control their own risk through their daily labor supply. It is not clear how this endogeneity impacts estimates. However, in the case of Los Angeles traffic officers, I estimate the average value of a statistical injury as between $125,446 and $250,891. This is higher than previous estimates, suggesting that the endogeneity created by daily labor supply choices causes VSI to be underestimated.

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

2 Data and Institutional Details

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

2.1 Institutional Details

The population of workers used for this analysis are Los Angeles traffic officers. Traffic officers are employees of the Los Angeles Department of Transportation. The traffic officers analyzed are union employees which were covered by the Memorandum of Understanding 18 (MOU) between the City of Los Angeles and Service Employees International Union, Local 721 during the analysis period.[3] According to MOU, they are overtime non-exempt employees under the Fair Labor Standards Act (MOU, 28), meaning they are paid time and

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

a half their regular rates of pay for all hours worked over 40 in a work week (Department of Labor 2017).

Traffic officers control their labor supply mainly by working additional shifts. Figure 1 provides a visual diagram of the overtime assignment process. It summarizes the following exposition.

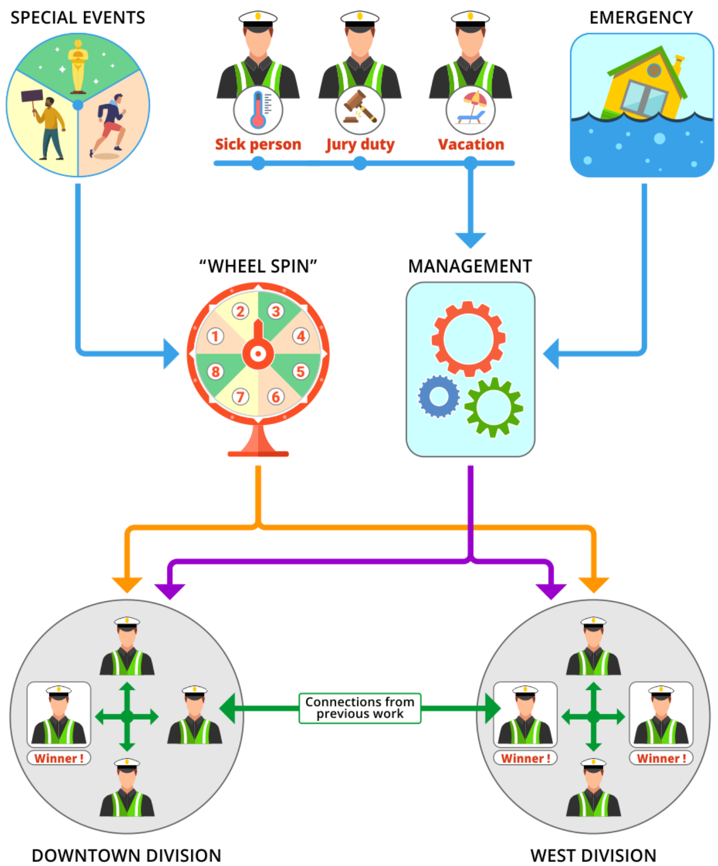


Figure 1: The Overtime Assignment Process

There are generally two types of overtime shifts. The first is referred to as *special events* overtime. Special events include things like the Los Angeles Marathon, Dodger Games, the Oscars, parades, and protests. When the event is not hosted by the city itself, the bill for traffic officer overtime incurred during the events is paid by the organizer. In fiscal year 2013-2014 (a year prior to the analysis period), special events accounted for \$5.9 million in overtime paid to LADOT officers. To put this in perspective, if I divide this by \$45 (officers earn around $30 an hour), I see this implies over 100,000 overtime hours were worked on special events. This represents a large fraction of total overtime, consider that in our analysis population for the year 2015, 150,867 hours are billed to overtime pay codes.

A report by the City Controller's office (Galperin 2015) states special event overtime is assigned using a mechanism called "spinning the wheel." In this mechanism, officers first volunteer to be on an overtime list. Then, when a shift becomes available, it is assigned randomly among volunteers conditional on seniority. Higher seniority officers are given the opportunity to take a shift first. Several "wheels" operate. The main wheel includes all officers across the city. This is used for pre-planned events like the Los Angeles Marathon and the Oscars. The secondary wheels assign unexpected special events among officers at the closest division.

Officers regularly trade and sell their shifts on an informal market. The wheel system provides ex-ante equal *opportunity* for special event overtime. In a sense all officers start with the same endowment of special events overtime. But after the wheel spin occurs, officers are free to trade the shifts they win. This leads to ex-post differences in the number of extra shifts worked. Trading can involve future favors (for example, future overtime). But it can also involve direct payments, as Galperin 2015 notes: "Traffic Officers can work high amounts of overtime by using their relationships with other officers to trade or even sell the overtime assignment." Thus, as long as an officer knows someone who won the wheel spin, he/she can acquire a shift if he/she is willing to pay.

The cost of getting a special events overtime shift consists of two parts: the search cost of finding someone to trade with and the actual cost of acquiring the shift once a partner is found. Notice that as an officer becomes more connected, both costs go down. An officer is more likely to know a winner directly (and avoid having to seek out a friend of a friend) and an officer is more likely to have multiple trading options (so they can choose whichever shift is cheaper). As Galperin 2015 states: "Traffic Officers may be able to receive more overtime if they have nurtured relationships and know how to network, treating overtime assignments as a privilege that can be traded." I use this to support the size of an officer's network as an instrument which induces an officer to work.

In theory only volunteers should ever work special events overtime. However, Galperin 2015 states that while only 192 officers signed up to volunteer in FY 2013-2014, 471 officers actually ended up working overtime. This suggests that either management occasionally forces non-volunteers to work or the informal process of trading induces non-volunteers to work.

The second type can best be described as typical overtime. This type arises due to officer leave (sick, vacation, jury duty, bereavement) or other sources (for example, traffic redirection after a water main break). This type of overtime is not well described in Galperin 2015. All that is known is from the MOU, which states that overtime must be assigned equitably by management.

Traffic officers are an ideal setting for exploring how injury risk affects labor supply decisions. They receive frequent opportunities to choose to work additional shifts. 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.[4] 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).

2.2 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

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

the sample is constructed are listed in the Appendix. The result of the data construction process is an unbalanced daily panel of 533 traffic officers across a 609 day period. In the analysis population, the distribution of injuries across officers is described in Table 1. Some officers are never injured, some are injured once and others are injured several times.

Table 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 one injury.

Table 2 reports some basic demographic information. The typical officer is around 45 years old, has been with the department around 12 years. and is observed in only one division (work location) during the analysis period. Injured officers are generally slightly older than uninjured officers.

Table 2: Basic Characteristics of Officers

	mean	sd	p10	p50	p90
Not Injured					
Age	44.48	10.09	30.11	44.06	58.43
Tenure (years)	13.11	8.63	2.86	12.41	26.49
Divisions Worked In	1.26	0.46	1.00	1.00	2.00
Injured					
Age	46.43	8.88	35.13	46.63	58.31
Tenure (years)	14.26	8.24	6.20	11.99	26.49
Divisions Worked In	1.24	0.45	1.00	1.00	2.00
Total					
Age	45.14	9.73	32.03	44.65	58.31
Tenure (years)	13.49	8.51	3.42	11.99	26.49
Divisions Worked In	1.25	0.46	1.00	1.00	2.00
Observations	553				

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

Table 3 present the distribution by Claim Cause and Nature of Injury, two major descriptive variables from the workers' compensation data. The distribution of Claim Cause helps paint a picture of the hazards faced by the traffic officers. Most injuries are related to the fact that traffic officers work outside in heavy traffic: they can be sideswiped, get into car accidents, or suffer heat-induced injuries. The distribution of the Nature of Injuries reveals that while some injuries are minor and perhaps superficial (things like strains or mental stress) many injuries are quite serious.

Table 3: 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"

Note: The table displays the distribution of injuries across two injury classification variables.

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

Table 4: Distribution of Time 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				

(a) Daily Hours Worked

	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				

(b) Days Worked in Four Week Period

Note: The table displays the distribution of work at the hourly and daily margins. 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 5 contains aggregate pay statistics, including rates and typical weekly pay amounts, and what percentage of pay is overtime-related pay. Most individuals earn a wage that is a little less or a little more than \$30 per hour. This is consistent with the common wage schedule which is set during negotiations between the union and the city. Overtime on average represents 12 percent of pay, but this masks a highly skewed distribution. At least 50 percent of officer-weeks do not have overtime pay, while 10 percent are more than 33 percent overtime pay. Again these statistics indicate that schedules vary most in terms of number of days worked rather than number of hours worked per day.

Table 5: Pay 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 Reduced Form Evidence

In this section I establish reduced-form evidence that officers are more likely to work on days when they are less likely to be injured. The point of this exercise is to establish that the selection documented in this paper is a feature of the data and does not hinge on the modeling choices in the next section.

Denote injury outcome as $y_{i,t}$, the work decision as $w_{i,t}$, the variables that impact the injury outcome $X_{i,t}$ and the variables which impact the work decisions $Z_{i,t}$. Consider a linear probability model of the injury outcome. This generally gives an estimating equation of the form:

$$y_{i,t} = X'_{i,t}a_1 + w'_{i,t}a_2 + \epsilon^1_{i,t} \tag{1}$$

Note that generally the decision to work $w_{i,t}$ may be correlated with $\epsilon^1_{i,t}$. If I estimate this equation using OLS, I will not consistently estimate a_2, but rather:

$$a_2^{OLS} = a_2 + \frac{Cov(w_{i,t}, \epsilon^1_{i,t})}{Var(w_{i,t})}$$

a_2^{OLS} will be approximately $E[y_{i,t}|w_{i,t} = 1]$, that is the observed injury rate among shifts worked. Suppose that we assume a linear probability model for the work decision. That is:

$$w_{i,t} = Z'_{i,t}b_1 + \epsilon^2_{i,t}$$

As long as $Z_{i,t}$ satisfies a rank condition and the moment condition: $E[\epsilon^1_{i,t}|Z_i] = 0$ we can consistently estimate a_2 using fixed effects two-stage least squares. To interpret a_2, I take conditional expectations of Equation 1 which yields:

$$a_2 = E[y_{i,t}|X_{i,t}, w_{i,t} = 1, \epsilon^1_{i,t} = e] - E[y_{i,t}|X_{i,t}, w_{i,t} = 0, \epsilon^1_{i,t} = e]$$

In words, a_2 is the average probability of injury if we remove endogeneity induced by the work decision. Roughly, it is the injury rate we would observe if we chose a random officer and required them to work. If officers choose to work when their injury risk is lower I have that $Cov(w_{i,t}, \epsilon^1_{i,t}) < 0$. This implies that the observed injury rate (a_2^{OLS}) should be much smaller than the true a_2. Intuitively, if injury risk plays a role in labor supply, I should observe injury-reducing self-selection.

Estimation of Equation 1 using fixed effects two-stage least squares and ordinary least squares confirms the presence of injury-reducing self-selection. Specifically, $a_2 = 0.108\% < 0.905\% = a_2$. This finding that $a_2^{OLS} << a_2$ is robust to a number of specifications, which are reported in Tables B.9 and Appendix Table B.3. This finding gives confidence that there is selection against injury does not depend on the modeling assumptions introduced in the next section. Rather, it is a prominent pattern observed in the data. While the reduced form evidence is helpful to establish the existence of selection, they do not allow me to quantify the size of selection effects, interpret my estimates as labor supply functions, or perform counterfactual exercises.

4 Model

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 partial observed injury outcome y_{it}^*. y_{it} can be interpreted as the true underlying injury outcome, which is only observed when an individual works. I assume it is determined by the below equation:

$$y_{it}^* = \begin{cases} 1 \text{ if } \zeta_2 + X_{it}'\beta + \underbrace{c_{i2} + u_{it2}}_{\text{unobserved injury propensity}} \geq 0 \\ 0 \qquad \text{otherwise} \end{cases} \tag{2}$$

In this equation c_{i2} represents time-invariant, person-specific injury risk. It includes factors like chronic health conditions (obesity, heart disease, diet, etc) and demographics. u_{it2} represents idiosyncratic injury risk that make a particular officer more likely to be injured on a particular day. It includes factors an officer may know about before coming to work (the quality of sleep the night before, whether the officer has a slight cold). it also includes things that happen during the shift that could not have been predicted (car crashes, water main bursts, road conditions). The sum $c_{i2} + u_{it2}$ represents unobservable injury risk. In the epidemiology literature this corresponds to *frailty*. In the terminology of the marginal treatment effect literature, $-(c_{i2} + u_{it2})$ represents the *resistance* to injury.

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 go to 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 partial observed injury potential. That is:

$$y_{it} = y_{it}^* \cdot w_{it} \tag{3}$$

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

$$w_{it} = \begin{cases} 1 \text{ if } Z_{it}'\alpha + \zeta_1 + \underbrace{c_{i1} + u_{it1}}_{\text{unobserved utility}} \geq 0 \\ \\ 0 \qquad \text{otherwise} \end{cases} \tag{4}$$

c_{i1} and u_{it1} are both fully observed by the officer, but unobserved by the analyst. 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, wanting to watch my child's soccer game, or not getting enough sleep the night before. The sum $c_{i2} + u_{it2}$ represents unobservable utility from work. In the terminology of the marginal treatment effect literature, $-(c_{i1} + u_{it1})$ represents the *resistance* to work.

Critically, the relationship between injury risk and labor supply is captured by dependence between unobserved injury propensity $c_{i2} + u_{it2}$ and unobserved willingness to work $c_{i1}+u_{it1}$. I wish to model this dependence in a way that is both simple and flexible (allowing negative correlation, positive correlation and independence). Thus, I specify that they 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:*

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

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

ρ summarizes the relationship between injury risk and labor supply. It captures the correlation between unobserved utility from work and unobserved injury propensity. If $\rho < 0$, then all else constant, officers which are more willing to work are less likely to be injured (positive selection). If $\rho > 0$, officers which are more willing to work are more likely to be injured (adverse selection). If $\rho = 0$, there is no relationship. $\bar{Z}_i\gamma_1, \bar{Z}_i\gamma_2$ are similar to individual fixed effects. They capture time invariant propensity to work and be injured.

Using this framework, I can discuss how individual injury risk enters the labor supply function.

Definition 1 *Denote individual unobserved injury risk as $v := c_{i2} + u_{it2}$ and the standard normal CDF Φ. Average labor supply as a function of individual unobserved injury risk ($L(v)$) can be written as:*

$$L(v) := E_{z_{i,t},\bar{z}_i}\left[\Phi\left(\frac{\zeta_1 + z'_{i,t}\alpha + \bar{z}'_i\gamma_1 + \rho v}{(1-\rho^2)^{1/2}}\right)\right]$$

Whether the function is upward or downward sloping depends on only one parameter.

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

Proof. Note that:

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

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:

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

The example of sleep is a good way to illustrate this framework. If too little sleep reduces utility from work and also increases injury risk, then this would enter as a negative correlation between u_{it2} and u_{it1}. This reduced form effect could be because the officer dislikes injury risk, and then u_{it1} can be interpreted as a private signal of elevated injury risk. It could also be because it is generally less pleasant to drive around Los Angeles on less sleep, and sleep deprivation also makes an officer a less attentive driver.

4.1 Estimation

If there exists at least one time-varying element in Z_{it} that is not in X_{it} (e.g., an excluded instrument), then Semykina and Wooldridge 2018 prove constructive identification of the model. Intuitively, identification of the main parameter, ρ, is driven by the excluded instruments. They induce more officers to work and thus allow the correlation between utility from work and injury risk to be understood. Put another way, the instruments trace out the patterns of selection.

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

- **Leave of Coworkers in Division:** The number of other officers in officer i's division (work location/station) who take leave on date t.

- **Cumulative Potential Contacts:** The number of colleagues an officer could have physically encountered. This is measured as cumulative number of other officers the target officer worked in the same division as on the same day in the past. This is a proxy measure for the potential size of an officer's network. For some officer i in division j, this measure will be constant until either a new officer joins division j, an officer in division j terminates, or officer i works in a division other than division j. Intuitively, it can be thought of as an address book of active officers which officer i may have encountered in the past.

- **Seniority Rank:** The rank of officer i in terms of number of years since hire among all officers in the current division.

Z_{it} includes all the variables in X_{it} as well as the these three instruments. $\bar{Z}_i$ includes officer-specific time averages of leave of coworkers, cumulative potential contacts, age and wage. Seniority rank, division, day of the week, month, and weather variables are excluded from $\bar{Z}_i$ because they do not vary enough (either temporally or across officers). For example, for two officers who were present throughout the analysis window, averages of day of the week indicators would be the same.[5]

Estimation proceeds using partial maximum likelihood, with the expressions of the likelihood presented in Appendix Section A.2. As pointed out in Semykina 2012, models of the type specified are pooled Heckman-selection probit models. As a result, I estimate the parameters using Stata's built-in 'heckprobit' command with the addition of person-specific means ($\bar{Z}_i$) in the selection and outcome equations. Standard errors are clustered at the officer level to account for within officer serial-correlation.

4.2 Instrument Validity

Identification of the model requires all instruments to be valid. They must be properly *excluded* from the injury equation and relevant to the work decision.[6] I provide statistical and then theoretical arguments that the instruments are valid.

Before proceeding, note Assumption 1 is weaker than the normal exclusion restriction. The model explicitly allows for person-specific mean dependence between the excluded instruments and injury. The burden is then to show independence conditional on person-specific means.

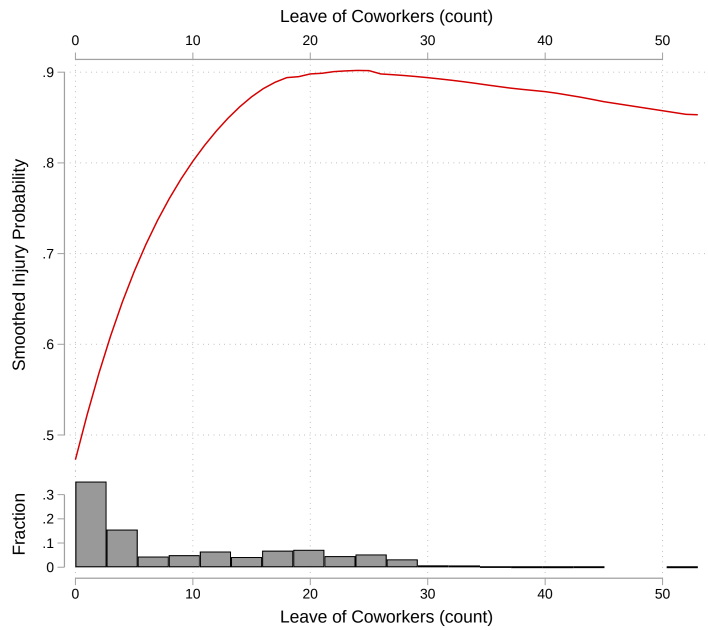
To statistically test the exclusion restriction I conduct a balance test using medical expenses of an injury as a proxy for injury severity. The idea behind the balance test is that if the instruments are properly excluded from the binary injury equation they should have

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

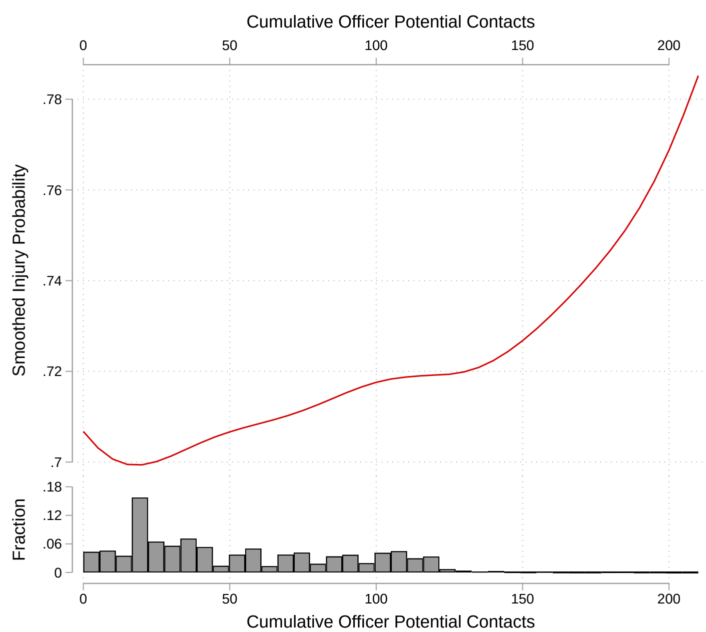
[6]Relevance means they must be properly *included* in the work equation.

no impact on injury severity. I find no evidence that the exclusion restriction is violated. The results are presented in Appendix Table B.10. None of the instruments display statistically significant coefficients, suggesting the variables satisfy the balance test. I also conduct over-identification tests of exogeneity in Appendix Table B.4 The details of these tests are discussed in Appendix Section A.5.

Figure 2 presents graphical evidence that both instruments are relevant to the work decision.The figure displays a local linear regression of injury probability among groups of officers binned according to their leave of coworkers and then by cumulative potential contacts. The line is generally upward sloping, indicating a positive relationship between the instruments and work probability. As a statistical test, I present F-statistics of an analogous linear probability model of work on the leave of others and potential cumulative contacts in Table B.4. All F-statistics are greater than 170. The coefficient on Division Leave (of others) 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.5. All tests support the assumption that both instruments are relevant to the work decision.



(a) Leave of Coworkers



(b) Cumulative Potential Contacts

Figure 2: Instrumental Relevance: Increasing the Probability of Working

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

Now for theoretical arguments. Conditional on x_{it} and $\bar{z}_i$, leave of others must only impact injury through the decision to work. For many forms of leave, like bereavement and jury duty, this seems likely to be satisfied. The death of an elderly family member of an officer's colleague is unlikely to be related to own work conditions or own health status. For other forms of leave, like vacation or floating holidays, I argue this is conditionally satisfied. That is, people may take vacations during times of the year with certain weather conditions (i.e., summer) that can impact injury risk (through heat exhaustion perhaps). But I control for holiday and monthly effects, and conditional on these controls, there is likely no dependence. For sick leave, there is a concern of contagion and thus a violation of the exclusion restriction. To address these concerns I estimate the main parameters using a leave instrument that does not include sick time. These estimates are in Appendix Table B.5 and are discussed in more detail in the robustness section.

Leave of others must also be relevant. Recall that LADOT uses a "spin the wheel" system to assign overtime. Under this system, officers who volunteer are randomly chosen for overtime. If more individuals call out sick or for bereavement, the supervisor will need to select a larger number of volunteers and the pool of people available to work will weakly decrease. 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 uses the word "required" to describe some overtime, implying that management can force officers to work in certain situations. The MOU also states that many rules are suspended during emergencies, meaning it is reasonable to assume the city can force officers to work during times of crisis (incidents like water main breaks, earthquakes, etc). As a result, the probability of working for non-volunteers should also be increasing in the number of other officers on leave.

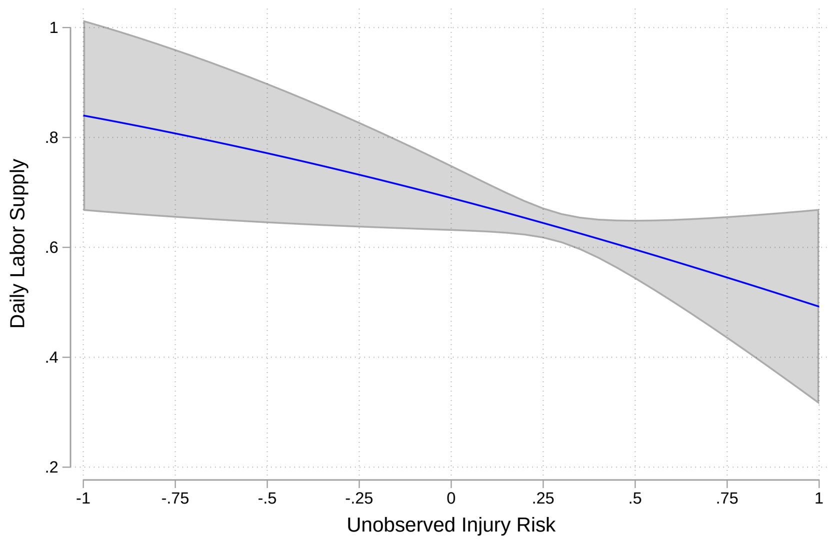
Variation in cumulative potential contacts must not impact injury propensity other than through the work decision. Because the main part of the job is not team-based (patrolling parking meters and directing traffic) there is little reason to think that coworker changes are correlated with injury propensity. However, it is possible more dangerous divisions have more personnel changes due to injuries. To account for this, I include division indicators in both the work and injury equations. Conditional on these indicators, it is hard to think of a reason why the instrument would impact injury directly.

Cumulative potential contacts must also be relevant. This measure approximates the size of an officer's network. Being at the same physical location (division) as another officer should increase the chance two officers form a connection (exchange contact information, etc). Thus, potential cumulative contacts is a proxy for the number of colleagues an officer meets on the job. Because overtime is generally desired, and everyone who volunteers has an ex-ante equal chance of being chosen, a larger network implies a greater chance at least one connection gets a shift.

5 Results

After estimating the model, I find $\hat{\rho} = -0.62$ and I can reject the null hypothesis that $\rho = 0$ at the 0.05 level. By Lemma 1, this implies average labor supply (as described in Definition 1) is downward sloping in unobserved injury risk. Put another way, elevated injury risk discourages work. Figure 3 visualizes the main result. Unobserved injury risk is a standard normal random variable. Therefore we can see from the plot that an officer with unobserved injury risk at the 84th percentile ($v = 1$) works a shift around 50 percent of the time, while an officer with unobserved injury risk at the 16th percentile ($v = -1$) works a shift around 85 percent of the time.

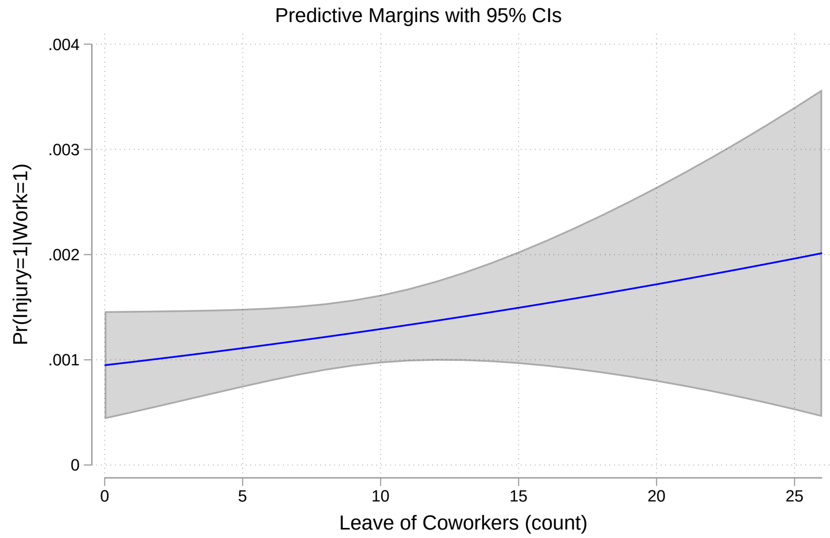
Figure 3: Average Daily Labor Supply and Unobserved Injury Risk



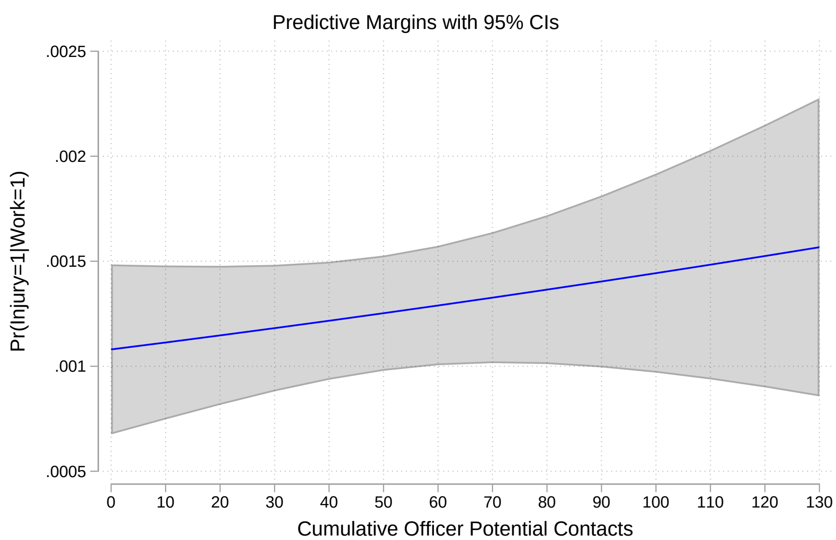
Note: This figure plots daily labor supply (in terms of probability of working) at different levels of unobserved injury risk. Injury risk is in units of v, where high values indicate high risk and low values indicate low risk.

As discussed previously, if officers exhibit injury aversion in their labor supply choices, this will induce positive selection in the pool of people who work on a given day. Figure 4 visualizes this selection by plotting the estimated probability of injury conditional on different values of the excluded instruments. Panel A does this for leave of coworkers. The upward slope means the pool of officers working on a day when more coworkers are on leave will be more injury prone. As the department has to dig deeper into the pool to fill open slots, it has to rely on officers who are both less willing to work and thus more likely to be injured. Panel B depicts the same plot for cumulative potential contacts. It is easier to access special event overtime when an officer has more connections. As a result, all else equal, a more connected officer will be willing to work under a larger range of unobserved injury risk than a less connected officer.

Figure 4: Average Probability of Injury Conditional On Working



(a) Leave of Coworkers



(b) Cumulative Potential Contacts

Note: The figure displays the estimated probability of injury conditional on working at different levels of the instruments. Point estimates are averages of both unobserved heterogeneity and covariates. The gray band represents a 95 confidence interval with a Bonferroni correction for multiple hypothesis testing. The x-axis is truncated from the right for better visualization.

Another way to understand this positive selection is to compare the probability of injury of an officer who is *willing* to work compared to a typical officer. Willingness to work corresponds to the value of unobserved utility from work, $c_{i1} + u_{it1}$ in my model. An eager officer, defined as one at the 75th percentile of unobserved utility, is on average 85.3 percent less likely to be injured than an officer at the median. Labor supply decisions represent a large source of positive self-selection.

The main coefficient estimates for the injury and labor supply model are reported in Table 6.

Table 6: **Labor Supply Model: Select Parameter Estimates**

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

Standard errors in parentheses

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

Note: This table displays the main coefficient estimates of the injury and work equations, estimated using a pooled Heckman Probit procedure. "Avg." variables are time averages within person. ρ represents the unobserved correlation between injury propensity and work utility.

Coefficients on leave of coworkers and cumulative potential contacts are positive and significant at the 0.05 level, indicating they both induce officers to work, as expected. Other structural estimates are presented in Table 7. As should be the case, the estimated probability of injury conditional on working is very close to the observed injury rate, which is 0.0014. Similar to the results presented in Section 3, the average underlying probability of injury is around 8.5 times larger than the observed injury rate.

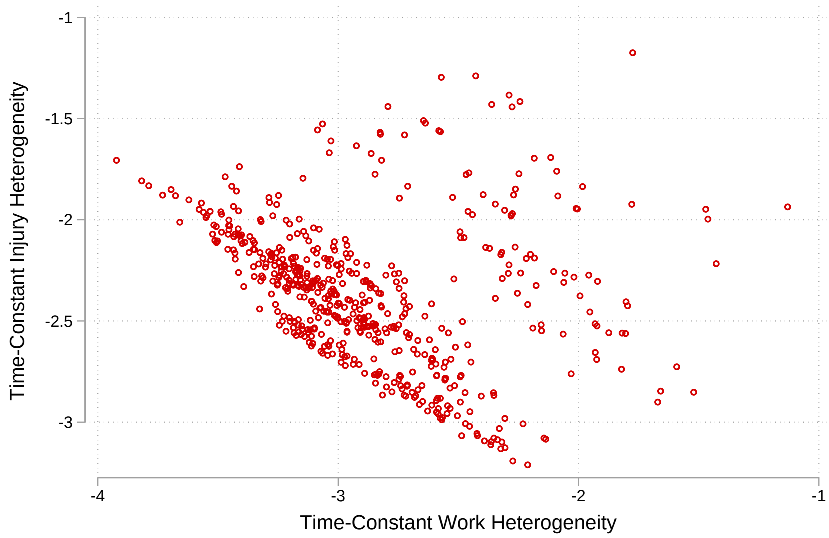
Table 7: Additional Model Estimates

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

Note: This table contains additional structural quantities of interest. Probabilities are averages over all officer-days, with standard errors accounting for sampling of covariates. Quantities involving a mixture of model parameters and covariate variances do not have reported standard errors.

There is also correlation between the unobserved person-specific time-invariant heterogeneity, reflected by the negative sign of $Cor(\bar{Z}_i'\gamma_1, \bar{Z}_i'\gamma_2)$ in Table 7. Because these are analogous to fixed-effects in a linear model, I interpret the negative correlation to mean the types of officers who prefer not to work are more likely to be injured. Figure 5 plots these "fixed-effect" pairs for all 553 officers.

Figure 5: Scatter Plot of Estimated Time-Constant Heterogeneity



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

Due to the non-linear nature of the model, I also report average elasticities of the work probability with respect to several variables in Tables 8. 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, cumulative potential contacts and seniority all have positive but more moderate elasticities. They increase the probability of work, but are not as salient as the wage.

Table 8: Average Elasticities: Labor Supply

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

Note: 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%.

Appendix Table B.7 reports average elasticities of injury conditional on work. That is, how the observed injury rate responds to changes in the main covariates.

6 Robustness

I perform several versions of my analysis to test the sensitivity of the main result and address potential threats to identification. A summary of major parameter estimates under each version is provided in Appendix Table B.6. I report the coefficient on the main instrument, leave of coworkers, as well as $\hat{\rho}$ and the percentage point difference in injury probability of an eager officer (one at the 75th percentile of willingness to work) compared to a median officer (one at the 50th percentile of willingness to work).

First, I construct a more conservative version of the leave instrument, which excludes sick time. I do this out of concern that sick leave violates the exclusion restriction: perhaps when there is more sick leave people are more prone to injury due to contagious diseases caught from coworkers. Alternatively, increased sick leave might make the remaining pool of officers on average more healthy. This conservative instrument has considerably less variation, because sick time represents a fourth to a third of leave.[7] The main coefficient

[7]See Appendix Table B.2.

estimates are provided in full in Appendix Table B.5.

Second, I test the sensitivity of my results to changes in the definition of injury. Because I measure injuries as workers' compensation claims, there is a concern that false reporting of injuries might be biasing my results. Claims are verified by medical professionals, but for hard to verify injuries, like strains and mental stress, over-reporting might still be a concern. If this is true, the selection I observe could just be because officers who are more likely to file false claims also prefer to work less. To address this, I estimate my model again with claims described as "Strains" not considered injuries. Out of 243 injuries, 118 are classified as a "Strain." Given this removes almost 50 percent of injuries, it is not surprising that my estimates fall in magnitude and statistical significance. What is reassuring is that all estimates remain the same sign: $\hat{\rho}$ remains negative and the change in probability is still negative.

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

7 Discussion

The traffic officers I analyze are assigned overtime mainly through a system called "spinning the wheel." This system amounts to randomly allocating extra shifts among those who volunteer, with informal trading happening after the fact. This wheel system is not designed to reduce injury rates. Indeed, in this section I demonstrate an alternative which is much better at leveraging selection to reduce injury. Given sub-optimality, the amount of positive selection which occurs is remarkable. The observed injury rate[8], is around 0.14%. However, my model estimates the average underlying injury rate[9] is much higher: 1.2%. Individual labor supply decisions within a sub-optimal system are responsible for making the observed injury rate 8.5 times smaller than the underlying average rate.

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). 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 officers who works almost everyday. However, my results indicate this overtime inequality reflects a process which is helping to reduce injury. Further, a policy which requires workers to work the same number of overtime shifts will likely raise injury rates.

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

To illustrate this last point: consider the probability of injury conditional on work as a proxy for the injury risk from voluntary work. The unconditional probability of injury

[8]The number of injuries divided by the number of person-days worked

[9]The expected injury rate if the Department of Transportation forced a random officer to work on a random day.

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

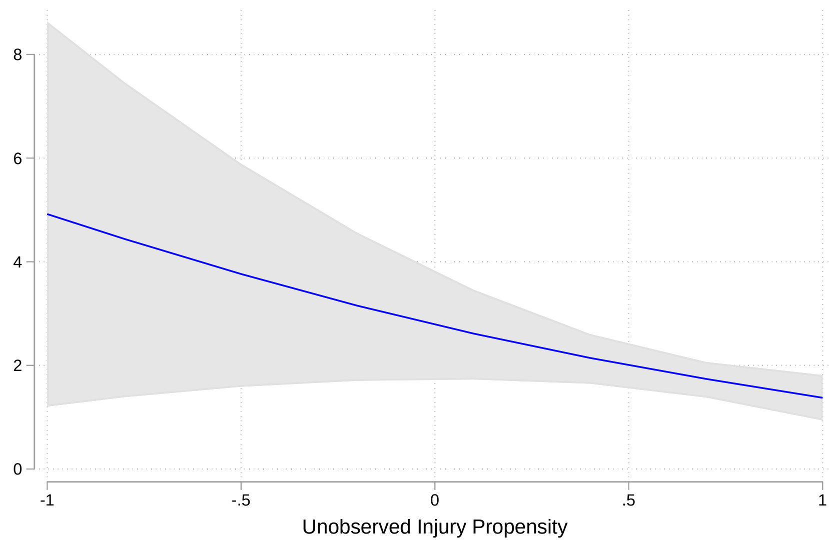
7.1 Labor Supply Wage Elasticities

So far I have established that, all else constant 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 us to estimate the elasticity of the probability of working a shift with respect to the wage conditional on different unobserved propensities to be injured. This allows me to see how elasticities vary at different levels of risk. Formally, I calculate the quantity:

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

and average over observed z_{it}. This yields an average labor supply elasticity for each value of v. I plot this relationship in Figure 6 and see that the elasticity is declining in unobserved injury propensity. Individuals with an injury propensity around the 16th percentile will have an elasticity of around 4.9, while those with an injury propensity around the 84th percentile will have an elasticity of around 1.4. As injury risk rises, labor supply becomes less sensitive to wage changes.

Figure 6: Average Labor Supply Elasticity By Injury Risk Propensities



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

Appendix Table B.11 contains point estimates with standard errors from Figure 6. Strikingly, even when injury is likely, labor supply is still elastic (greater than 1). Companies frequently use wage multipliers to encourage workers to take shifts on holidays and during periods of high demand. While my results suggest wage multipliers are an effective way to encourage work, they may not always encourage the best people to work. Even relatively risky employees have highly elastic labor supply. Consider the case when an organization offers a wage multiplier for working Christmas. It decides that if more people volunteer than needed, it will randomly choose who gets the shift. The wage multiplier will induce all types of employees to volunteer, and conditional on volunteering, the random allocation mechanism is just as likely to give it to a high risk volunteer as a low risk volunteer. What this mechanism is missing is a way to leverage competition among workers to optimally allocate the shift to the least risky employee among those who volunteer. An example of such a mechanism is a shift auction, which I describe fully in Section 7.2.

7.2 Shift Auctions

The main finding, that all else equal, officers with higher unobserved injury risk prefer to work less, means an organization can reduce injury rates by allowing individuals more freedom over which shifts they work. Los Angeles traffic officers are assigned to additional shifts using a *spin the wheel* mechanism. Informal trading occurs within the system, but it is limited by how connected officers are among themselves. This gives officers some freedom to select against their own injury risk. Indeed, the main finding of this paper is that individual use the current system to avoid working when they are most injury-prone. However, in this section I ask how much injury rates can be reduced when trading is formalized through a shift auction system.

In the last section, I discussed how officer labor supply is increasing in the wage. This means on average, officers who are less likely to be injured on a given day will require a lower wage. This motivates a potential improvement over the spin the wheel mechanism: shift auctions. By shift auctions, I refer to a process where a manager posts the available shifts, and officers may place a wage bid for the shift. The shift is then assigned to the officer who bids the lowest wage. Although shift auctions may seem unorthodox, many scheduling software companies list it as a built-in option.[10] One complication is that the data do not contain information to fully analyze the existing spin the wheel system. As a result, I compare shift auctions to something I call a random list mechanism. This is a system where all officers are asked if they want to work a shift in a random order.

A full description of the simulation of the list and shift auction mechanisms is given in Appendix Section A.6. I perform 1,000 iterations of the simulation. On average, shift auctions reduce the number of injuries by 34.26 percent. The effect is 30.26 percent and 38.11 percent at the 5th and 95th percentiles respectively. In terms of percentage point

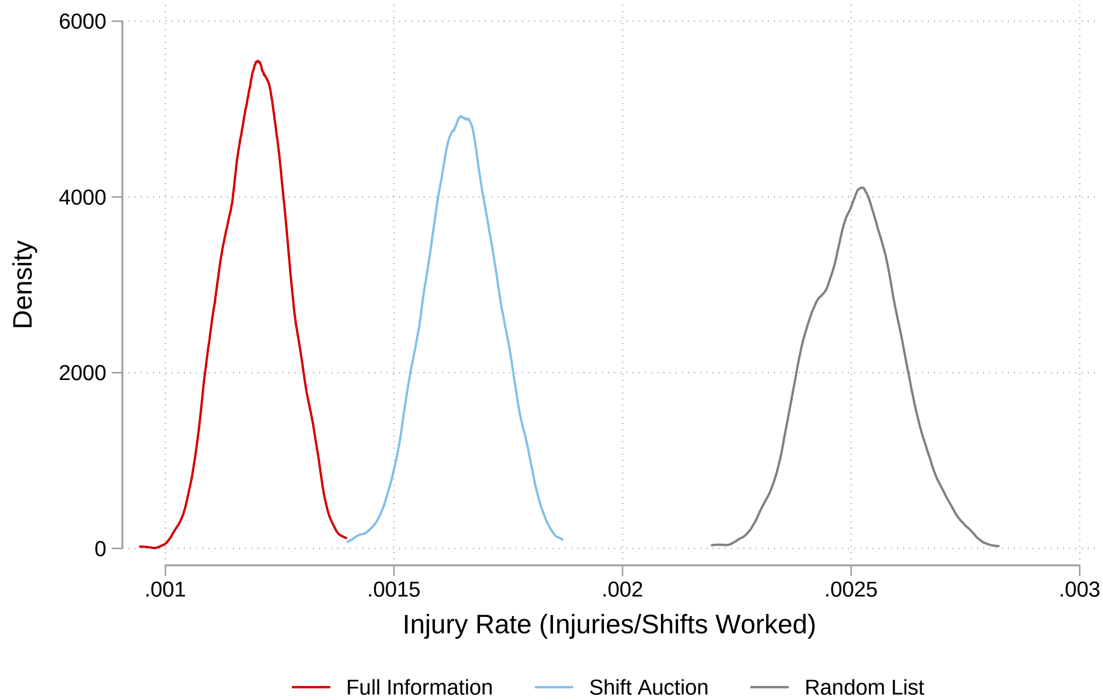
[10] Some examples: Stay Staffed, which produces a nurse scheduling software; Celayix Software, a multi-industry workforce management software company; EPay Software, a human capital management provider.

changes, shift auctions reduce the injury rate on average by 0.1220 percentage points.

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 I 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 propensity. The full information benchmark decreases injuries by 27.36 percent compared to shift auctions.

The simulation results are summarized in Figure 7. 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 shift bidding injury rate distribution approaches the full information benchmark, and yields much lower injury rates than the random list. This exercise highlights the importance of the main result: individual labor supply decisions on the part of officers can be leveraged by an organization to reduce the aggregate injury rate. Shift auctions accomplish this goal while also being available in several scheduling software packages.

Figure 7: Simulated Injury Rates Under Three Mechanisms



	Mean	p5	p95
Random List	0.0025	0.0024	0.0027
Shift Auction	0.0016	0.0015	0.0018
Full Information	0.0012	0.0011	0.0013
Simulations	1000		

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

7.3 The Value of a Statistical Injury

I use an approach similar to the literature (Kniesner and Viscusi 2019) and define the *value of a statistical injury* (VSI) as the amount of money an officer would be willing to pay to 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 B. I estimate that on average, the implied value of a statistical injury for Los Angeles traffic officers is between \$125,445 and \$250,891.[11]

Table 9: Value of a Statistical Injury

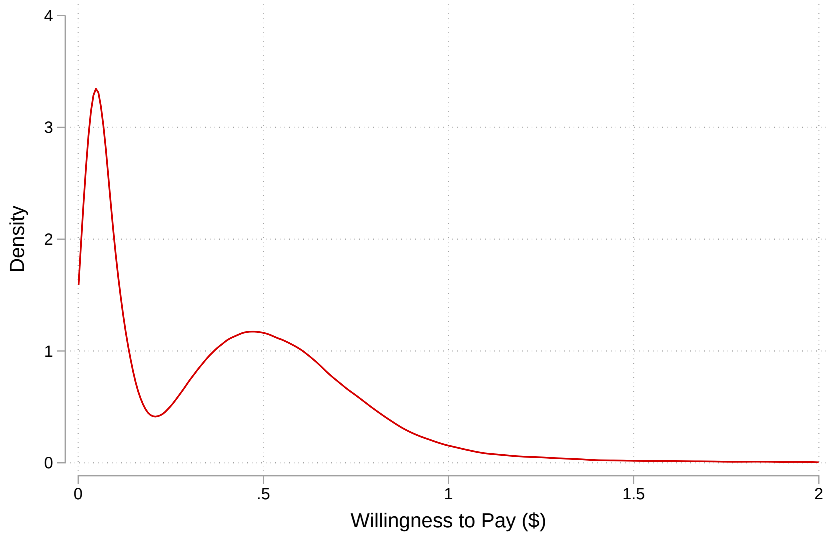
Lower Bound (M = 1)		Upper Bound (M = 2)	
Willingness to Pay	VSI	Willingness to Pay	VSI
\$0.483	\$125,445.6	\$0.965	\$250,891.2
(0.893)	(232,094.9)	(1.786)	(464,189.8)

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 8 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.

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

Figure 8: 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[12] 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

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

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.

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 within the the Los Angeles Department of Transportation. I establish 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 (against injury). I then show this plays a significant role in mitigating observed injury rates. For LA traffic officer, this selection results in an observed injury rate which is 8.5 times smaller than the estimated underlying injury rate.

In addition to the main result, I provide evidence increased injury risk makes labor supply elasticities with respect to the wage less elastic. I also estimate the value of a statistical injury, and show individual willingness to pay exhibits significant heterogeneity. Finally, I propose shift auctions as a mechanism which can leverage selection to reduce injury even more than traditional overtime assignment schemes. Such auctions, which assign shifts to the officers which bid the lowest wage, reduce the injury rate to a level which is close to the injury-minimizing assignment.

To my knowledge, this paper is the first to explore how workers within a single organization working the same job process idiosyncratic injury risk. 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 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-ante inequality may actually be mitigating injury.

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A Appendix

A.1 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.2 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.3 Data Cleaning and Population Definition

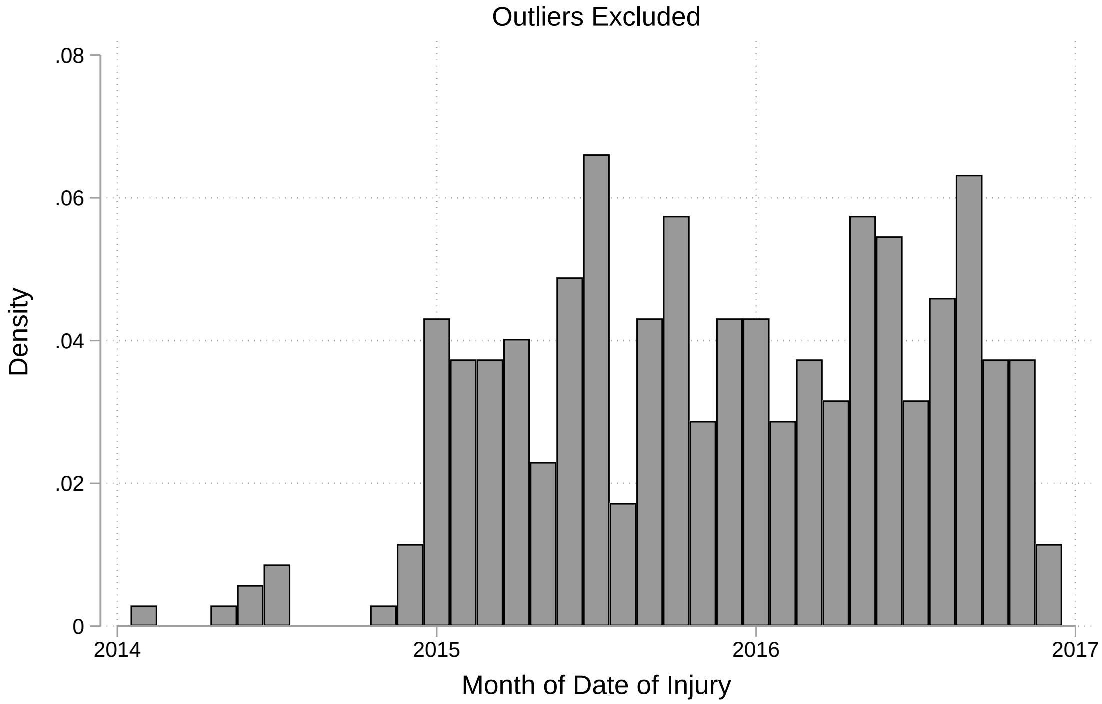
The worker's compensation and payroll data was provided by the City of Los Angeles. The data was de-identified, and spans from 2014 to 2016. It was first provided to a city employee, who performed the de-identification and merged together the two sources. Originally, only the worker's compensation files 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[13], the date on which the employee gained knowledge of the injury, the nature of the injury, and the cause of the injury. After removing duplicate records, there are 351 distinct worker compensation claims across 246 traffic officers in the time period. Of these, 295 have a non-zero value for "Med Pd" suggesting some sort of expense was paid out to the employee. Figure 9 displays the

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

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

Figure 9: Workers' Compensation Claims by Month



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

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.8 displays the classification process.

For analysis, I aggregate the pay and workers' compensation records into an officer-day panel data set with measures of daily hours worked and hours taken as leave. This process is non-trivial, and requires some assumptions which are outlined in the data-building section of the Appendix. I then perform several important exclusions to create the working sample.

First, I limit the data to workdays and injuries between January 1, 2015 through September 1, 2016. This is due to the missing claims issue observed in the last paragraph. Second, I exclude all part-time employees.This is because these employees have very irregular schedules. I define part-time officers as those which have more than three four week periods with less than 60 hours of leave and work.

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 idea is that the decision to return to work after an injury is a separate process. The days off work may be medically required. The first day returned also is part of the workers' compensation process and not subject to the normal labor supply decision process. I do this to focus on the decision of working a shift, not on the decision of using a sick or vacation day. Finally, I exclude all days between the date of injury up to and including the first observed work day. The reason for this is that the decision of when to return to work after an injury is separate from the decision to work when an officer is not injured. I do not model the return to work decision.10 injuries occurred on dates without positive work hours. 4 of these injuries are associated with the day prior (it appears that the work may have crossed over midnight). 6 injuries are assumed to have happened immediately, and the date is considered worked.

A.4 Justifying Identification

If one is willing to ignore Equation 2 and instead assume a linear probability model for the injury outcome, my model would be a special case of the switching model described in Chen, Zhou, and Ji 2018. Then I could achieve non-parametric identification with a single exclusion restriction and a symmetry condition on the unobservables. But I am not willing to make this simplification, because unlike in other applications, injury for a particular officer on a particular day is quite unlikely, so that $Pr(y_{it}) \approx 0$. Because there are continuous covariates in X_{it}, $X_{it}'\beta$ is unlikely to be bounded between $[0, 1]$ almost surely. According to Horrace and Oaxaca 2006, this makes the linear probability model implausible.

A.5 Statistical Tests of the Instrument Validity

There are several papers proposing tests of instrument validity in traditional sample selection models where the outcome is continuous and the data is cross-sectional. However, at the time of writing, I could not find any papers suggesting tests for instrument validity when the outcome is binary (i.e. when the link function is not the identity function). As a result, I implement an instrument validity test that is meant for continuous outcomes. First, I implement a modified version of the test designed in Semykina 2012. The procedure uses a flexible control function method to correct for selection. In my implementation, I use the semi-parametric estimator proposed in Gallant and Nychka 1987 with a fourth-degree polynomial for the selection equation and then insert the selection correction into the outcome equation using a linear spline with 5 knots. I then test whether the instruments from the selection equation, in my case *seniority rank* and *leave of others in division* satisfy over-identifying moment restrictions. The null hypothesis is the variables do satisfy the restrictions, and thus are uncorrelated with the injury outcome errors. Failing to reject the null hypothesis provides evidence that the variables satisfy the exclusion restriction. The test returns a J-statistic of 1.40 and a p-value of 0.496. Therefore I fail to reject the null hypothesis at the 0.05 level.[14]

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

[14]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.

or Sideswipe" had an average expense of \$3,385. In theory, leave of others and cumulative potential contacts should only impact injury by inducing more people to go into work. Both instruments should not impact the severity of the injury. If they do, then there is reason to suspect the exclusion restriction. In Table B.10, 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.9, 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} was continuous). Across all specifications, using the Kleinbergen-Paap rK LM test, I reject the null hypothesis of under-identification. Using the Hansen-J test of over-identification, I fail to reject the null hypothesis the moment restrictions are satisfied for all instruments. 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.9) 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 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.

A.6 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, where from here on I suppress the t subscript. Denote the monetary value of a shift to officer i as θ_i. I can derive the monetary value by setting utility equal to 0 and solving for the wage variable. This yields: $\theta_i := (z_i'\alpha + \zeta_1 + \bar{z}_i'\gamma_1 - v_{i1})/\alpha_{wage}$ where z_i does not include the wage variable and α_{wage} is the coefficient on the wage variable. The utility from working at bid wage b_i is given by $U_i = \theta_i + b_i$. Recall that the injury outcome is denoted y_i. θ_i and y_i are correlated both through the shared elements of z_i that enter both the work and injury outcomes and through unobserved correlation.

There are a number of complexities related to how overtime shifts can be assigned. I abstract from these complexities, and consider a simple situation where each division on each date requires $s_{d,t}$ officers, where $s_{d,t}$ is determined as the number of people observed working. Denote total shifts in the the entire analysis period in division d as S_d. I assume that some number of the positions, denoted $r_{d,t}$ are filled by regular 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.[15] Call this numbers R_d. I also assume the fraction of shifts which are regular is time invariant. This allows us to approximate $r_{d,t}$ as $R_d/S_d \times s_{d,t}$ rounded to the nearest whole number. $k_{d,t}$ is then $s_{d,t} - r_{d,t}$. With these in hand, the simulation procedure I use to obtain injury rates under the random list and shift auctions is as follows:

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

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

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

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

B 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

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

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:

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

where note that I have integrated out v, the unobserved utility from work.[16] 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

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

officers are presented in Table 9.

Table B.1: 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.2: 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). Other contains several small division codes.

Table B.3: OLS Estimates of Injury on Work

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

Standard errors in parentheses

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

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. Each column adds additional controls. Standard errors are clustered at the officer level.

Table B.4: Linear Probability Models of Work Decision

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

Standard errors in parentheses

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

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

Table B.5: Model Parameters with Sick Time Excluded

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

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.6: Robustness Analyses

	Leave Coef.	Coef SE	Rho	Rho SE	%. Incr.	% SE
Base Model	0.0189	0.0024	-0.6241	0.1780	-0.8528	0.1436
Sick Time Excluded from Leave	0.0247	0.0031	-0.6035	0.1883	-0.8358	0.1581
Strains Not Considered Injuries	0.0189	0.0024	-0.5676	0.3368	-0.8238	0.2899
Med Exp $\leq$0 Not Injury	0.0189	0.0024	-0.7220	0.1257	-0.9285	0.0749
Med Exp $\leq$200 Not Injury	0.0189	0.0024	-0.7386	0.1153	-0.9387	0.0637
Med Exp $\leq$400 Not Injury	0.0189	0.0024	-0.7407	0.1208	-0.9417	0.0645

The table displays results of a number of robustness analyses. The first row provides the reference values from the primary specification. The second row removes sick time from the leave instrument. The third row does consider strains to be non-injuries. The fourth through sixth rows recode injuries with medical expenditures less than different amounts as non-injuries. Estimates of ρ remain negative across all specifications.

Table B.7: Average Elasticities: Injury Conditional on Working

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

This table reports averages elasticities of the injury outcome conditional on working. 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.8: 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.9: Fixed Effects IV: Testing Instrument Validity

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

Standard errors in parentheses

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

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

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

Standard errors in parentheses

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

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.11: Labor Supply Elasticities

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

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