Labor Market Tightness, Wage Inequality and Workplace Amenities

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Abstract

Workplace-specific pay premiums and their dispersion increases with labor market tightness. We study the role of compensating wage differentials in explaining this relationship: as competition for workers intensifies, firms are compelled to pay higher compensation for poor job attributes. We directly measure job attributes by estimating workplace-specific injury rates using a model with additive worker and firm effects. We find that that while workplace-specific injury rates remain largely unaffected by labor market tightness, firm-specific wage premium paid in compensation for hazardous working conditions does respond: a 10 percentage points decrease in the unemployment rate leads to 2.2 percent higher wages at high-risk firms. The additional compensation for workplace-specific injuries accounts for around 7 percent of the increase in wage dispersion. Interestingly, despite offering higher wages, firms with poor amenities struggle to retain workers as market tightness increases. We interpret these findings through the lens of a model of imperfect competition, in which firms offer lower compensating differentials when labor market slackness reduces workers' outside opportunities. Our results underscore how labor market tightness can amplify compensating wage differentials, contributing to increased wage inequality.

Keywords: inequality, amenities, labor market tightness, workplace injury
JEL Codes: E24, J28, J31, J32

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1 Introduction

Persistent and high within-country wage inequalities are of major economic concern in many countries (e.g., European Commission, 2023). Simultaneously, labor markets in Europe and beyond exhibit high levels of tightness, characterized by very low unemployment rates and significant labor shortages (European Commission, 2023; EURES, 2024). Tightness itself is a key driver of wage inequalities. For example, the well-known 'wage Phillips curve' emphasize the positive relationship between labor market tightness and wage growth (Katz and Krueger, 1999; Autor et al., 2023).

A significant share of wage inequality arises from differences in wages paid by firms to similar workers (Card et al., 2013). These firm-level components appear to strongly respond to labor market tightness. In Hungary, we find that as local unemployment declines (i.e., tightness increases), both the growth of firm-specific wage premiums and their *dispersion* expand. Thus, understanding the link between wage inequality and tightness requires a deeper examination of the role of firms in shaping wage structures.

A key explanation for firm-specific wage dispersion is compensating wage differentials. Rosen, 1974 seminal paper argues that wage dispersion could simply reflect compensation for undesirable working conditions. A key component of this theory is that workers are willing to accept lower wages for more favorable working condition, something that has been document in numerous surveys (e.g., Mas and Pallais, 2017). However, it is less clear whether these preferences are consistently reflected in wage determination, as predicted by theory (Mas, 2024). Moreover, the extent to which workers are compensated for poor working conditions likely depends on broader labor market conditions. In this paper, we examine whether labor market tightness increases compensation for firm-specific injury rates, a significant disamenity at the workplace.

We start our analysis by constructing a novel measure of firm-specific injury risk. We exploit Hungarian employer-employee administrative data that is linked to public health records of workers. We observe in our data if a worker is injured in a given month and the severity of that injury (e.g., how long it takes to recover). These injuries can be attributed to personal characteristics, work-place specific factors, and idiosyncratic factors. To separate these, we estimate an additive fixed effect model analogously to the estimation approach of workplace-specific wage premiums pioneered by Abowd et al. (1999). We focus on blue-collar workers who are mainly affected by workplace injury rates.[1]

The estimated firm fixed effects construct a firm-specific injury risk that is not tainted by workers' sorting to firms. Following Card et al. (2013), we also present several diagnostic test results supporting that our firm-specific injury risk measure captures a genuine risk attributed to firms. We provide reassuring evidence that moving between high- and low-injury firms affects injury rates, and these effects are symmetric—suggesting a limited

[1]We find limited role for workplace-specific injury rates for white collar workers.

role for Roy-type selection based on workers' susceptibility to injury. We also show that change in injury rate for movers between high and low firms are not driven by pre-trends – suggesting that mobility is not reflecting permanent or transitory shocks affecting workers' injury rate.

Next, we quantify compensating wage differentials by estimating the relationship between the firm-specific injury risk and the firm-specific wage premium, and how that relationship is influenced by labor market tightness. We document that firms pay higher wage premiums when their workplace-specific injury risk increases, consistent with compensating wage differentials. This relationship becomes stronger with tightness: when the unemployment rate is 10% lower, a one standard deviation (SD) increase in firm-specific injury risk is associated to 2.2 percent (s.e. 0.007) higher wage premium. Importantly, this increased compensation for risk does not reflect the change in injury rate with market tightness. We find no indication that tightness influences firm-specific injury risks.[2]

The increased role of compensating variation is substantial. We find that if firms in the tightest labor markets compensated for injury risk similarly to those in slack markets, the difference in the dispersion of firm-specific wage premiums between tight and slack markets would be by around 7–10 percent lower. This suggests that a significant portion of the increased wage dispersion associated with market tightness is due to higher compensation for a single, yet crucial, workplace disamenity: injury risk.

The increasing role of compensating variation suggests that workers receive higher pay for the same level of injury risk. However, whether this pay increase is sufficient to retain workers depends on the level of compensation offered when the labor market was slack. If workers were adequately compensated during periods of high unemployment, increased labor market tightness and greater job mobility may not significantly affect high-risk firms. Conversely, if compensation was insufficient in slack markets, retention rates are likely to decreasae witn tightness, leading to higher worker turnover. This latter is precisely what we find: as market tightness increases, retention rats at high-risk firms falls, and worker turnover rises.

We present a framework consistent with our findings. The standard model of compensating variation emphasizes worker selection based on preferences for job amenities—those more indifferent to injury risk are expected to sort into high-risk firms. Under this preference based sorting mechanism, the average worker at a high-risk firm should be better off, while the marginal worker is just indifferent between high- and low-risk firms. If workers receive higher compensation for the same risk, they should be more likely to stay. However, our findings reveal the opposite: despite receiving increased compensation, workers left, suggesting that the average worker was not fully compensated for the risk when the labor market was slack. When better opportunities arose, they exited the firm.

[2]The correlation between injury risk and other amenities remains stable throughout the business cycle. Therefore, our results are unlikely to reflect changes in other amenities.

Our model, therefore, highlights that the sorting mechanism often emphasized in the compensating variation literature is likely to be muted, particularly when the labor market is slack. Furthermore, compensation for bad amenities will depend strongly on the labor market conditions.

Our findings on firm wage premium and retention rate are robust to using alternative injury and tightness measures, and to including numerous firm-specific variables and their interaction with tightness and time effects. Furthermore, our results are robust to using a shift-share instrumental variable strategy that addresses the concern that wages and tightness are simultaneously determined in equilibrium, and over time, large firms may affect the tightness they face in their respective local labor markets.

We contribute to various strands of the literature on compensating wage differentials, originating from Rosen (1974, 1986) who provides a theoretical framework for the trade-off between wages and amenities in labor markets. First, there is plenty of direct evidence on preferences for amenities (e.g., Mas and Pallais, 2017; Maestas et al., 2023), yet evidence on how preferences for amenities are priced in equilibrium is scarce (Mas, 2024). We show new evidence on the pricing of injury risk in equilibrium, by analyzing the relationship between the firm-specific injury risk and the wage premium, in tight and slack markets. Previous papers documented relationship between market conditions and offering valuable amenities Adams-Prassl et al. (2022). In our case, we examine an amenity that is difficult to change, prompting firms to respond by increasing compensation rather than altering its level. This allows us to directly test the role of compensating wage differentiation and quantify its contribution to wage inequality.

Second, with our novel injury risk measure, we contribute to the existing direct evidence on the wage effects of observed amenities (e.g., workplace safety, as in Lee and Taylor, 2019; Lavetti, 2020; Lavetti and Schmutte, 2023), and on the indirect evidence for compensating wage differentials from voluntarily moves to a new job that pays less (e.g., Sorkin, 2018; Taber and Vejlin, 2020; Lamadon et al., 2022). In this literature, Mas (2024) presents the most important application of compensating wage differentials to fatality risk. Our similar, albeit less radical, injury risk measure has several advantages. It is a relatively common event and so it easier to study firm-specific injury rates. We can also control for person effects since, unlike fatality events, injuries are not absorbing states. Finally, by borrowing the diagnostic tests developed in the literature of AKM firm and worker effects (see Card et al. (2013), we can show that the estimated injury rates are not tainted by selection of workers.

Third, we contribute to the small literature that analyzes the relationship between compensating wage differentials and the unemployment rate (Dorman and Hagstrom, 1998; Bender and Mridha, 2011; Mridha and Khan, 2013; Mridha, 2022). These papers emphasize that the compensation for fatality risk is likely to be context-dependent, but the evidence provided is at best mixed. Furthermore, this literature uses occupation-

and/or sector-specific injury risk, not firm-specific ones. Our richer data that allows us to estimate firm-specific injury risk. This not only strengthens identification but also allows us to focus on firms that appear to contribute more to rising wage inequality than industry or occupation (see Card et al. (2013)).

Furthermore, in addition to documenting the effect on wages, we examine changes in retention rates, worker turnover, and firm size. Interestingly, despite higher compensation, high-risk firms experience a decline in retention rates as market tightness increases. This provides evidence that workers were not fully compensated in slack labor market conditions—a novel finding in the literature.

In what follows, Section 2 presents the data and measurement, with the focus on our novel firm-specific injury risk measure. Section 3 presents our baseline empirical strategy and Section 4 our baseline estimates. Section 5 shows numerous robustness checks, Section 6 presents our model that rationalizes our empirical results, and Section 7 concludes.

2 Data and Measurement

2.1 Data Sources

Our main data is an employer-employee linked panel dataset, covering a 50 percent random sample of the Hungarian population in 2003, which, besides information on workers' labor outcomes for 2003–2017, also contains their administrative health data for 2009–2017.[3] The health data include detailed information on drug expenditures and both inpatient and outpatient healthcare use and detailed diagnoses in the public healthcare system, which accounts for the overwhelming share of the Hungarian healthcare system.[4]

We observe sex, age, living area (district), employment status, for each person in each month. For employees, we observe their wage, occupation (International Classification of Occupations, ISCO codes), firm and industry. We also observe in the data the employer of the worker (or self-employment). For employers with double-bookkeeping, we have yearly data on firm size, revenue, costs, and value of capital from the tax records of the firm.

The yearly county-specific unemployment statistics used for constructing our labor market tightness measure stems from the Hungarian Central Statistical Office. For background information on workplace amenities, we use survey data from the 2010 and 2015 waves of the European Working Conditions Survey (see Appendix A for details).

[3]The sample was drawn in 2003 and the same people were followed until 2017. The health-related variables are available only from 2009. This administrative data is owned by the National Health Insurance Fund Administration, the Central Administration of National Pension Insurance, the National Tax and Customs Administration, the National Employment Service and the Educational Authority of Hungary. The data was processed by the Databank of the HUN-REN Centre for Economic and Regional Studies.

[4]The role of private care in the treatment of injuries – which is in the focus of ou paper – is small, although we lack evidence on the exact magnitude of the share of private care. Hüttl and Nagy (2017) estimate that in 2012, less than 10 percent of hospital care was provided by private hospitals.

2.2 Firm-Specific Wage Premium

To estimate the firm-specific wage premium, generally we follow the approach of Abowd et al. (1999), and estimate the following model of log wages:

$$\ln w_{ijt} = X'_{ijt}\beta^w + \alpha_i^w + \delta_t^w + \phi^w_{j(i,t),t} + \varepsilon_{ijt}, \tag{1}$$

where i denotes individuals, j denotes firms, t denotes a time period. Wage w is net of employer payroll tax; this wage measure is calculated before income tax and employee social security contributions are deducted and includes base payment, bonuses and overtime pay. The vector X_{ijt} includes the square and cube of (age $-$ 40), α_i^w is the person effect, δ_t^w is the full set of time indicator for each time period, and $\phi^w_{j(i,t),t}$ is the firm-specific wage premium that is allowed to vary over time. The time-varying firm fixed effect is an extension of the approach of Abowd et al. (1999), where we follow Lachowska et al. (2023). Note, that we assume that the individual fixed effect is constant over time.

2.3 Labor Market Tightness and the Wage Phillips Curve

We capture labor market tightness at the county $\times$ year level with the negative unemployment rate, which we construct with the steps below.

Hungary (a country with a population of ca. 9.6 million) is divided to 20 counties. The unemployment rate is the number of unemployed at the end of year, divided by the number of population aged 18–59 in a given county in a given year. In the administrative data, we observe the location (district of the address) of the individuals but not of the firms. For each firm, we define the mode of the county of its workers, which we consider the county of the firm and merge the unemployment statistics based on this county indicator.

In tight markets workers can more easily find better-paying jobs, leading to faster wage growth. We confirm this positive relationship between tightness and growth of individual wages – the standard 'wage Phillips curve' – with the regression of Autor et al. (2023)[5]:

$$\Delta \ln w_{ct} = \beta(1 - UR_{c,t-1}) + X'_{ct}\gamma + \alpha_c + \delta_t + \varepsilon_{ct}, \tag{2}$$

where c indicates counties, t indicates years, UR is the unemployment rate, and the vector of X incudes variables capturing the share of each one-digit industry in county c in year t.

Panel (a) of Figure 1 indicates that a 10 percentage points lower unemployment rate implies, on average, 5.9% additional annual wage growth. When we standardize the measure of (1 – unemployment rate) as in Autor et al. (2023), this estimate corresponds to an average 2.1% additional wage growth if tightness is higher by one standard deviation, where the corresponding estimate of Autor et al. (2023) is very close at 2.6%.

[5]Our equation (2) corresponds to equation (5) on page 20 in Autor et al. (2023).

Next, we add new evidence for the relationship between the local unemployment rate and the *level* of firm-specific wage premium, as well as the local unemployment rate and the *dispersion* of both individual-level wages and the firm-specific wage premium. For this, we estimate firm-specific wage premia with model (1) at the yearly level.

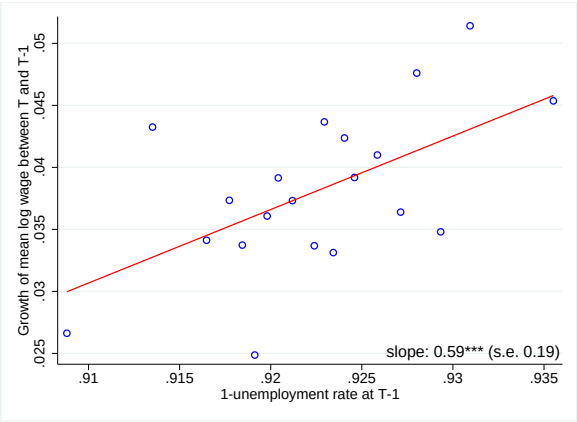
In panel (c) of Figure 1 we relate the the county- and year-specific growth of the level of the firm wage premium to the local labor market tightness. The significantly positive relationship in panel (c) suggests that the positive relationship observed in panel (a), the 'wage Phillips curve' is due to firms: not only the individual-level wage, but also the firm wage premium grows faster in tighter labor markets.

Finally, we analyze the dispersion of wages. Panels (b) and (d) if Figure 1 show that the growth of the standard deviation of individual wages and the firm-specific wage premium is also positively related to labor market tightness (with the relationship in panel (d) being statistically stronger and significant at all usual levels).

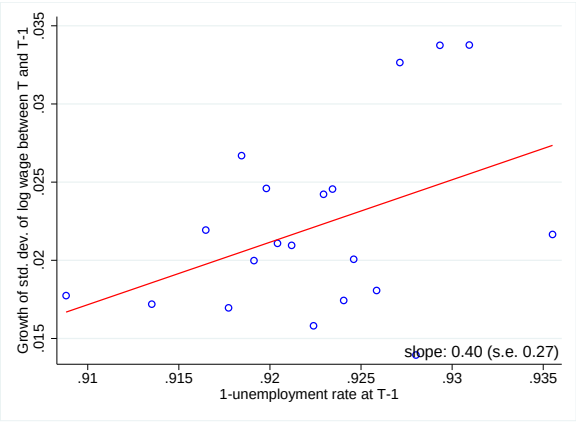
In Appendix Figure D1 we show that these patterns are similar if we relate the three-yearly wage and firm premium measures to three-yearly unemployment rate, and restrict the sample to blue-collar workers, as we do in the remaining part of the empirical analysis.

Figure 1: Wage Phillips Curves

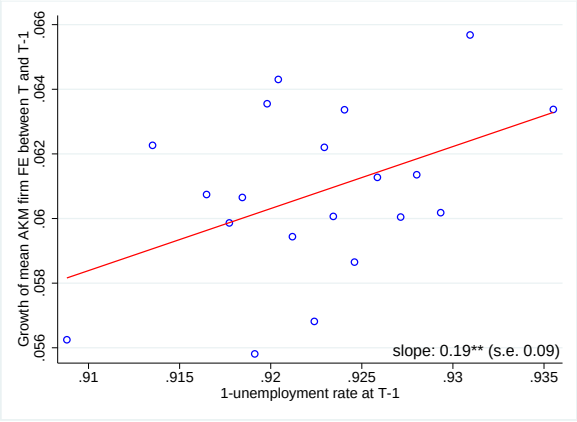
(a) Mean log wage



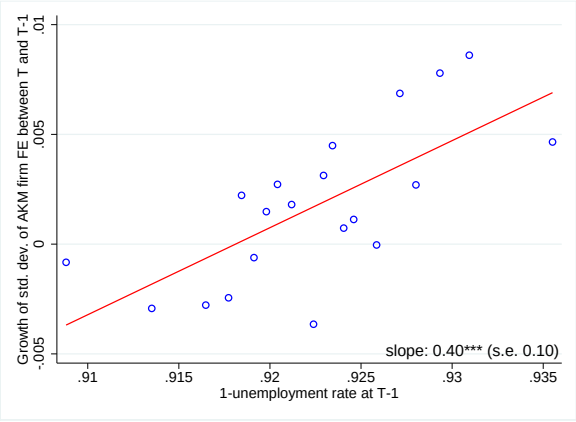
(b) Std. dev. log wage



(c) Mean AKM firm FE



(d) Std. dev. AKM firm FE



Notes: Figure shows binscatter plots with county- and year-level values of 1 – unemployment rate at year $T-1$ on the x-axis, and the year $T-1$ to T growth of the average of or the standard deviation of the yearly log wage or yearly firm-specific wage premium on the y-axis. Control variables: county and time effects, and industry composition. Data: Hungarian administrative data, years 2009–2017. Standard errors are clustered at the county level.

2.4 Sample Selection

Throughout the rest of the paper, we focus on blue-collar workers in the private sector, aged 20–60. Individuals are defined to be private sector employees if they are employed on the 15^{th} of a month at a private sector firm with double-entry bookkeeping.

2.5 Firm-Specific Injury Risk

2.5.1 Measurement

To create the firm-specific injury risk, we first define injuries at the person level.

Before describing the construction of this person-specific injury measure, we note that we define it conditional on the receipt of sickness benefit. In the Hungarian healthcare system, workers who are not able to work due to health reason are eligible for 15 days of

"sick leave" for which the employer pays 70% percent of their wage. After 15 days, workers who are still not able to perform at work, are entitled to receive sickness benefit. Sickness benefit is paid by the state, for a maximum of 1 year, during which workers can not be laid off. The amount of the benefit is 50–60% of the wage (60% if the worker has paid social security contributions throughout the past two years). In the case of workplace injuries, the amount of the benefit is 100% of the wage, with an immediate entitlement to the benefit which is to be paid by the firm if the firm is responsible for the injury. Importantly, those who receive sickness benefit remain legally employed – we observe their firm identifier – but do not receive wage while being absent from work.

Our person-specific injury measure is defined as follows. Using diagnosis codes (ICD-10 codes) recorded at public outpatient clinics and hospitals, we flag individuals who suffer an injury in a given month.[6] To exclude minor injuries, we consider only those injuries for which in the month when the injury is recorded, the injured person receives sickness benefit at least for one day. This procedure gives us the binary indicator of *injury diagnosis*. Then, we set the binary indicator of *injury* to one when the *injury diagnosis* indicator equals one, and in all those consecutive months for up to 12 month, in which the injured person receives sickness benefit at least for a day, conditional on non-zero sickness benefit in all months between the month of the injury and the current month. We denote the resulting binary indicator of *injury* of individual i at firm j at monthly date t, by S_{ijt}.

Among blue-collar workers for whom the *injury* indicator is one, 36% receive benefits for workplace accidents. On average, injured people receive sickness benefits for 39 days (with median of 22 and 90^{th} percentile of 83). Of the injured people, 2.1% start to receive disability benefits within 18 months after the injury, and 0.6% die within 18 months.

Next, restricting the sample to blue-collar workers in the private sector, aged 20–60, we estimate the firm-specific risk of injury. We further restrict the sample to those firm-year pairs in which, on average, we observe at least 20 blue collar workers on average in our data. Using data from 2009–2017, we estimate the following model:

$$S_{ijt} = X'_{ijt}\beta^S + \alpha_i^S + \delta_T^S + \phi_{j(i,t),T}^S + \varepsilon_{ijt}, \tag{3}$$

where T denotes 3-year intervals (2009–2011, 2012–2014, 2015–2017), the vector X_{ijt} includes the square and cube of (age $-$ 40), α_i is the person effect, δ_T is the full set of three-year specific time effects, and $\phi_{j(i,t),T}^S$ is the three-year specific firm effect. This model follows the approach of Abowd et al. (1999), with the binary indicator injury as the outcome, instead of the traditionally used wage outcome. The time-varying firm fixed

[6]Note, that healthcare at public outpatient clinics and hospitals is funded by the social security, and thus no out-of-pocket payment is required. ICD stands for International Classification of Diseases. We include all S and T ICD-10 diagnosis codes, making up the diganosis group "injury, poisoning and certain other consequences of external causes" but exclude diagnoses *T36–T65*, which include poisoning by drugs and toxic effects of substances.

effect is an extension of the approach of Abowd et al. (1999), where we follow Lachowska et al. (2023). Note that unlike in the model with time-invariant firm fixed effects, which are identified by movers only, here $\phi^S_{j(i,t),T}$ is identified both by workers staying at the same firm, and by movers between firms. To alleviate the noise originating from the large number of estimated parameters, we apply empirical Bayes shrinkage to the estimated $\phi^S_{j(i,t),T}$ parameters (details are in Appendix C, following Walters (2024)).

In our empirical approach, we use the standardized (mean zero, standard deviation one) estimated value of $\phi^S_{j(i,t),T}$ as the firm-specific indicator of injury risk. Appendix Figure D2 shows the histogram of the firm-specific injury risk before standardization.

Table 1: Variance Decomposition of Injury Risk

	2009-2011	2012-2014	2015-2017
Var of injury rate	0.008	0.007	0.009
Variance shares			
Var of firm effects	0.011	0.009	0.007
Var of person effects	0.148	0.101	0.089
Var of Xb	0.001	0.001	0.001
2*Cov of firm and person effects	-0.014	-0.012	-0.008
2*Cov of [firm+person effects] and Xb	-0.001	-0.001	-0.001
Residual terms	0.856	0.902	0.912

Notes: Table shows results from estimating equation (3). Xb includes dummies of three-year groups, and the square and cube of (age − 40).

We show the variance decomposition of injury (S_{ijt}) in Table 1; the variance share of firm effects is much smaller than the variance share of person effects, suggesting that it is important to net out person effects when estimating firm-specific injury risk. In Table 2, we show descriptives on how the firm-specific injury risk and the firm-specific wage premium are related to firms' observable characteristics.

Finally, in Appendix A we show that health risk at work (a 'bad' amenity) is negatively related to 'good' workplace amenities, such as working hours fitting family life, no abuse at work, the quality of the boss being high, and being satisfied with working conditions. Importantly, this negative relationship does not differ by labor market tightness.

Table 2: Relation of Injury Risk and Wage Premium to Firm Characteristics

	Firm-specific injury risk	Firm-specific wage premium
Panel A: Size (ref.: 20-49)		
50-249	0.176***	0.059***
	[0.030]	[0.009]
250+	0.181***	0.125***
	[0.028]	[0.010]
Panel B: Location		
Budapest commuting zone	-0.145***	0.036***
	[0.030]	[0.009]
Panel C: Firm productivity		
Above median TFP	0.208***	0.241***
	[0.025]	[0.007]
Panel D: Industry (ref.: manufacturing)		
Wholesale and retail	-0.359***	-0.054***
	[0.037]	[0.011]
Construction	-0.019	-0.056***
	[0.067]	[0.019]
Transportation	-0.260***	-0.068***
	[0.050]	[0.016]
Services	-0.353***	-0.104***
	[0.035]	[0.010]
Other	-0.117**	-0.020*
	[0.047]	[0.012]
Number of observations	11,070	11,070
Number of firms	5,319	5,319
Mean	0.003	0.097
Std. dev.	0.996	0.324

Notes: Table shows OLS regression results for the relation of firm-specific injury risk (estimated by equation (3)) and firm-specific wage premium (estimated by equation (**??**)) to firm characteristics. Each panel corresponds to a separate regression. In each OLS regression, the regressor is displayed in the row, the outcome in the column of the table. Heteroskedasticity robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

2.5.2 Diagnostic Tests

We provide three diagnostic tests supporting our measure of firm-specific injury risk.

First, we apply a simulation exercise for the estimation of the firm-specific injury risk. For each person–firm–year cell in the monthly data, we calculate in our data the injury rate, which we denote by $\bar{S}_{ijt}$. Then, we simulate a binary risk indicator that takes value one with probability $\bar{S}_{ijt}$, zero otherwise. We estimate equation (3) on this simulated data. Finally, we compare the estimated person effect to the person-specific injury rate in the simulated data, and the estimated three-year specific firm effect to the three-yearly firm-specific injury rate in the simulated data. Appendix Figure D3 shows the results of this exercise, indicating that the distributions of the estimated fixed effects are very close to the distributions of the injury probabilities in the simulated data.

The second diagnostic test follows Card et al. (2013, 2018), and is based on the idea that since identification of model (3) partly relies on movers between firms, the estimated

person and firm effects are biased if there is endogenous mobility, i.e., if worker mobility is correlated with the time-varying residual components of injury rates. Following Card et al. (2013, 2018), we provide indicative evidence that the issue of endogenous mobility is not present in our case. We construct two equal-sized group of firms based on the injury rate of the co-workers (high vs. low injury risk firms). In Appendix Figure D4, we plot for movers the injury rate around the transition between firms, split by the risk category of the origin and destination firms. Two important patterns emerge. First, we see no evidence for transitory change in the injury rates before the transition between firms in any category of movers. Second, the injury rate decreases for workers who move from a firm with high injury rate to one with low injury rate, whereas the opposite holds for workers who move from a firm with low injury rate to a firm with high injury rate. These patterns reassure that we can capture the dynamics of injuries with movers between firms.

The third diagnostic test follows Chetty et al. (2014) and Sorkin (2017). Here, we regress the change in the person-level three-year change in injury rate on the tree-year change of firm-specific injury risk. If the firm-specific injury risk is unbiased then the slope parameter of this regression should be around 1. The estimated slope, shown in Appendix Figure D5, is 0.95, suggesting that the firm-specific injury risk is unbiased.

2.5.3 Cyclicality of Injury Risk

Throughout the paper, we focus on how firm-level responses to injury risk vary with labor market tightness. Before presenting our main results, in this subsection we present reassuring evidence that firm-specific injury risk itself does not vary with tightness.

Whether injury risk is cyclical is an empirical question. Tight labor markets may imply higher workload, possibly leading to adverse health effects at the workplace. Indeed, there is some evidence in the literature that workplace injury rates are pro-cyclical, albeit to different extent across industries (Davies et al., 2009; Asfaw et al., 2011), and Boone et al. (2011) argue that observed cyclicalities are driven by differences in the reporting of workplace injuries, not by differences in the rate of injuries, per se.

To check the cyclicality of firm-specific injury risk, we first estimate the correlation between the change in labor market tightness and the change in firm-specific injury risk, between consecutive periods of 2009–2011, 2012–2014, and 2015–2017. This correlation estimate is close to zero: 0.002 in the first two, and 0.008 in the second and third periods.

Next, based on the pooled data, in Appendix Figure D6 we show binscatter plots for the relation between labor market tightness and firm-specific injury risk, and between labor market tightness and healthcare use (number of outpatient clinic visits and hospital days) conditional on injury risk. The healthcare use indicators can capture the severity of the injury. We do not see any evidence for cyclicality in the injury rate or injury severity.

Finally, in Appendix Table D2 we report regression results on the cyclicality of firm-

specific injury risk: firm-specific injury risk is strongly correlated with its lagged value (i.e., its value in the preceding three-year period), but, reassuringly, it does not correlate with county-level labor market tightness or its interaction with lagged risk.

2.6 Outcome Variables in Main Analysis: Firm-Specific Wage Premium, Workforce Dynamics and Firm Size Measures

Firm-specific wage premium. To estimate the firm-specific wage premium for our main analysis, we estimate equation (1) at the three-yearly level (2009–2011, 2023–2014, 2015–2017), and use the sample as for equation (3), but further restrict it to full-time workers, and for those who suffer an injury (as defined above), we exclude their observations after the injury. We make this exclusion because absence following the injury and productivity loss due to the injury may have direct impacts on workers' wages (see, e.g., Bíró et al., 2024). We estimate $\phi^{w}_{j(i,t),T}$, the firm-specific wage premium, which – similarly to the firm-specific injury risk – is allowed to differ across the three three-year periods.

We show the variance decomposition of log wage in Appendix Table D1, showing that the variance shares of firm and person effects are similar. Note, that if we do not restrict the sample of equation (1) to blue-collar workers, then the variance share of person effects is bigger (0.483 for all workers vs. 0.273 for blue-collar workers over 2009–2017).

We show the relationship between the estimated firm-specific injury risk and the firm-specific wage premium to a set of firm characteristics in Appendix Table 2. Except for the location indicator (the firm being based in the Budapest commuting zone, which is the area around the capital city), the associations of each firm characteristic with the firm-specific injury risk and the firm-specific wage premium have the same signs. For instance, firm size and productivity are positively related to both risk and wage premium. Relative to the manufacturing industry, in each industry group the average firm-specific injury risk and firm-specific wage premium are smaller.

Next, we define the measures of workforce dynamics and firm size, which we use as further outcome variables in our empirical strategy besides the firm-specific wage premium.

Narrow retention rate. We define our first measure of retention rate of blue collar workers based on a narrow definition of separation rate. We calculate the employer-to-employer transition rate of blue collar workers, i.e., the share of blue collar workers who switch to another firm. We do not consider those separations where the worker returns to the firm within three month, and clean the transitions from changes of firm identifiers.[7] When calculating the separation rate, we exclude those who ever suffered an injury, using

[7]To make sure that a change of the firm identifier does not lead to a false move, we apply the worker-flow method of detecting firm identifier changes as in Saygin et al. (2021), when we calculate both the hiring and separation rates.

the injury definition as specified above, to ensure that injuries do not have mechanical effect on the separation rate (as being on sickness benefit may affect job search behavior, and workers cannot be laid-off while receiving sickness benefit). Furthermore, when calculating the separation rate, we exclude workers who retire or go on parental leave.

We use the three-yearly average of monthly employer-to-employer transition rate, multiplied by 12, to capture annual rates. One minus the so defined employer-to-employer transition rate is then our narrow retention rate, labeled later as *retention rate (1-EE)*.

Broad retention rate. Our second measure of retention rate of blue collar workers is *1-separation rate (broadly defined)*. We calculate the monthly, broadly defined, separation rate as the share of blue-collar workers who exit the firm, applying the same data cleaning procedures and restrictions as for the narrow retention rate measure. We use the three-yearly average of monthly separation rate, multiplied by 12. One minus the so defined separation rate is then our broad retention rate, labeled later as *retention rate (1-exit)*.

Turnover rate. We generate the three-yearly turnover rate of blue-collar workers as the sum of the three-yearly hiring rate and the three-yearly separation rate (broadly defined).

The three-yearly measures are the three-yearly averages of the corresponding monthly measures multiplied by 12, to capture annual rates. We calculate the *separation rate (broadly defined)* as explained in the previous paragraph. We calculate the monthly *hiring rate* as the ratio of newly hired blue-collar workers and the total number of blue-collar workers. We exclude workers returning from parental leave as newly hired workers, and those from new hires who worked at the same firm two or three months before. As for the retention rates, we clean the transitions from changes of firm identifiers.

Firm size. We take the logarithm of the average number of blue collar workers at the firm in the given year, to capture the size of the firm.

3 Empirical Strategies

In this section, we describe our empirical strategies to assess the extent to which the relationship between firm-specific risk and firm-specific wage premium and revealed preferences as outcomes depend on the level of labor market tightness.

3.1 Baseline Specification: With Firm Fixed Effects

Our baseline specification 'without time effects' for firm j in three-year period t is the following, in which all coefficients are constant across time and none are time-specific:

$$y_{jt} = \beta \text{tight}_{r(j),t} \times \text{risk}_{jt} + \gamma_1 \text{tight}_{r(j),t} + \gamma_2 \text{risk}_{jt} + \theta X_{jt} + \mu_j + \delta_t + \varepsilon_{jt}, \qquad (4)$$

where the outcome variable, y_{jt}, is either the firm-specific wage premium (AKM firm FE) or one of the revealed preference measures for the firm. risk_{jt} is the standardized firm-specific injury risk (i.e., the standardized value of $\phi^S_{j(i,t),T}$ from equation (3)). Labor market tightness is $\text{tight}_{r(j)t}$, defined as $(10 \times (-\text{unemployment rate}))$, where unemployment rate is the three-year average of the country-specific unemployment rate; thus, a unit increase in tightness corresponds to 10 percentage points decrease in unemployment rate. The vector of control variables X_{jt} includes the mean age, sex, person fixed effect of the injury (mean of α^S_i from equation (3)), and occupation composition of the workers (with one-digit occupation categories). Finally, μ_j are firm fixed effects, and δ_t are time effects.

The firm fixed effects (μ_j) capture time invariant characteristics of the firm (such as location, ownership structure and specific production characteristics) that may be related both to the average labor market tightness in the given county, and also to the firm-specific injury risk. By including μ_j, the coefficient of interest, β, is identified from within-firm variation in risk and tightness over time. To see the consequences of including μ_j, we present OLS regression results (without the inclusion of the firm fixed effects) in Appendix Table D3, in which we extend the X's with county and industry effects.

In equation (4), the coefficients of the injury risk and tightness are not allowed to vary with time, and thus a potential concern arises that the coefficient estimate on the interaction term ($\hat{\beta}$) may be driven by aggregate time trends either in risk or in tightness. To address this, we also estimate the following specification 'with time effects' for firm j in t (2009-2011, 2012-2014, 2015-2017) is the following, in which the γ's are t-specific:

$$y_{jt} = \beta \text{tight}_{r(j),t} \times \text{risk}_{jt} + \sum_{t=1}^{3} \gamma_{1t} \text{tight}_{r(j),t} + \sum_{t=1}^{3} \gamma_{2t} \text{risk}_{jt} + \theta X_{jt} + \mu_j + \delta_t + \varepsilon_{jt}. \quad (5)$$

3.2 Shift-Share Instrumental Variable Strategy

A potential concern regarding our baseline empirical strategy is that wages and tightness are equilibrium objects, determined simultaneously in the economy. Furthermore, over time, individual firms may affect the tightness they face in a given labor market. To address such a concern, we apply a shift-share instrument for labor market tightness. Our methodology follows Bartik (1991) and Borusyak et al. (2024).

Specifically our instrument for labor market tightness in county $r(j)$ at t is:

$$z_{r(j)t} = \sum_{k=1}^{K} s^0_{r(j)tk} g_{tk}, \quad (6)$$

where k denotes one-digit industry codes (there are 17 such industry categories in our data); $s^0_{r(j)tk}$ is the employment share of industry k in county $r(j)$ at the first year of the

three-year period t; and g_{tk} is the aggregate (country-level) employment share if industry k in three-year period t in the population aged 20–60. We calculate the $s^0_{r(j)tk}$ ("share") and g_{tk} ("shift") variables based on the administrative data used in the main analysis. We instrument the $\text{tight}_{r(j)t}$ variable in equation (5) with $z_{r(j)t}$.[8]

4 Baseline Results

In this section, we first present our baseline estimates for the relationship between firm-specific injury risk and firm-specific wage premium, and to what extent this relationship depends on the level of labor market tightness in a given county (in Section 4.1). Second, we present the estimates for the relationship between firm-specific injury risk and workforce dynamics and firm size, also by tightness (in Section 4.2). The presented point estimates stem from equations (4) and (5) in Section 3.1. Our estimation sample is at the firm × three-year period level, excluding those cells in which the firm did not exist in all three periods (and we perform a robustness check using a balanced sample of firms).

Our baseline specification for firm j in three-year period t is the following:

$$y_{jt} = \beta \text{tight}_{r(j),t} \times \text{risk}_{jt} + \gamma_{1t}\text{tight}_{r(j),t} + \gamma_{2t}\text{risk}_{jt} + \theta X_{jt} + \mu_j + \delta_t + \varepsilon_{jt}, \tag{7}$$

where y_{jt} is the firm-specific wage premium (AKM firm FE) or preference indicator for the firm; risk_{jt} is the standardized firm-specific injury risk (standardized value of $\phi^S_{j(i,t),T}$ from equation (3), with simplifying the notation of using here t as the index of three-year periods). Labor market tightness is $\text{tight}_{r(j)t}$, defined as $(10 \times (-\text{unemployment rate}))$, where unemployment rate is the three-year average of the country-specific unemployment rate, thus, a unit increase in tightness corresponds to 10 percentage points decrease in unemployment rate. The vector of control variables X_{jt} includes the mean age, sex, person fixed effect of the injury (mean of α^S_i from equation (3)), and occupation composition of the workers (with one-digit occupation categories). In the OLS specification, we extend the list of controls with county and industry effects. Finally, μ_j are firm fixed effects, δ_t are time effects. Note, that the coefficients of the injury risk and tightness indicators are allowed to vary with time, to ensure that the coefficient of the interaction term (β), which is of main interest, is not driven by aggregate time trends either in risk or in tightness.

We also estimate a modified version of equation (7), in which we do not include time effects and all coefficients are constant over time. The firm fixed effects (μ_j) capture time invariant characteristics of the firm (such as location, ownership structure and specific production characteristics) that may be related both to the average labor market tightness

[8] Specifically, we predict $\text{tight}_{r(j)t}$ with $z_{r(j)t}$, $z_{r(j)t} \times \text{risk}_{jt}$ and $z_{r(j)t} \times D_t$ (and the other X_{jt}'s of the baseline model), where D_t denotes three-year dummies. We obtain the predicted value $\widehat{\text{tight}}_{r(j)t}$, and instrument $\text{tight}_{r(j)t} \times \text{risk}_{jt}$ and $\text{tight}_{r(j)t} \times D_t$ with $\widehat{\text{tight}}_{r(j)t} \times \text{risk}_{jt}$ and $\widehat{\text{tight}}_{r(j)t} \times D_t$.

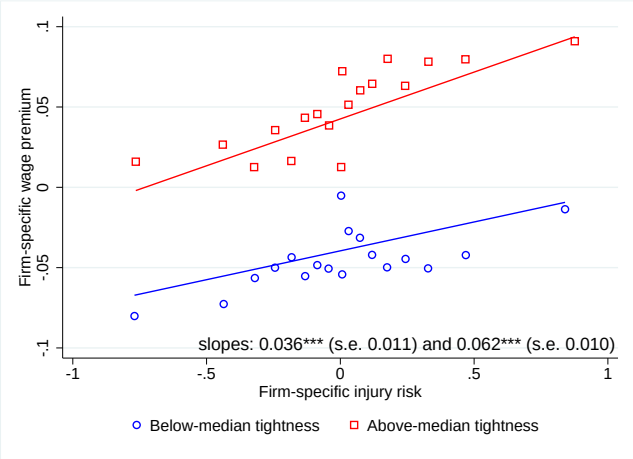
in the given county, and also to the firm-specific injury risk. We present OLS regression results (without the inclusion of the firm fixed effects) in Appendix Table D3.

4.1 Results for the Firm-Specific Wage Premium

4.1.1 Baseline Results

Figure 2 illustrates the relation between firm-specific injury risk and firm-specific wage premium, splitting the sample at the median of county-level labor market tightness. This figure suggests that the relationship between the firm-specific injury risk and the firm-specific wage premium is positive, and even more positive in tight labor markets – and our main (baseline) regression results in column (1) of Table 3 confirm these relationships.

Figure 2: Relation Between Injury Risk and Firm-Specific Wage Premium



Notes: Figure shows binscatter plots with firm-specific injury risk on the x-axis, and demeaned AKM firm FE on the y-axis. Control variables: mean age, sex, and injury person FE, and occupation composition of workers, firm and time effects.

We present the estimation results of equation (5) in the top panel of Table 3, and we report the full set of coefficients in column (1) of Appendix Table D4. In the bottom panel of Table 3 we report the results without time effects or time-varying coefficients, stemming from equation (4). Focusing on the baseline estimates (column (1)), and on the estimated coefficient of the interaction term, the estimate is similar under the two specifications (4) and (5). We consider the model with time effects (5) as our preferred specification because that takes aggregate time trends into account.

The first rows of both panels in Table 3 show the first main result of this paper: the marginal effect of firm-specific injury risk on the firm-level wage premium increases with labor market tightness. Specifically, a one standard deviation increase in firm-specific injury risk leads to 2.2 percent (s.e. 0.007) higher firm-specific wage premium if labor market tightness increases (i.e., unemployment rate decreases) by 10 percentage points, and this point estimate is significantly different from zero at all usual significance levels.

Table 3: Relation of Risk and Tightness to Firm-Specific Wage Premium

	(1) Baseline	(2) No controls	(3) Excluding Budapest CZ	(4) Excluding construction	(5) Balanced sample
With time effects					
tight × risk	0.022***	0.022***	0.020**	0.021***	0.023***
	[0.007]	[0.007]	[0.008]	[0.007]	[0.008]
Without time effects					
tight × risk	0.025***	0.024***	0.024***	0.025***	0.026***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.007]
tight	0.939***	0.968***	0.902***	0.941***	0.938***
	[0.008]	[0.007]	[0.008]	[0.008]	[0.009]
risk	0.019***	0.018***	0.014**	0.019***	0.024***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.007]
observations	9,208	9,208	7,014	8,733	6,842

Notes: Table shows estimated coefficients of equations (4) and (5). Variable "tight" refers to the county-level labor market tightness, "risk" refers to the firm-specific injury risk. Control variables: mean age, sex, and injury person FE, and occupation composition of workers, firm and time effects. Budapest commuting zone (CZ) refers to the capital city Budapest and the county surrounding the capital. Number of firms in the baseline specification: 3,467. Standard errors in brackets, clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

In columns (2)-(5) of Table 3, we present four pieces of robustness checks to estimates in column (1): (i) in column (2), we exclude the control variables (vector X_{jt} in equation (5)); (ii) in column (3), we exclude the Budapest commuting zone (i.e., the capital city and the county surrounding it, that is the most densely populated area of the country, with low unemployment rate); (iii) in column (4), we exclude the construction industry, in which, due to the high-risk work environment and the high ratio of workers with low education level, the effect of injury risk and labor market tightness on wages may differ from the rest of the economy; (iv) in column (5), we keep only those firms that were present throughout the estimation sampl of 2009–2017. Reassuringly, our estimates, especially the estimated coefficient on the interaction between labor market tightness and firm-specific injury risk, are very similar across these robustness checks around the baseline estimate of 0.022.

4.1.2 Back-Of-The-Envelope Estimates

Next, we quantify what our baseline estimate of 0.022 implies for the importance of Compensating Wage Differentials (CWD). Specifically, we quantify the share of CWD in explaining the larger dispersion of the firm-specific wage premium in tighter markets. For this, we connect two results: on the one hand, firms in tighter labor markets compensate more for risk than firms in slack labor markets; on the other hand, the dispersion (SD) of the firm-specific wage premium is larger in tight markets than in slack ones. We ask the following counterfactual question: *If firms in the 'tightest' markets compensated for risk the same way as firms in the 'slack' markets, by how much would the SD of* $\tilde{y}_{jt}$ *be lower?*

First,[9] we consider a county in a year-group as one market, and classify markets into deciles based on the unemployment rate (UR), by year-groups. Then, we consider markets in Decile 2 as the 'slack', and markets in Deciles 9–10 as the 'tight' markets.

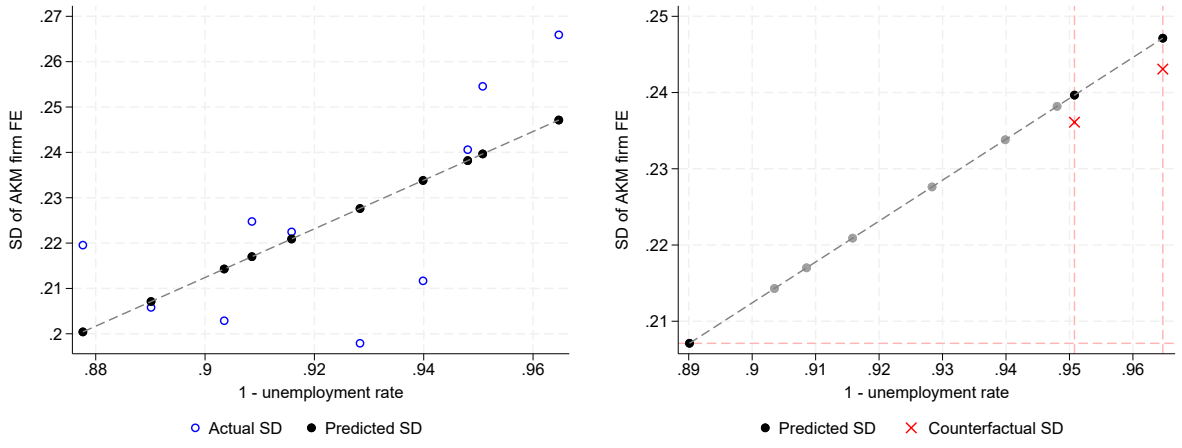
Second, our baseline model (5) implies that if firms compensated for risk as those in the slack markets, the decrease in compensation, captured by the firm-specific wage premium $\hat{y}_{jt}$, would be $\hat{\beta} \times \Delta UR \times risk_{jt}$, where ΔUR is the difference in the unemployment rate between tight and slack markets, and $\hat{\beta}$ is the estimated interaction coefficient.

Using our baseline $\hat{\beta} = 0.022$, if firms in tight markets in Decile 9 (10) compensated for risk as firms in Decile 2, the SD of the (de-meaned) firm-specific wage premium would be by 0.0024 units lower, implying a CWD share of 7.35 (7.07) percent (column (4) in Table 4). With the upper bound of $CI^{95}_{\hat{\beta}}$, these shares are 10.9 and 10.1 percents, respectively.

Table 4: Predicted SD of Actual ($\tilde{y}_{jt}$) and Counterfactual ($\tilde{y}^{CF}_{jt}$) Firm-Specific Wage Premia, and Implied Compensating Wage Differential (CWD) Shares in Tight Markets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			$\hat{\beta} = 0.022$		$\hat{\beta} = 0.00828$		$\hat{\beta} = 0.03572$	
Tightness decile	SD $\tilde{y}_{jt}$	ΔUR	SD $\tilde{y}^{CF}_{jt}$	CWD	SD $\tilde{y}^{CF}_{jt}$	CWD	SD $\tilde{y}^{CF}_{jt}$	CWD
Decile 2	0.2071							
Decile 9	0.2397	6.60 pp	0.2373	7.35%	0.2386	2.98%	0.2361	10.91%
Decile 10	0.2471	7.85 pp	0.2443	7.07%	0.2459	2.95%	0.2430	10.12%

Figure 3: Relation Between Labor Market Tightness and (i) the SD of (Residualized Predicted) Firm-Specific Wage Premium, (ii) the Predicted SD, and (iii) the SD of Counterfactual Firm-Specific Wage Premium in the Tightest Markets (Deciles 9 and 10)



Notes: Each dot represents a decile of labor market tigthness.

We illustrate these results in Figure 3. On the left panel of Figure 3, the hollow blue dots show the actual SD of the firm-specific wage premium, $\tilde{y}_{jt}$; there is a strong positive

[9]We describe these steps in detail in Appendix B.

relationship between labor market tightness $(1 - UR)$ and inequality in the firm-specific wage premium, $\tilde{y}_{jt}$. The dashed line shows the best fit line, and the black dots show the predicted SD, as predicted by the best fit line. On the right panel of Figure 3, we also show the best fit line and predicted SD for tightness deciles 2 to 10. With red crosses we denote the counterfactual SD in the top two tightness deciles, i.e., the SD if firms compensated for risk as firms in Decile 2.

4.2 Results for Workforce Dynamics and Firm Size

Figure 4 illustrates the relation between firm-specific injury risk and workforce dynamics and firm size, splitting the sample at the median of county-level labor market tightness: firms are less able to retain workers when their risk increases, and this relationship becomes even more negative with more fierce competition, suggesting that negative preferences for high-risk firms increase with tightness. The main regression results are in Table 5, with the full set of coefficients in columns (2)-(5) of Appendix Table D4.

We present the estimation results of equation (5) in the top panel of Table 5. In the bottom panel of Table 5 we report the results without time effects or time-varying coefficients stemming from equation (4). Focusing on the interaction coefficient estimate, it is stronger under the specification with time effects, except for the log size outcome. The results show that the marginal effect of firm-specific injury risk on workforce turnover rate increases with labor market tightness, whereas the marginal effect of firm-specific injury risk on workforce turnover rate decreases with labor market tightness. Thus, the negative preferences for high-risk firms indeed increase in absolute value with labor market tightness. The interaction term is statistically insignificant for firm size.

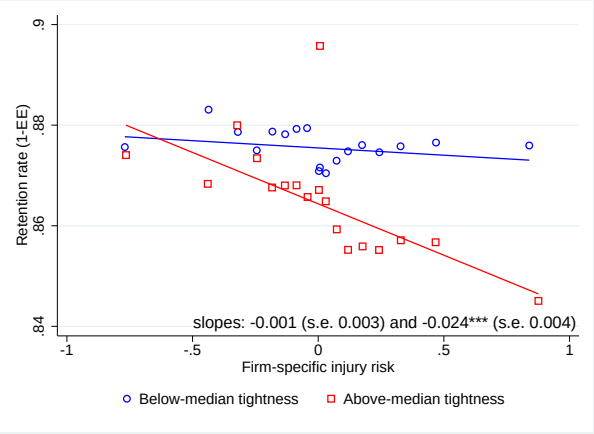
Table 5: Relation of Risk and Tightness to Workforce Dynamics and Firm Size

	(1) Retention rate (1-EE)	(2) Retention rate (1-exit)	(3) Workforce turnover rate	(4) Log size
With time effects				
tight × risk	-0.017***	-0.029***	0.051**	-0.008
	[0.005]	[0.011]	[0.021]	[0.018]
Without time effects				
tight × risk	-0.008**	-0.012**	0.037***	-0.034***
	[0.003]	[0.006]	[0.011]	[0.012]
tight	-0.136***	-0.063***	0.106***	0.102***
	[0.005]	[0.009]	[0.016]	[0.017]
risk	-0.011***	-0.017***	0.037***	-0.008
	[0.003]	[0.006]	[0.012]	[0.011]
observations	9,208	9,208	9,208	9,208

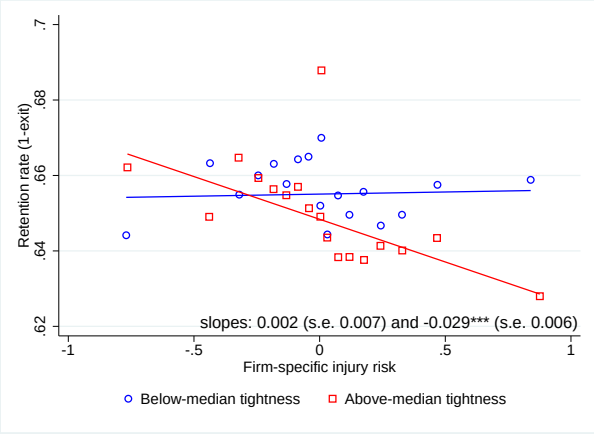
Notes: Table shows estimated coefficients of equations (4) and (5).Variable "tight" refers to the county-level labor market tightness, "risk" refers to the firm-specific injury risk. Control variables: mean age, sex, and injury person FE, and occupation composition of workers, firm and time effects. Number of firms: 3,467. Standard errors in brackets, clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

Figure 4: Relation Between Injury Risk, Workforce Dynamics and Firm Size

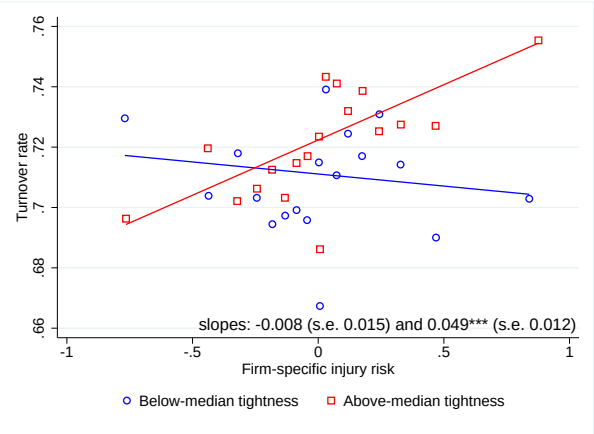
(a) Retention rate (1-EE)



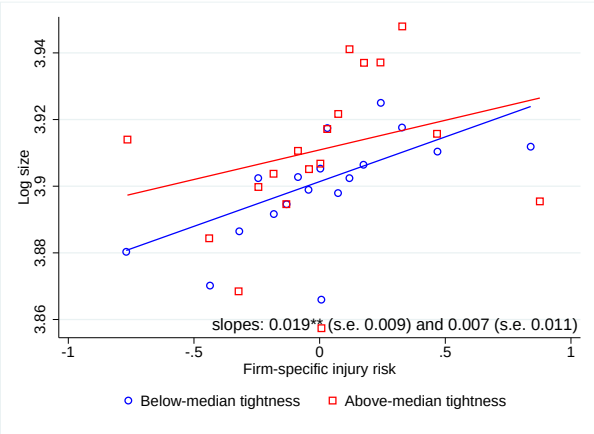
(b) Retention rate (1-exit)



(c) Workforce turnover rate



(d) Log Size



Notes: Figure shows binscatter plots with firm-specific injury risk on the x-axis, and revealed preference indicators on the y-axis. Control variables: mean age, sex, and injury person FE, and occupation composition of workers, firm and time effects.

We perform the same robustness checks as for the firm-specific wage premium in Section 4.1, including time effects in the regressions. We report the estimated coefficient of the heterogeneity term in Table 6. Overall, the results are robust to the analyzed checks. Note, that if we exclude the Budapest commuting zone from the sample (column (3)) then the coefficient estimate of the interaction term becomes statistically weaker for all revealed preference measures, but the estimated patterns remain unchanged.

5 Heterogeneity and Further Robustness Checks

In this section, we assess heterogeneity in the results presented in Section 4. Then, we analyze the robustness of our baseline results to (1) alternative injury risk definitions; (2) alternative labor market tightness definitions; (3) using a shift-share instrument for labor market tightness; and (4) controlling for productivity and other firm-level characteristics.

Table 6: Robustness Checks for the Relation of Risk and Tightness to Workforce Dynamics and Firm Size

	(1) Baseline	(2) No controls	(3) Excluding Budapest CZ	(4) Excluding construction	(5) Balanced sample
Dependent var.: retention rate (1-EE)					
tight × risk	-0.017***	-0.016***	-0.013**	-0.016***	-0.017***
	[0.005]	[0.005]	[0.006]	[0.005]	[0.005]
Dependent var.: retention rate (1-exit)					
tight × risk	-0.029***	-0.028**	-0.019	-0.031***	-0.026**
	[0.011]	[0.011]	[0.014]	[0.011]	[0.011]
Dependent var.: workforce turnover					
tight × risk	0.051**	0.048**	0.051*	0.049**	0.044**
	[0.021]	[0.022]	[0.027]	[0.020]	[0.022]
Dependent var.: log size					
tight × risk	-0.008	-0.010	-0.014	-0.001	-0.016
	[0.018]	[0.018]	[0.022]	[0.018]	[0.019]
observations	9,208	9,208	7,014	8,733	6,842

Notes: Table shows estimated β coefficients of equations (5). Variable "tight" refers to the county-level labor market tightness, "risk" refers to the firm-specific injury risk. Control variables: mean age, sex, and injury person FE, and occupation composition of workers, firm and time effects. Budapest commuting zone (CZ) refers to the capital city Budapest and the county surrounding the capital. Number of firms in the baseline specification: 3,467. Standard errors in brackets, clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

We also show that there is no heterogeneous response to injury risk by labor market tightness in productivity, management practices, sickness absences, or white collar wages.

5.1 Heterogeneity Analyses

To analyze heterogeneities in the relation of injury risk and labor market tightness to firm-specific wage premium and revealed preferences, we extend equation (5) with interacting each term on the right hand side of the model with selected heterogeneity variables (indicators). We report the coefficient of the interaction term between firm-specific injury risk and labor market tightness, and its further interaction with the specified heterogeneity variables in Table 7. We estimate a separate regression for each heterogeneity variable.

Generally, we do not find major and statistically significant heterogeneities for the following four dimensions: (1) broad industry groups (manufacturing, construction, other, making up 46%, 5.5%, and 48.5% of firms in our sample, respectively); (2) firm size categories, based on the number of blue-collar workers at the firm (20–49 vs. 50+ workers, making up 62.1% and 37.9% of firms in our sample, respectively); (3) foreign ownership, based on whether more than 50% of the firm's capital is owned by foreign owners (domestic vs. foreign firms, making up 71.5% and 28.5% of firms in our sample, respectively); and (4) concentration of firms included in our sample on the county and three-year level, captured by the Herfindahl–Hirschman index[10] being below vs. above its median.

[10]We calculate the Herfindahl–Hirschman index at the county and three-year level as $\sum_j p_j^2$, where p_j is the employment share of firm j in the given county in the given three-year period.

Finally, we observe clearer heterogeneities by the per capita income of the population. Within three-year intervals, we divide the counties to below vs. above median income per capita groups, where the income per capita is the total sum of income tax base over the number of taxpayers, based on the T-STAR database of the Hungarian Central Statistical Office. The results reported in the last panel of Table 7 indicate that the relation of risk to firm-specific wage premium and revealed preferences varies more with labor market tightness in those regions where the per capita income is higher.

Table 7: Heterogeneity Analyses: Relation of Risk and Tightness to Firm-Specific Wage Premium, Workforce Dynamics and Firm Size

	(1) AKM firm FE	(2) Retention rate (1-EE)	(3) Retention rate (1-exit)	(4) Workforce turnover rate	(5) Log size
Baseline (9,208)					
tight × risk	0.022***	-0.017***	-0.029***	0.051**	-0.008
	[0.007]	[0.005]	[0.011]	[0.021]	[0.018]
Industry group (reference: manufacturing)					
tight × risk	0.021**	-0.019***	-0.031***	0.057***	0.000
	[0.010]	[0.005]	[0.012]	[0.021]	[0.023]
construction × tight × risk	0.004	-0.002	0.008	0.029	-0.130**
	[0.030]	[0.021]	[0.046]	[0.090]	[0.053]
other × tight × risk	-0.001	0.008	0.008	-0.030	-0.014
	[0.013]	[0.009]	[0.020]	[0.038]	[0.035]
Firm size (number of blue-collar workers, reference: 20–49)					
tight × risk	0.026***	-0.019***	-0.034***	0.057**	-0.005
	[0.008]	[0.005]	[0.012]	[0.025]	[0.015]
50+ workers × tight × risk	-0.013	0.010	0.022	-0.031	0.003
	[0.011]	[0.009]	[0.019]	[0.036]	[0.026]
Firm ownership (reference: domestic)					
tight × risk	0.024***	-0.018***	-0.022*	0.041	-0.022
	[0.008]	[0.006]	[0.013]	[0.027]	[0.020]
foreign × tight × risk	-0.008	0.005	-0.017	0.018	0.024
	[0.012]	[0.008]	[0.018]	[0.034]	[0.035]
Market concentration (reference: below-median)					
tight × risk	0.029***	-0.018***	-0.035**	0.063**	-0.015
	[0.008]	[0.006]	[0.014]	[0.027]	[0.021]
above-median concentr. × tight × risk	-0.014*	0.003	0.012	-0.019	0.008
	[0.008]	[0.006]	[0.012]	[0.023]	[0.023]
County-level income per capita (reference: below-median)					
tight × risk	0.015	-0.006	-0.001	0.008	0.012
	[0.014]	[0.012]	[0.022]	[0.043]	[0.033]
above-med inc per capita × tight × risk	0.016	-0.019	-0.072**	0.128**	0.021
	[0.019]	[0.016]	[0.031]	[0.061]	[0.052]

Notes: Table shows estimated β coefficients and their interaction terms with the indicated heterogeneity variables from equation (5) extended with interaction terms between the heterogeneity variable and each regressor. Variable "tight" refers to the county-level labor market tightness, "risk" refers to the firm-specific injury risk. Control variables: mean age, sex, and injury person FE, and occupation composition of workers, firm and time effects. We estimate split sample regressions, we indicate number of observations in parentheses. The sum of the observations in the subsamples may be smaller than the baseline sample size due to the dropping of singleton observations from the regressions. Standard errors in brackets, clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1. Number of observations: 9,208.

5.2 Shift-Share Instrument for Labor Market Tightness

In this subsection, we apply the shift-share IV strategy introduced in Section 3.2, and report the IV estimates of the interaction coefficient between firm-specific risk and tightness in Table 8 (for comparison, we also report the baseline estimates (without instrumenting)).

Reassuringly, the IV estimates are very close to the baseline ones, indicating that our baseline results are unlikely to be affected by simultaneity bias between tightness and wages, and also addressing the concern that large firms, especially in the longer run, may affect the tightness they face in their respective labor markets. For instance, in column (1) we continue to find that the increase in the firm-specific wage premium to a one SD increase in risk is 2.2 percentage points higher when the unemployment rate is by 10 percentage points lower. Or, the decrease in the retention rate to a one SD increase in risk is by 1.8 and 3.3 percentage points larger (in absolute value) and the increase in the turnover rate is by 5.7 percentage points larger when the unemployment rate is by 10 percentage points lower (whereas the baseline estimates are 1.7, 2.9 and 5.1, respectively).

Table 8: Instrumental Variables Regressions: Relation of Risk and Tightness to Firm-Specific Wage Premium, Workforce Dynamics and Firm Size

	(1) AKM firm FE	(2) Retention rate (1-EE)	(3) Retention rate (1-exit)	(4) Workforce turnover rate	(5) Log size
With time effects, no IV					
tight × risk	0.022***	-0.017***	-0.029***	0.051**	-0.008
	[0.007]	[0.005]	[0.011]	[0.021]	[0.018]
With time effects, IV					
tight × risk	0.022***	-0.018***	-0.033***	0.057**	-0.012
	[0.007]	[0.005]	[0.011]	[0.022]	[0.018]
Without time effects, no IV					
tight × risk	0.025***	-0.008**	-0.012**	0.037***	-0.034***
	[0.006]	[0.003]	[0.006]	[0.011]	[0.012]
Without time effects, IV					
tight × risk	0.024***	-0.008***	-0.013**	0.039***	-0.036***
	[0.006]	[0.003]	[0.006]	[0.011]	[0.012]

Notes: Table shows estimated β coefficient of equation (5), where we instrument labor market tightness with the shift-share instrument $z_{r(j)t}$. Variable "tight" refers to the county-level labor market tightness, "risk" refers to the firm-specific injury risk. Control variables: mean age, sex, and injury person FE, and occupation composition of workers, firm and time effects. Number of firms: 3,467; number of observations: 9,208. Standard errors in brackets, clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

When forming our IV, the prediction for $\text{tight}_{r(j)t}$ with $z_{r(j)t}$, $z_{r(j)t} \times \text{risk}_{jt}$ and $z_{r(j)t} \times D_t$ yields a partial F statistics of $2,432$; then, the first-stage F statistics for $\text{tight}_{r(j)t}$ is $8,431$, indicating a very strong first-stage relationship, and no concerns of weak instruments.

5.3 Other Injury Risk Measures

In Table 9, we report the baseline coefficient of the interaction term in equation (5), and the same coefficient with five other firm-specific injury risk definitions: (1) baseline risk

measure but without applying the empirical Bayes shrinkage; (2)-(3) firm-specific risk of injuries that are followed at least 14 or 28 days of sickness absence; (4) firm-specific risk of those injuries that took place at the workplace, as indicated by the category of sickness benefit (in the case of workplace injuries, the amount of benefit is 100% of the wage, to be paid by the firm if responsible for the injury); (5) baseline risk measured at the first three-year period (i.e., 2009–2011). All firm-specific risk measures are standardized values, and are based on the estimation of equation (3).[11] Note, that we do no use definition (4) as our base baseline risk definition because it is known that there is substantial under-reporting of workplace accidents[12], whereas our baseline definition is not subject to such reporting issues because it is based on diagnosis codes and all categories of sickness absence. The correlation coefficient of the baseline firm-specific injury risk with measures (2), (3), and (4), respectively, is 0.87, 0.83, and 0.65.

The results presented in Table 9 show that the estimated interaction term is essentially unaffected by applying the empirical Bayes shrinkage. Intuitively, this is because we analyze the firm fixed effect for a low probability event, and at firms with no injuries, the bootstrap estimates for the injury risk are always zero, i.e., have no variation. Based on the further panels of the table, the interaction term estimates are qualitatively robust to the alternative risk measures, although the point estimates are smaller in absolute value with stricter definitions of the injury risk (except for the coefficient in the log size model, which is statistically insignificant under all specifications). Finally, the in the last specification, when we use the baseline risk of period 1, the point estimates of the interaction term are bigger in absolute value and statistically significant for the outcomes of wage premiums and retention rates.

5.4 Other Tightness Measures

Our baseline measure of labor market tightness is negative unemployment rate. Autor et al. (2023) argue that the tightness measure should incorporate both the unemployment rate and the employment-to-employment (EE) transition rate. Following their approach, we define an alternative measure of tightness as the standardized EE transition rate minus standardized unemployment rate. We rescale this measure to have the same standard deviation as the baseline tightness measure (i.e., negative unemployment rate).

Based on Bell and Blanchflower (2013), negative unemployment rate may not fully capture labor market tightness if there are discrepancies between actual hours worked and preferred hours worked. They propose a measure of *underemployment* that reflects the willingness of workers to vary their hours at the current pay rate. Following their proposed

[11] For the risk indicators (2) and (3), we apply the empirical Bayes shrinkage, using the bootstrap estimate of the variance of the estimated baseline risk.

[12] See a report by the Association of Hungarian Insurance Companies: https://mabisz.hu/szemle/?p=46639, suggesting that only around half of the actual workplace accidents are reported.

Table 9: Robustness to Risk Measures: Relation of Risk and Tightness to Firm-Specific Wage Premium, Workforce Dynamics and Firm Size

	(1) AKM firm FE	(2) Retention rate (1-EE)	(3) Retention rate (1-exit)	(4) Workforce turnover rate	(5) Log size
Baseline					
tight × risk	0.022***	-0.017***	-0.029***	0.051**	-0.008
	[0.007]	[0.005]	[0.011]	[0.021]	[0.018]
Risk without shrinkage					
tight × risk	0.022***	-0.017***	-0.030***	0.052**	-0.008
	[0.007]	[0.005]	[0.011]	[0.021]	[0.018]
At least 14 days absence after injury					
tight × risk	0.018***	-0.010**	-0.022**	0.038**	-0.009
	[0.007]	[0.005]	[0.010]	[0.019]	[0.017]
At least 28 days absence after injury					
tight × risk	0.017***	-0.008*	-0.019**	0.033*	-0.016
	[0.006]	[0.004]	[0.009]	[0.019]	[0.017]
Risk of workplace accident					
tight × risk	0.012*	-0.011**	-0.016	0.025	-0.016
	[0.007]	[0.005]	[0.010]	[0.019]	[0.019]
Baseline risk of period 1					
tight × risk	0.049***	-0.030***	-0.044**	0.043	0.008
	[0.017]	[0.009]	[0.021]	[0.039]	[0.042]

Notes: Table shows estimated β coefficients of equation (5). Variable "tight" refers to the county-level labor market tightness, "risk" refers to the firm-specific injury risk. Control variables: mean age, sex, and injury person FE, and occupation composition of workers, firm and time effects. Number of firms: 3,467 (in the last panel: 2,882); number of observations: 9,208 (in the last panel: 8,038). Standard errors in brackets, clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

method, based on the Hungarian Labor Force Survey, we calculate the three-year period and county specific underemployment rate. Underemployment rate is calculated as the sum of number of unemployed (U) multiplied by average working hours ($\bar{h}$) and the desired changes in hours of the employed ($\sum \tilde{h}$), divided by the sum of number of unemployed multiplied by average working hours and the total hours worked by the employed ($\sum h$):

$$\text{underemployment} = \frac{U\bar{h} + \sum \tilde{h}}{U\bar{h} + \sum h}. \tag{8}$$

We define tightness measured based on the underemployment indicator as ten times the negative underemployment rate.

We report in Table 10 the coefficient of the interaction term in equation (5) using the baseline tightness measure, and the two alternative definitions of tightness. Although there are some variations in the point estimates, the results are qualitatively robust.

5.5 Role of Further Firm-Level Outcomes

We consider our measure of firm-specific injury risk as a proxy for negative workplace amenities. However, in principle, risk may capture other firm-level outcomes, the role of which in firm-specific wage premium and revealed preferences may also vary with labor

Table 10: Robustness to Tightness Measures: Relation of Risk and Tightness to Firm-Specific Wage Premium, Workforce Dynamics and Firm Size

	(1) AKM firm FE	(2) Retention rate (1-EE)	(3) Retention rate (1-exit)	(4) Workforce turnover rate	(5) Log size
Baseline					
tight × risk	0.022***	-0.017***	-0.029***	0.051**	-0.008
	[0.007]	[0.005]	[0.011]	[0.021]	[0.018]
Tightness à la Autor et al. (2023)					
tight × risk	0.025***	-0.021***	-0.038***	0.070**	-0.013
	[0.009]	[0.006]	[0.014]	[0.028]	[0.022]
Tightness à la Bell and Blanchflower (2013)					
tight × risk	0.016***	-0.014***	-0.031***	0.051***	0.004
	[0.006]	[0.005]	[0.010]	[0.019]	[0.017]

Notes: Table shows the estimated β coefficient of equation (5). Variable "tight" refers to the county-level labor market tightness, "risk" refers to the firm-specific injury risk. Control variables: mean age, sex, and injury person FE, and occupation composition of workers, firm and time effects. Tightness à la Autor et al. (2023) is standardized employment-to-employment transition rate minus standardized unemployment rate, rescaled to have same std. dev. as baseline tightness. Tightness à la Bell and Blanchflower (2013) is ten times negative underemployment rate. Number of firms: 3,467; number of observations: 9,208. Standard errors in brackets, clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

market tightness. Because of this concern, we extend equation (1) with the following variables and their interaction with labor market tightness and with time effects (we estimate a separate regression for each extension): (1) one-digit industry code; (2) three-year specific total factor productivity (TFP); (3) three-year specific number of hierarchical layers at the firm, following the approach of Caliendo et al. (2015); Friedrich (2022)[13]; (4) three-year specific turnover rate of managers at the firm (i.e., hiring rate plus separation rate); (5) three-year specific quality (wage premium) of white-collar workers, captured by the α_i^w parameter in equation (1) estimated for white-collar workers; (6) three-year specific average annual days of sickness absence of blue-collar workers. The last variable (sickness absence) addresses the concern that firms where the injury rate is higher, need to find replacement for the absent workers, possibly through the overtime of co-workers, and the estimated relations between injury risk and wage premium might reflect compensations of overtime work (which we do not observe in our data, only the regular working hours).

We report the estimated coefficients of the interaction term between firm-specific injury risk and labor market tightness in Table 11. The results are very robust to the analyzed extensions, indicating that our results are not driven by varying effects of labor market tightness across industries, by productivity, management structure and quality, quality of white-collar workers, or sickness absence of blue-collar workers.

In Appendix Table D5 we also show that the relation of firm-specific injury risk to TFP, hierarchy structure, management turnover rate, and quality of white-collar workers does not vary significantly with labor market tightness. For sickness absence of blue-

[13]Similarly to Friedrich (2022), we count the number of occupation layers in which the firm reports at least one employee in a given three-year period. We consider three occupation layers: managers, professionals, technicians and associate professionals, other.

Table 11: Robustness to Further Firm-Level Controls: Relation of Risk and Tightness to Firm-Specific Wage Premium, Workforce Dynamics and Firm Size

	(1) AKM firm FE	(2) Retention rate (1-EE)	(3) Retention rate (1-exit)	(4) Workforce turnover rate	(5) Log size
Baseline					
tight × risk	0.022***	-0.017***	-0.029***	0.051**	-0.008
	[0.007]	[0.005]	[0.011]	[0.021]	[0.018]
With industry					
tight × risk	0.019***	-0.016***	-0.026**	0.045**	-0.014
	[0.007]	[0.005]	[0.010]	[0.020]	[0.018]
With TFP					
tight × risk	0.020***	-0.016***	-0.026**	0.044**	-0.004
	[0.007]	[0.005]	[0.010]	[0.020]	[0.017]
With number of hierarchy levels					
tight × risk	0.022***	-0.017***	-0.030***	0.051**	-0.010
	[0.007]	[0.005]	[0.011]	[0.021]	[0.018]
With management turnover rate					
tight × risk	0.020***	-0.017***	-0.032***	0.061***	-0.005
	[0.007]	[0.005]	[0.011]	[0.022]	[0.019]
With white-collar avg AKM person FE					
tight × risk	0.021***	-0.018***	-0.036***	0.065***	-0.009
	[0.007]	[0.005]	[0.011]	[0.021]	[0.019]
With blue-collar sickness absence days					
tight × risk	0.021***	-0.015***	-0.029***	0.053**	-0.013
	[0.007]	[0.005]	[0.011]	[0.021]	[0.018]

Notes: Table shows estimated β coefficient of equation (5). Each row corresponds to a separate regression – each extends equation (5) with the indicated firm-specific variable and its interaction with labor market tightness and with time effects. Variable "tight" refers to the county-level labor market tightness, "risk" refers to the firm-specific injury risk. Control variables: mean age, sex, and injury person FE, and occupation composition of workers, firm and time effects. Number of firms: 3,467; number of observations: 9,208. Standard errors in brackets, clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

collar workers, we estimate a negative interaction term between injury risk and tightness, which goes against the potential concern that the estimated positive interaction term for firm-specific wage premium were driven by increased absence of blue-collar workers.

6 Model

In this Section, we present our theoretical framework that is consistent with our empirical results. As a reminder, our main empirical results are the following:

1. The firm-specific injury risk and firm-specific wage premium are positively related; the relationship is even more positive in labor markets with more competition.

2. Risk and retention rate are negatively related; the relationship is even more negative in labor markets with more competition

Setup. Let b be the utility while not working. Firms differ in the disamenity a they provide, and in their productivity z. The workers are homogeneous, and all have the same

distaste for disamenity (ϵ). Then, the utility of working for firm (z, a) paying wage w is

$$u = w - \epsilon a. \tag{9}$$

Under perfect competition, workers are perfectly compensated for the disamenity such that worker utility only depends on z, which leads to the following result:

$$u(z, a) = u(z, a') \Rightarrow w(z, a) = w(z, a') + \epsilon(a - a') \Rightarrow w = z - b + \epsilon a. \tag{10}$$

On the other hand, under a situation with only one firm in the market (i.e., a pure monopsony), the firm extracts all rents, in which case the wage equals to:

$$w = b + \epsilon a. \tag{11}$$

Thus, under both the perfect competition case and the pure monopsony case, the compensation for disamenity a is exactly equal to the worker distaste ϵ.

We develop a model of imperfect competition, in which firms have wage setting power but still compete for workers on the margin of how much they compensate workers for the disamenity. Note that for every wage w chosen by a firm, we can find an ϵ^* such that

$$w = b + \epsilon^* a. \tag{12}$$

So, without loss of generality, we consider firms to compete via their choice of how much to compensate workers for the disamenity (ϵ^*) and to set wages according to $w = b + \epsilon^* a$. In this framework, compensating differentials are captured by the compensation firms give for the disamenity, ϵ^*. Under imperfect competition, this object varies from one equilibrium to the other, while under both perfect competition and pure monopsony, it is simply equal to a time-invariant preference parameter, ϵ.

The utility of the worker of being employed by firm with disamenity a paying ϵ^* is

$$u = b + (\epsilon^* - \epsilon)a. \tag{13}$$

A worker will only accept to work for a firm (z, a) if $\epsilon^*(z, a) \geq \epsilon$. Furthermore, the firm would never offer more than the competitive market wage, and so, $b + (\epsilon^* - \epsilon)a < z - b, \forall a, z$.

At the beginning of the period, each firm meets a measure Λ of workers. Workers then decide whether they want to work for the firm or remain unemployed. Once a worker starts working for a firm, they meet competing firms with probability $p(\theta)$ (where $p'(\theta) > 0$). Each firm can also poach workers from competing firms; with probability $q(\theta)$, firms meet a worker from a competing firm (where $q'(\theta) < 0$). Thus, an increase in θ means more fierce competition for workers, with both a higher probability that the worker of a firm

meets a competing firm, and a lower probability that a firm meets a worker to poach.

Each competing offer is associated with a risk compensation ϵ' and the firm type of the competing firm a'. A worker of type ϵ employed at firm a being paid ϵ^* accepts a competing offer (a', ϵ') if

$$b + (\epsilon' - \epsilon)a' \geq b + (\epsilon^* - \epsilon)a, \tag{14}$$

which implies that

$$\epsilon' \geq (\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon. \tag{15}$$

Each competing offer is drawn from the distribution of firm type a, $F(a)$. The distribution of compensating differentials in the economy for a given firm type a is given by $G(\epsilon^*|a)$. *Timing.* The timing in the model is as follows:

1. Firms choose their risk compensation ϵ^*.
2. Firms meet unemployed workers, workers accept job offer if $\epsilon^* > \epsilon$.
3. With probability $p(\theta)$ each worker gets a competing offer and with probability $q(\theta)$ the firm meets workers from competing firms.
4. The worker quits the firm if the competing offer is better, the firm poaches workers from competing firms if their offer is better than the offer(s) of competing firm(s).
5. Production takes place and profits are realized.

The retention probability of a worker hired by a firm with disamenity a paying ϵ^* is:

$$1 - p(\theta)\int [1 - G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')]dF(a'). \tag{16}$$

The measure of workers poached by a firm with disamenity a paying compensation ϵ^* is:

$$q(\theta)\int G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a'). \tag{17}$$

Firm's maximization problem. By taking n as given, the firm chooses ϵ^* to maximize:

$$\max_{\epsilon^*}(z - (b + \epsilon^* a))n, \tag{18}$$

where

$$n = \Lambda(1-p(\theta)\int [1-G((\epsilon^*-\epsilon)\frac{a}{a'}+\epsilon|a')]dF(a'))+q(\theta)\int G((\epsilon^*-\epsilon)\frac{a}{a'}+\epsilon|a')dF(a'). \tag{19}$$

The first order condition (FOC) gives

$$z\frac{dn}{d\epsilon^*} = (b + \epsilon^* a)\frac{dn}{d\epsilon^*} + an. \tag{20}$$

Finally, the distribution G must be consistent with the choice made by firms such that

$$G(x|a) = \int^{\hat{z}(x,a)} dI(z) = I(\hat{z}(x,a)), \forall x, \tag{21}$$

where $I(z)$ is the distribution of z in the economy and $\hat{z}(x,a)$ is the value of z such that, $\epsilon^*(a,z) \geq x$ if $z \geq \hat{z}(x,a)$ and $\epsilon^*(a,z) < x$ if $z < \hat{z}(x,a)$. From the FOC above,

$$\hat{z}(x,a) = b + xa + a\frac{n(x,a)}{\frac{dn(x,a)}{dx}} = b + xa + a\frac{\Lambda(1-p(\theta)) + (p(\theta)+q(\theta))\int G((x-\epsilon)\frac{a}{a'} + \epsilon|a')dF(a')}{(\Lambda p(\theta) + q(\theta))\int \frac{a}{a'} g((x-\epsilon)\frac{a}{a'} + \epsilon|a')dF(a')}. \tag{22}$$

Proposition 1. *If $i(z) = I'(z)$ is a sufficiently flat distribution, in particular if $i'(z) \approx 0, \forall z$ (for example a uniform distribution, or exponential distribution with sufficiently low parameter), then, $g'(x|a) = 0, \forall x \forall a$, and $\frac{dg(x|a)}{d\theta} = 0$.*

For the remainder of the paper, we will use the result in Proposition 1.

Proposition 2. *Let RR denote the retention rate and w the wage.*

$$(\frac{d^2RR}{dad\theta} < 0 \quad and \quad \frac{d^2w}{dad\theta} = a\frac{d^2\epsilon^*}{dad\theta} + \frac{d\epsilon^*}{d\theta} > 0) \Rightarrow \frac{du}{da} \equiv (\epsilon^* - \epsilon) + a\frac{d\epsilon^*}{da} < 0 \Rightarrow \frac{d\epsilon^*}{da} < 0$$

$$\frac{d\epsilon^*}{da} < 0 \Rightarrow \frac{dw}{da} = a\frac{d\epsilon^*}{da} + \epsilon^* < \epsilon^* \tag{23}$$

The first part of Proposition 2 tells us that if higher competition for workers ($\Uparrow \theta$) leads to higher response of wages to disamenity ($\frac{d^2w}{dad\theta} > 0$) and lower retention rates for high disamenity firms a ($\frac{d^2RR}{dad\theta} < 0$), then it must be that high disamenity a firms provide less utility to workers ($\frac{du}{da} < 0$) because they compensate less for the disamenity ($\frac{d\epsilon^*}{da} < 0$). Intuitively, this tells us that workers of high a firms are the ones receiving the lowest share of match rents, thus they would benefit the most from a move to perfect competition.

Furthermore, the second part of Proposition 2 tells us that the correlation between wages and disamenity is a lower bound to how much firms pay workers for the disamenity. In other words, under imperfect competition, we can have the existence of compensating differentials (firms compensate workers for the disamenity $\epsilon^* > 0$) while being consistent with an absence of correlation between wages and disamenity a. The model tell us that simply looking at the correlation between wages and disamenity a is not sufficient to infer the existence of compensating differentials, whether or not $\epsilon^* > 0$.

This result is in line with Bell (2022) and Lavetti (2023), discussing that the rate at which market wages change as amenity levels change may provide little information about the preferences of an average worker. Similarly, Ferreira et al. (2025) show that the partial effect of amenities on wages is not a complete measure of the implicit price of amenities, as it omits the effect of amenities on utility that is not capitalized in wages. The

distinction between the correlation of wages and disamenity versus the compensation for the disamenity ($\epsilon^* > 0$) also relates to the Rosen versus Mortensen motive (Sorkin, 2018; Sockin, 2022). Following the discussion of Sockin (2022), on the one hand, among firms of similar productivity levels, those with a comparative advantage in amenity provision provide better amenities but lower wages (i.e., the Rosen motive). On the other hand, more productive firms can afford to offer greater wages and more amenity value than less productive firms (i.e., the Mortensen motive).

Next, Proposition 3 below tells us that as competition for workers increase ($\Uparrow \theta$), firms compensate workers more for disamenity ($\Uparrow \epsilon^*$).

Proposition 3.

$$\frac{d\epsilon^*}{d\theta} = \frac{(z-(b+\epsilon^* a))(\Lambda p'(\theta)+q'(\theta))\int(\frac{a}{a'})g((\epsilon^*-\epsilon)\frac{a}{a'}+\epsilon|a')dF(a')}{2a(p(\theta)+q(\theta))\int \frac{a}{a'}g((\epsilon^*-\epsilon)\frac{a}{a'}+\epsilon|a')dF(a')}$$
$$+\frac{-a[-\Lambda p'(\theta)\int[1-G((\epsilon^*-\epsilon)\frac{a}{a'}+\epsilon|a')]dF(a')+q'(\theta)\int G((\epsilon^*-\epsilon)\frac{a}{a'}+\epsilon|a')dF(a')]}{2a(\Lambda p(\theta)+q(\theta))\int \frac{a}{a'}g((\epsilon^*-\epsilon)\frac{a}{a'}+\epsilon|a')dF(a')} > 0. \tag{24}$$

Turning to the change in average utility $E[u]$ in the economy, we have

Proposition 4.

$$\frac{dE[u]}{d\theta} = \int\int a\frac{d\epsilon^*}{d\theta}n(a)\frac{dF(a)dI(z)}{\Lambda} + \int\int(b+(\epsilon^*-\epsilon)a)(\frac{dn(a)}{d\theta})\frac{dF(a)dI(z)}{\Lambda}, \tag{25}$$

where $n(a)$ is the size of a firm with disamenity a and

$$\int\int n(a)dF(a)dI(z) = \Lambda. \tag{26}$$

The above tells us that higher θ has two effects, (1) it increases average utility due to higher compensation (term with $\frac{d\epsilon^*}{d\theta}$), and (2) it changes the size distribution of firms, which could affect average utility depending which firms become larger. We know from the results of Proposition 2 that high a firms deliver lower utility to workers. It follows that if an increase in competition for workers ($\Uparrow \theta$) leads to an increase in the relative size of low a firms, the average utility in the economy increases with θ.

In sum, through the lens of our model, our main empirical results imply that firms with higher firm-specific injury risk provide less utility to workers, because they compensate less for risk than low-risk firms do (Proposition 2). Also, competition increases compensation for risk (Proposition 3), and whether average utility increases depends on whether the share of high- or low-risk firms increases due to more fierce competition.

We plan to extend our model with endogenous disamenity, where firms are able to endogenously choose their level of disamenity. Our preliminary results show that for ϵ

sufficiently small, we recover the result that we had under exogenous disamenity.

7 Conclusion

In this paper, we present new evidence on how one key disamenity at work – injury risk – is priced into wages in equilibrium, and show that disamenity pricing is context-dependent: injury risk is reflected more in firms' wage premia when they face more fierce competition in their respective labor markets. Also, in tight labor markets, risky firms have an even lower retention rate and an even higher turnover rate than in slack labor markets.

Our results, through the lens of our model of imperfect competition, imply that high-risk firms provide less utility and thus lose workers even if they compensate for risk to some extent. Our results suggest that firms under-compensate workers for risk, which is in stark contrast with the standard framework that emphasizes more than full compensation for the (inframarginal) workers. In sum, competition increases compensation for risk, leading to more dispersion in wages but not necessarily to higher levels of worker utility.

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Appendix

A Analysis Using Data From the EWCS

To see how health risks at a workplace are related to other amenities at the workplace, we use the 2010 and 2015 waves of the European Workplace Conditions Survey (EWCS).[14]

In the EWCS dataset, two (binary) questions capture the health risk attached to the respondents' work environments, and we take the average of the following two variables to form $HealthRisk$: (1) "*Do you think your health or safety is at risk because of your work?*" (yes/no); (2) "*Does your work affect your health?*" (yes negatively / yes positively or no). To capture other ('good') amenities ($Amenity$) of respondents' work environments, we consider the following 4 (yes/no) binary variables: (i) "*Working hours fit family life very well*"; (ii) "*Experienced no abuse at work last month*" (only in 2015); "*Quality of immediate boss is above median*"; (iv) "*Satisfied with working conditions*". In the 2010 EWCS wave, when only country information is available, we merge country-specific unemployment rate (UR) for 2010 information to the respondents from Eurostat. In the 2015 EWCS wave, when also region information is available, we also merge NUTS2-level region-specific unemployment (UR) for 2010 information to 18,404 respondents from Eurostat.[15]

In our first model (A.1), we assess the relationship between $HealthRisk$ and one of the aminities (i)–(iv), and the extent to which such a relationship varies by the level of UR, accounting for within-country variation across regions in the 2015 EWCS wave:

$$HealthRisk_i = \beta_0 + \beta_1 Amenity_i + \beta_2 UR_r \times Amenity_i + \beta_3 UR_r + \mu_c + \epsilon_i, \qquad (A.1)$$

where i indexes individual, r indexes region, and μ_c includes a full list of country effects.

In our second model (A.2), we use the UR information at the country-level for both time periods 2010 and 2015, and are able to include year effects (μ_y), but no country effects (μ_c). In both models, standard error estimates are clustered at the country level.

$$HealthRisk_i = \gamma_0 + \gamma_1 Amenity_i + \gamma_2 UR_c \times Amenity_i + \gamma_3 UR_c + \mu_y + \eta_i. \qquad (A.2)$$

In both specifications, the coefficients on the given $Amenity$ (β_1 and γ_1) capture the overall relationship between $HealthRisk$ and $Amenity$, and the coefficient on the interaction (β_2

[14]The EWCS provides an overview on the state of working conditions in Europe, indicating the nature and content of changes affecting the workforce and the quality of work. The 2010 wave included 34 countries, including the EU Member States, NO, HR, NM, TU, AL, MN, KS, while the 2015 wave included 35 countries, including the EU Member States, NO, CH, AL, NM, MN, SB, and TU. For more information, see https://www.eurofound.europa.eu/en/surveys/european-working-conditions-surveys-ewcs.

[15]Source: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Unemployment_statistics (country; 2010/2015) and https://ec.europa.eu/eurostat/databrowser/view/tgs00010/default/table?lang=en (region; 2015); date of access: 2024/10/19. For 18,404 respondents in 2015 in the following countries region-level UR can be merged: AT, BE, CZ, DK, FI, DE, GR, HU, IT, NL, PL, PT, RO, SK, SP, SW, SB, NO, CH.

and γ_2) capture the extent to which such a relationship varies by the level of UR.

Tables A.1 and A.2 present the results of estimating models (A.1) and (A.2), respectively. Irrespective of whether within-country variation in 2015 or within-year variation across countries in 2010 and 2015 is exploited, $HealthRisk$ (a 'bad' amenity) is negatively related to 'good' workplace amenities, such as working hours fitting family life, experiencing no abuse at work, quality of the boss being high, and being satisfied with working conditions. Notably, the aforementioned relationships do not differ by the level of unemployment rate (UR), capturing labor market tightness.

Table A.1: Relation Between Workplace Health Risk ($HealthRisk$) and Other Workplace Amenities, Potentially by the Level of Region-Specific Unemployment Rate (UR)

	(1)	(2)	(3)	(4)
1: hours fit family well	-0.131***			
	[0.013]			
UR × 1: hours fit family well	0.000			
	[0.001]			
1: satisfied with working conditions		-0.164***		
		[0.020]		
UR × 1: satisfied with working conditions		0.001		
		[0.002]		
1: boss is good			-0.212***	
			[0.032]	
UR × boss is good			-0.002	
			[0.001]	
1: no abuse at workplace				-0.203***
				[0.021]
UR × 1: no abuse at workplace				-0.003
				[0.002]

Notes: The underlying regression model is (A.1), using the 2015 wave of EWCS. Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A.2: Relation Between Workplace Health Risk ($HealthRisk$) and Other Workplace Amenities, Potentially by the Level of Country-Specific Unemployment Rate (UR)

	(1)	(2)	(3)
1: hours fit family well	-0.125***		
	[0.017]		
UR × 1: hours fit family well	0.000		
	[0.001]		
1: satisfied with working conditions		-0.172***	
		[0.019]	
UR × 1: satisfied with working conditions		0.001	
		[0.001]	
1: boss is good			-0.141***
			[0.020]
UR × boss is good			-0.003*
			[0.002]

Notes: The underlying regression model is (A.2), using the 2010 and 2015 waves of EWCS. Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

B Back-Of-The-Envelope Estimates for the Compensating Wage Differential (CWD) Share

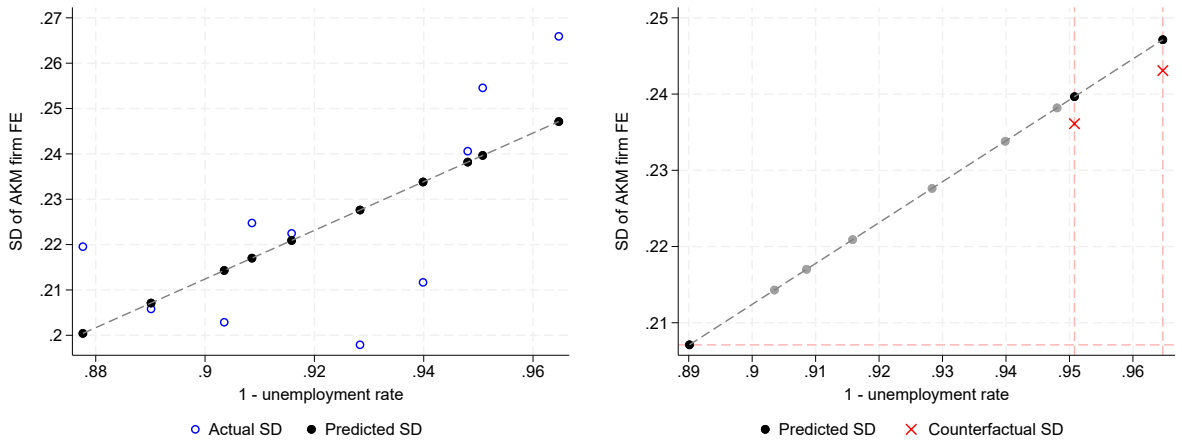
In this section, the specific question we ask: *how much do Compensating Wage Differentials ('CWDs') account for the difference in Standard Deviations (SDs) of the firm-specific wage premium between tight and slack labor markets?* To answer it, we connect two results: (1) firms in tighter labor markets compensate more for risk than firms in slack labor markets, and (2) the firm-specific wage premium varies more in tight labor markets than in slack ones. Our interest is in quantifying how much the more compensation for risk in tight labor markets explains from the larger variance of the firm-specific wage premium in those markets. To arrive at a back-of-the-envelope estimate, we perform the following steps.

Step1. We consider a county in a given year-group as one market, and classify markets into deciles based on their unemployment rate (UR), separately by year-groups.

Step2. We predict the firm-specific wage premium ($\hat{y}_{jt}$), using the model estimates of baseline model (5), presented in Column (1) of Table 3.

Step3. We residualize $\hat{y}_{jt}$ by netting out time and county effects, and graph the SD of residualized $\tilde{y}_{jt}$ against the average tightness measure, in the 10 deciles in Figure B.1:

Figure B.1: Relation Between Labor Market Tightness and (i) the SD of (Residualized Predicted) Firm-Specific Wage Premium, (ii) the Predicted SD, and (iii) the SD of Counterfactual Firm-Specific Wage Premium in the Tightest Markets (Deciles 9 and 10)



Notes: Each dot represents a decile, as specified in *Step1*.

On the left Figure B.1, the hollow blue dots show the actual SD of the firm-specific wage premium, $\tilde{y}_{jt}$; there is a strong positive relationship between labor market tightness $(1-UR)$ and inequality in the firm-specific wage premium, $\tilde{y}_{jt}$. The dashed line shows the best fit line, and the black dots show the predicted SD, as predicted by the best fit line.

Step4. We select markets in Decile 2 – falling almost exactly on the best fit line – as the typical baseline 'slack' market, and ask the following counterfactual question: *If firms*

in the 'tightest' markets in Deciles 9 and 10 compensated for risk the same way as firms in the 'slack' market in Decile 2, by how much would the SD of $\tilde{y}_{jt}$ decrease, relative to the predicted SD (by the best fit line)? Thus, e.g., the actual SD in Decile 9 is 0.2545 and the predicted SD is 0.24, and we want to capture the counterfactual SD of $\tilde{y}_{jt}$ relative to 0.24, assuming that firms in Decile 9 compensated for risk the same way as firms in Decile 2.

Step5. Our baseline model (5) implies that the change (decrease) in compensation, captured by the firm-specific wage premium $\hat{y}_{jt}$, would be $\hat{\beta} \times \Delta UR \times risk_{jt}$, where ΔUR is the difference in the unemployment rate between tight markets in Deciles 9 and 10 and slack markets in Decile 2, and $\hat{\beta}$ is the estimated interaction coefficient between risk and labor market tightness stemming from our baseline model (5). Then, using our baseline estimate, $\hat{\beta} = 0.022$, with its 95 percent Confidence Interval, we estimate various counterfactual firm-specific wage premiums for firms ($\tilde{y}_{jt}^{CF}$) in Deciles 9 and 10.

Table B.1: Predicted SD of Actual ($\tilde{y}_{jt}$) and Counterfactual ($\tilde{y}_{jt}^{CF}$) Firm-Specific Wage Premia, and Implied Compensating Wage Differential (CWD) Shares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			$\hat{\beta} = 0.022$		$\hat{\beta} = 0.00828$		$\hat{\beta} = 0.03572$	
Tightness decile	SD $\tilde{y}_{jt}$	ΔUR	SD $\tilde{y}_{jt}^{CF}$	CWD	SD $\tilde{y}_{jt}^{CF}$	CWD	SD $\tilde{y}_{jt}^{CF}$	CWD
Decile 2	0.2071							
Decile 9	0.2397	6.60 pp	0.2373	7.35%	0.2386	2.98%	0.2361	10.91%
Decile 10	0.2471	7.85 pp	0.2443	7.07%	0.2459	2.95%	0.2430	10.12%

In Table B.1, the predicted SD of $\tilde{y}_{jt}$ in column (1) is the same as in Figure B.1; the tighter the labor market with a lower UR, the higher the predicted SD of $\tilde{y}_{jt}$ (e.g., in Decile 9, it is by 15 percent or by $0.2397 - 0.2071 = 0.0326$ units higher than in Decile 2).

Step6. Using differences in mean UR's across deciles, the decrease in risk compensation from $\hat{y}_{jt}$ is $\hat{\beta} \times \Delta UR \times risk_{jt}$, and we arrive at the counterfactual $\hat{y}_{jt}^{CF}$. Similarly to $\hat{y}_{jt}$ in *Step3*, we net out year and county effects from $\hat{y}_{jt}^{CF}$, and shift it with the ratio of the predicted SD to the actual SD (e.g., $\frac{0.2397}{0.2545}$ in Decile 9), as we capture the counterfactual SD relative to the predicted SD (0.24 in Decile 9). See red crosses in the right Figure B.1.

Using our baseline point estimate, $\hat{\beta} = 0.022$ in Columns (3)–(4), if firms in Decile 9 compensated for risk the same way as firms in Decile 2, the SD of the $\tilde{y}_{jt}$ would decrease from 0.2397 to 0.2373, and the difference in SDs would be by 0.0024 units lower, implying a CWD share of 7.35 percent.[16] Moving to Columns (7)–(8) and using the upper bound of the 95 percent CI, $\hat{\beta} = 0.03572$, if firms in Decile 9 compensated for risk as firms in Decile 2, the SD of the $\tilde{y}_{jt}$ would decrease from 0.2397 to 0.2361, implying a CWD share of 10.91 percent. The analogous CWD shares in Decile 10 are 7.07 and 10.12 percent, respectively.

[16]The exact calculation is $0.0735 = \frac{0.2397-0.2373}{0.2397-0.2071} = \frac{0.0024}{0.032591}$.

C Empirical Bayes Shrinkage

We follow Walters (2024) in applying linear empirical Bayes shrinkage to $\phi^S_{j(i,t),T}$, the firm-specific indicator of injury risk. This method is this known to improve aggregate mean squared error for a broad class of data-generating process (James and Stein, 1961).

Intuitively, we estimate a large number of firm-specific parameters (firm-specific injury risk), and use distributional information to refine the estimate for each unit.

The Empirical Bayes posterior prediction of firm-specific injury risk is given by:

$$\phi^{S*}_{jT} = \frac{\sigma^2_T}{\sigma^2_T + s^2_{jT}}\hat{\phi}^S_{jT} + \frac{s^2_{jT}}{\sigma^2_T + s^2_{jT}}\hat{\mu}_\phi, \tag{C.1}$$

where $\hat{\phi}^S_{jT}$ is the noisy estimate based on the estimation method described in Section 2.5, and $\hat{\mu}_\phi$ is the mean of these (noisy) estimates. s^2_{jT} is variance of $\hat{\phi}^S_{jT}$, which in our case is a bootstrap estimate with 50 replications. Finally, the σ^2_T "hyperparameter" is:

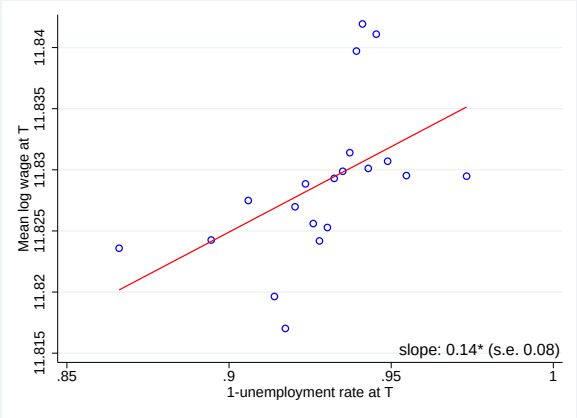
$$\sigma^2_T = \frac{1}{J}\sum_{j=1}^{j=J}\left[(\hat{\phi}^S_{jT} - \hat{\mu}_\phi)^2 - s^2_{jT}\right]. \tag{C.2}$$

In equation (C.1) the posterior mean ϕ^{S*}_{jT} shrinks the noisy estimate $\hat{\phi}^S_{jT}$ towards the prior mean $\hat{\mu}_\phi$ in proportion to its signal-to-noise ratio (see Walters, 2024 for further details).

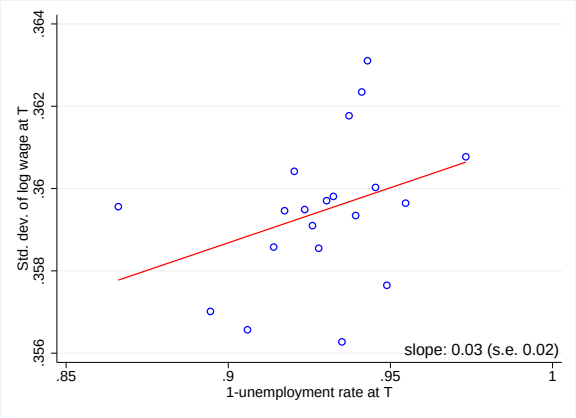
D Further Figures and Tables

Appendix Figure D1: Mean and standard deviation of wage and firm wage premium of blue-collar workers as function of local labor market tightness, in three-year periods

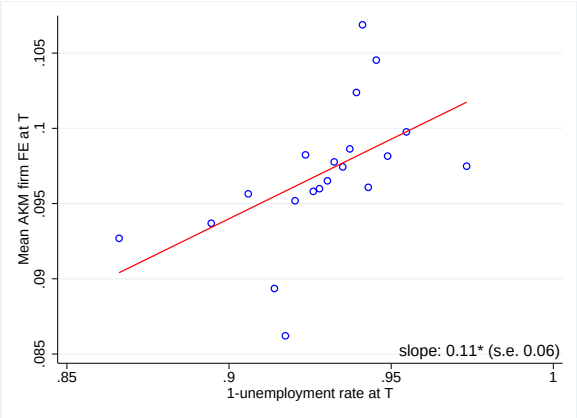
(a) Mean log wage



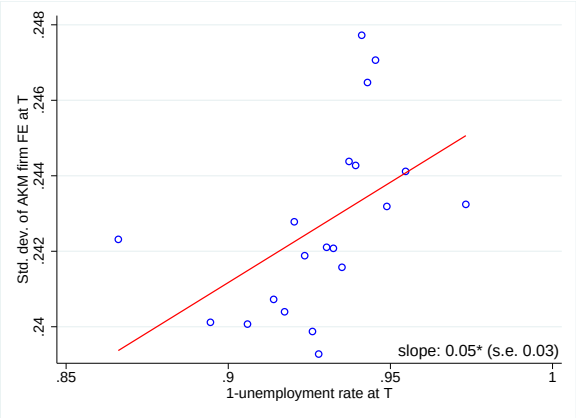
(b) Std. dev. log wage



(c) Mean AKM firm FE

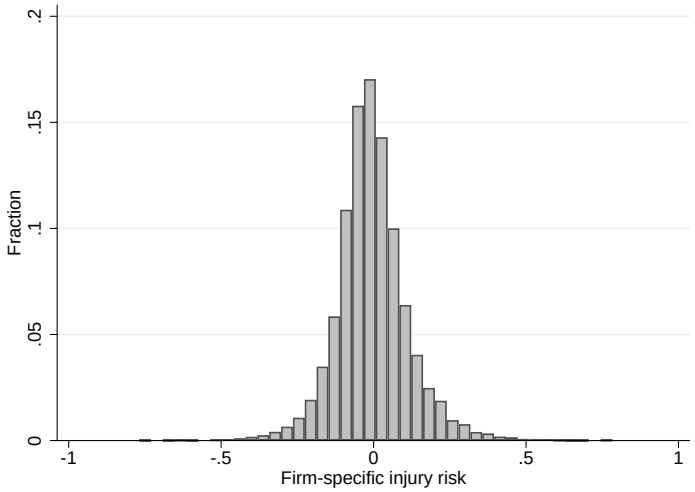


(d) Std. dev. AKM firm FE



Notes: Figure shows binscatter plots with county- and year-level values of 1 – unemployment rate at three-year period T on the x-axis, and the average of or the standard deviation of the yearly log wage or yearly firm-specific wage premium on the y-axis. Control variables: county and time effects, and industry composition. Data: Hungarian administrative data restricted to blue-collar workers, years 2009–2017. Standard errors are clustered at the county level.

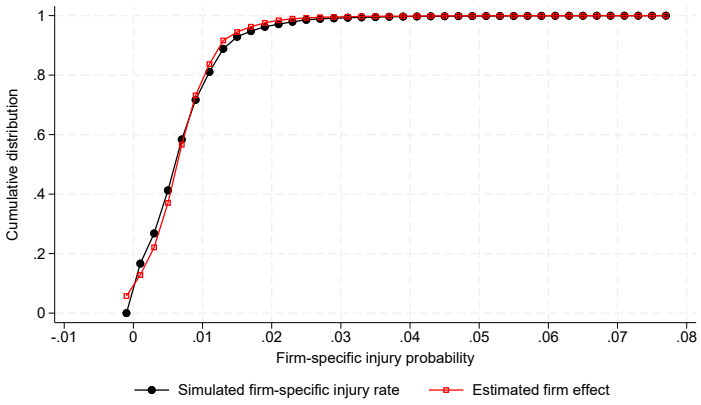
Appendix Figure D2: Distribution of Firm-Specific Injury Risk



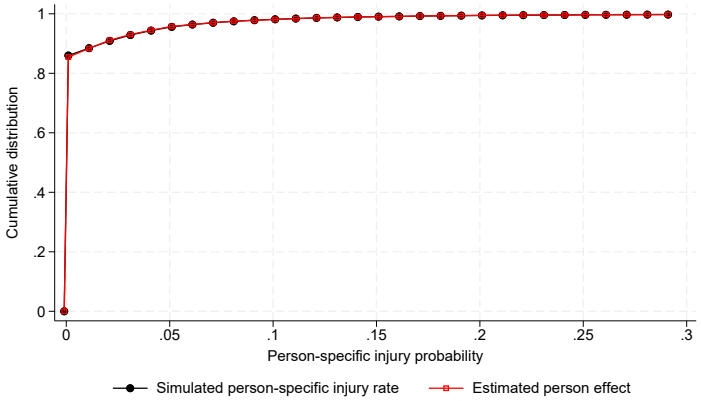
Notes: Figure shows the distribution of firm-specific injury risk, without standardizing the risk indicator. Mean: -0.004, standard deviation: 0.123.

Appendix Figure D3: Firm and Person Effects on Simulated Data

(a) Firm effects

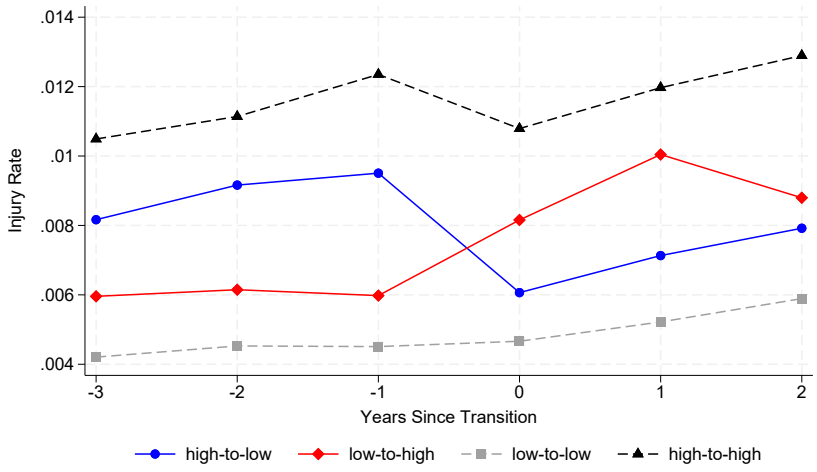


(b) Person effects



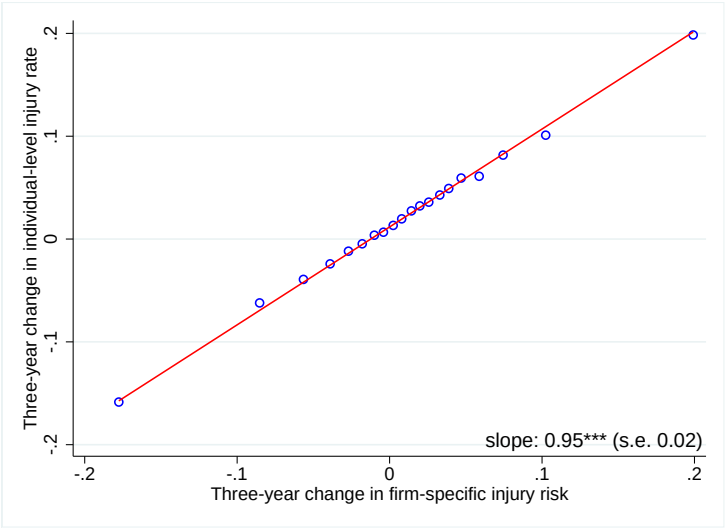
Notes: Figure shows with back line and dots the cumulative probability of three-yearly firm-specific injury rate and person specific injury rate in the simulate data, as is explained in Section 2.5.2. Figure shows with red line and squares the cumulative probability of the estimated firm effect and person effect, based on equation (3).

Appendix Figure D4: Injury Rate of Movers Between Firms



Notes: Figure shows the dynamics of injury rates of workers who move between firms. Firms are categorized to two equal-sized groups based on the injury rate of co-workers. Sample is split based on the so defined risk category of the origin and destination firms.

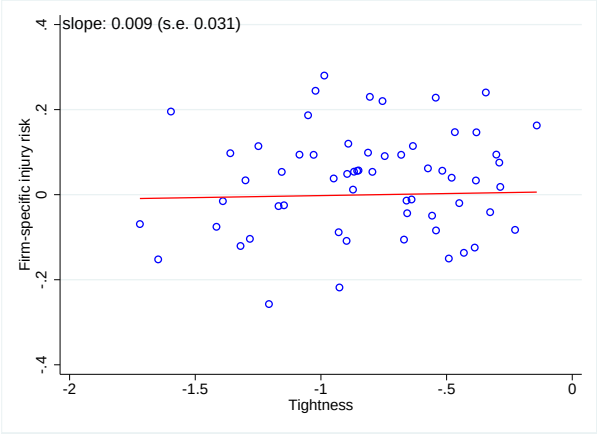
Appendix Figure D5: Change in Injury Rate Related to Change in Firm-Specific Injury Risk



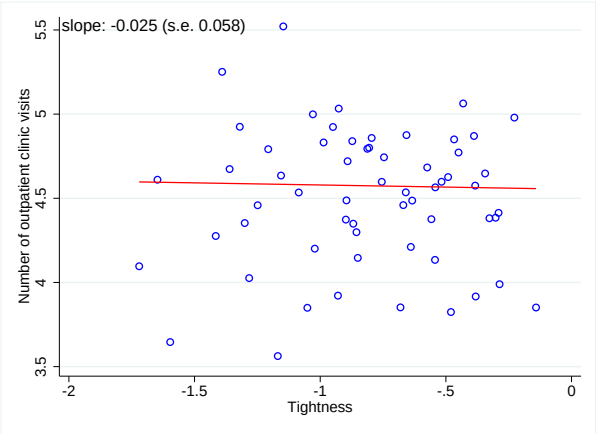
Notes: Figure shows how the person-level injury rate changes between three-year periods relate to the three-year change in firm-specific injury risk. The change in firm-specific injury risk can originate both from movers between firms and from within-firm changes of injury risk. Figure shows a binscatter plot with 20 equal sized bins of the change in firm-specific injury risk.

Appendix Figure D6: Cyclicality of Injury Risk

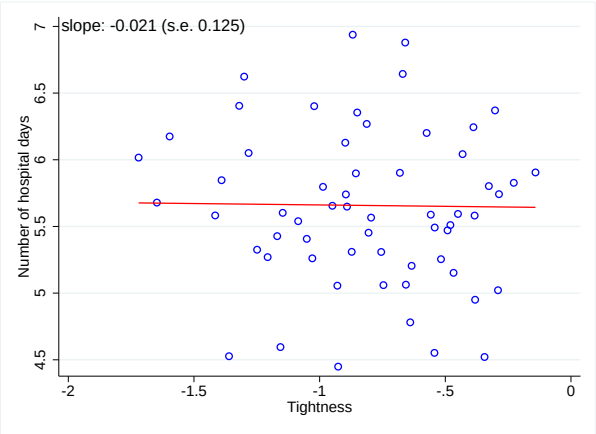
(a) Firm-specific injury risk



(b) Monthly outpatient clinic visits



(c) Monthly hospital days



Notes: Figure shows binscatter plots with tightness rate on the x-axis (which is $(-10)\times$ unemployment rate on the level of county and three-year interval), and firm-specific injury risk, and monthly outpatient specialist visits and hospital days on the y-axis. The healthcare use measures are conditional on injury.

Appendix Table D1: Variance Decomposition of Log Wage

	2009-2011	2012-2014	2015-2017
Var of log wage	0.269	0.290	0.352
Variance shares			
Var of firm effects	0.299	0.275	0.258
Var of person effects	0.293	0.297	0.249
Var of Xb	0.016	0.014	0.030
2*Cov of firm and person effects	0.114	0.157	0.156
2*Cov of [firm+person effects] and Xb	0.000	-0.004	0.007
Residual terms	0.278	0.260	0.300

Notes: Table shows results from estimating equation (**??**). Xb includes dummies of three-year groups, and the square and cube of (age − 40).

Appendix Table D2: Cyclicality of firm-specific injury risk

	Firm-specific injury risk
tightness × lagged risk	-0.027
	[0.037]
tightness	-0.030
	[0.026]
lagged risk	0.747***
	[0.027]
Number of observations	5,674
Number of firms	3,385

Notes: Table shows results of the regression of firm-specific injury risk on county-level labor market tightness, measured as (−10 × unemployment rate), on lagged firm-specific risk (measured at the previous three-year period), on their interaction term, and three-year period effects (not reported). Standard errors in brackets, clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table D3: Relation of Risk and Tightness to Firm-Specific Wage Premium, Workforce Dynamics and Firm Size, OLS Estimates

	(1) AKM firm FE	(2) Retention rate (1-EE)	(3) Retention rate (1-exit)	(4) Workforce turnover rate	(5) Log size
With time effects					
tight × risk	0.028***	-0.001	-0.009	0.019	0.021
	[0.009]	[0.004]	[0.011]	[0.022]	[0.026]
Without time effects					
tight × risk	0.026***	0.003	-0.004	0.013	0.030
	[0.007]	[0.003]	[0.009]	[0.017]	[0.020]
tight	1.001***	-0.140***	-0.010	0.053**	0.016
	[0.009]	[0.006]	[0.012]	[0.024]	[0.024]
risk	0.040***	-0.002	-0.008	0.007	0.181***
	[0.007]	[0.003]	[0.008]	[0.016]	[0.023]
observations	11,045	11,045	11,045	11,045	11,045

Notes: Table shows estimated coefficients of equation (5), excluding firm fixed effects. Variable "tight" refers to the county-level labor market tightness, "risk" refers to the firm-specific injury risk. Control variables: mean age, sex, and injury person FE, and occupation composition of workers, county, one-digit industry and time effects. Number of firms: 5,304. Standard errors in brackets, clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table D4: Relation of Risk and Tightness to Firm-Specific Wage Premium, Workforce Dynamics and Firm Size, All Estimated Coefficients

	(1) AKM firm FE	(2) Retention rate (1-EE)	(3) Retention rate (1-exit)	(4) Workforce turnover rate	(5) Log size
tight × risk	0.022***	-0.017***	-0.029***	0.051**	-0.008
	[0.007]	[0.005]	[0.011]	[0.021]	[0.018]
tight	0.091***	0.033*	0.054*	-0.133**	-0.063
	[0.021]	[0.018]	[0.032]	[0.062]	[0.059]
year 2012–2014 × tight	-0.008	0.005	-0.009	0.018	0.013
	[0.006]	[0.006]	[0.012]	[0.023]	[0.020]
year 2015–2017 × tight	0.010	0.000	-0.005	0.002	0.052
	[0.014]	[0.012]	[0.023]	[0.045]	[0.043]
risk	0.023***	-0.021***	-0.034***	0.051**	0.022
	[0.008]	[0.005]	[0.012]	[0.022]	[0.019]
year 2012–2014 × risk	-0.010***	0.004**	0.008*	-0.008	-0.012*
	[0.002]	[0.002]	[0.004]	[0.008]	[0.006]
year 2015–2017 × risk	-0.017***	0.011***	0.017**	-0.017	-0.027**
	[0.004]	[0.003]	[0.007]	[0.013]	[0.010]
mean age of workers	-0.001*	0.007***	0.022***	-0.053***	-0.028***
	[0.001]	[0.001]	[0.002]	[0.003]	[0.003]
share of men among workers	0.058**	0.048*	0.161***	-0.204*	-0.368***
	[0.026]	[0.026]	[0.057]	[0.118]	[0.094]
mean injury person FE of workers	0.032	-0.062***	-0.064	0.208**	0.378***
	[0.028]	[0.022]	[0.044]	[0.082]	[0.078]
share of skilled blue-collar workers	-0.026**	0.025**	0.056**	-0.085	-0.043
	[0.012]	[0.012]	[0.025]	[0.054]	[0.041]
share of assemblers, machine operators	-0.050***	0.029**	0.061**	-0.105*	-0.105**
	[0.012]	[0.013]	[0.027]	[0.057]	[0.045]
year 2012–2014	0.251***	-0.035***	-0.012	0.055***	0.049***
	[0.005]	[0.005]	[0.009]	[0.017]	[0.016]
year 2015–2017	0.490***	-0.094***	-0.065***	0.132***	0.124***
	[0.008]	[0.006]	[0.011]	[0.021]	[0.022]
constant	-0.026	0.617***	-0.313***	2.891***	5.306***
	[0.044]	[0.044]	[0.091]	[0.190]	[0.145]
observations	9,208	9,208	9,208	9,208	9,208

Notes: Table shows estimated coefficients of equation (5). Variable "tight" refers to the county-level labor market tightness, "risk" refers to the firm-specific injury risk. Firm fixed effects are included in the models. The reference time period is 2009–2011. Note, that among the occupation composition variables, the share of unskilled workers is omitted due to collinearity. Number of firms: 5,304. Standard errors in brackets, clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table D5: Relation of Risk and Tightness to Further Firm Characteristics

	(1) TFP	(2) Nr of hierarchy levels (1 to 4)	(3) Management turnover rate	(4) White-collar AKM person FE	(5) Blue-collar sickness absence
With time effects					
tight × risk	0.018	0.036	0.030	0.010	-0.632*
	[0.026]	[0.029]	[0.068]	[0.009]	[0.377]
Without time effects					
tight × risk	0.009	0.002	0.007	0.003	-0.561**
	[0.018]	[0.019]	[0.047]	[0.006]	[0.252]
tight	0.433***	-0.046**	0.020	-0.024***	0.262
	[0.023]	[0.023]	[0.060]	[0.007]	[0.270]
risk	0.014	0.027	0.000	-0.002	2.827***
	[0.016]	[0.018]	[0.033]	[0.005]	[0.233]
number of observations	9,079	9,208	8,171	8,658	9,208
mean outcome	9.939	3.486	0.433	-0.021	9.012

Notes: Table shows estimated coefficients of equation (5) with outcome variables indicated at the top of each column. Variable "tight" refers to the county-level labor market tightness, "risk" refers to the firm-specific injury risk. Control variables: mean age, sex, and injury person FE, and occupation composition of workers, firm and time effects. Standard errors in brackets, clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

E Proofs of Model Propositions

Proof of Proposition 1. From the expression for G we get

$$g(x|a) = i(\hat{z}(x,a))\frac{d\hat{z}(x,a)}{dx} \tag{E.1}$$

and

$$g'(x|a) = i'(\hat{z}(x,a))\frac{d\hat{z}(x,a)}{dx} + i(\hat{z}(x,a))\frac{d^2\hat{z}(x,a)}{dx^2}. \tag{E.2}$$

where

$$\frac{d\hat{z}(x,a)}{dx} = a + a - a\frac{n(x,a)}{\frac{dn(x,a)}{dx}}\frac{d^2n(x,a)}{dx^2} \tag{E.3}$$

Consider $I(z)$ is a distribution with high flatness such that $i'(z)$ is close to zero. Now conjecture that $g'(x|a) = 0, \forall x \forall a$. Then in this case

$$\frac{d^2n(x,a)}{dx^2} = (\Lambda p(\theta) + q(\theta))\int (\frac{a}{a'})^2 g'((x-\epsilon)\frac{a}{a'} + \epsilon|a')dF(a') = 0. \tag{E.4}$$

which implies $\frac{d\hat{z}(x,a)}{dx} = 2a$ and so $\frac{d^2\hat{z}(x,a)}{dx^2} = 0$, which confirms our conjecture

$$g'(x|a) = 0. \tag{E.5}$$

Finally note that the results above also implies

$$\frac{dg(x|a)}{d\theta} = i'(\hat{z}(x,a))\frac{d\hat{z}(x,a)}{dx}\frac{d\hat{z}(x,a)}{d\theta} + i(\hat{z}(x,a))\frac{d}{d\theta}(\frac{d\hat{z}(x,a)}{dx}) = 0. \tag{E.6}$$

Totally differentiating the first order condition with respect to z and ϵ^* gives

$$dz\frac{dn}{d\epsilon^*} = a\frac{dn}{d\epsilon^*}d\epsilon^* + a\frac{dn}{d\epsilon^*}d\epsilon^* \tag{E.7}$$

which implies

$$\frac{d\epsilon^*}{dz} = 2a > 0. \tag{E.8}$$

□

Proof of Proposition 2. Retention rates are given by

$$RR = \frac{\Lambda(1 - p(\theta)\int[1 - G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')]dF(a'))}{\Lambda} \tag{E.9}$$

And so

$$\frac{dRR}{da} = p(\theta)((\epsilon^* - \epsilon) + a\frac{d\epsilon^*}{da})\int \frac{1}{a'}g((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a') \tag{E.10}$$

and

$$\begin{aligned}\frac{d^2RR}{dad\theta} = p'(\theta)((\epsilon^* - \epsilon) + a\frac{d\epsilon^*}{da})\int \frac{1}{a'}g((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a') \\ + p(\theta)(\frac{d\epsilon^*}{d\theta} + a\frac{d^2\epsilon^*}{dad\theta})\int \frac{1}{a'}g((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a').\end{aligned} \tag{E.11}$$

where we have used the fact that $g'(x|a) = 0, \forall x \forall a$ and $\frac{dg(x|a)}{d\theta} = 0$. In the data we know that

$$\frac{d(b + \epsilon^* a)}{dad\theta} = \frac{d}{d\theta}(a\frac{d\epsilon^*}{da} + \epsilon^*) = \frac{d\epsilon^*}{d\theta} + a\frac{d^2\epsilon^*}{dad\theta} > 0. \tag{E.12}$$

and

$$\frac{d^2RR}{dad\theta} < 0. \tag{E.13}$$

The only way for that to happen is if

$$\frac{du}{da} \equiv (\epsilon^* - \epsilon) + a\frac{d\epsilon^*}{da} < 0. \tag{E.14}$$

High a firms give less compensation for risk, and as a result give lower utility to their workers. □

Proof of Proposition 3. Totally differentiating the first order condition with respect to θ and ϵ^* gives

$$z\frac{d^2n}{d(\epsilon^*)^2}d\epsilon^* + z\frac{d^2n}{d\epsilon^* d\theta}d\theta = 2a\frac{dn}{d\epsilon^*}d\epsilon^* + (b + \epsilon^* a)\frac{d^2n}{d(\epsilon^*)^2}d\epsilon^* + (b + \epsilon^* a)\frac{d^2n}{d\epsilon^* d\theta}d\theta + a\frac{dn}{d\theta}d\theta \tag{E.15}$$

Using the fact that

$$\frac{d^2n}{d(\epsilon^*)^2} = (\Lambda p(\theta) + q(\theta)) \int (\frac{a}{a'})^2 g'((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a') = 0, \tag{E.16}$$

the above simplifies to

$$z\frac{d^2n}{d\epsilon^* d\theta}d\theta = 2a\frac{dn}{d\epsilon^*}d\epsilon^* + (b + \epsilon^* a)\frac{d^2n}{d\epsilon^* d\theta}d\theta + a\frac{dn}{d\theta}d\theta \tag{E.17}$$

which can be rewritten as

$$(z - (b + \epsilon^* a))\frac{d^2n}{d\epsilon^* d\theta}d\theta - a\frac{dn}{d\theta}d\theta = 2a\frac{dn}{d\epsilon^*}d\epsilon^* \tag{E.18}$$

We use the fact that

$$\begin{aligned}\frac{d^2n}{d\epsilon^* d\theta} &= (\Lambda p'(\theta) + q'(\theta)) \int (\frac{a}{a'}) g((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a') \\ &\quad + (\Lambda p(\theta) + q(\theta)) \int (\frac{a}{a'}) \frac{dg((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a')}{d\theta} \\ &= (\Lambda p'(\theta) + q'(\theta)) \int (\frac{a}{a'}) g((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a'),\end{aligned} \tag{E.19}$$

and

$$\begin{aligned}\frac{dn}{d\theta} &= -\Lambda p'(\theta) \int [1 - G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')]dF(a') + q'(\theta) \int G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a') \\ &\quad + (\Lambda p(\theta) + q(\theta)) \int \frac{\partial G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')}{\partial \theta} dF(a').\end{aligned} \tag{E.20}$$

Next, note that

$$\frac{\partial G(x|a')}{\partial \theta} = i(\hat{z}(x, a))\frac{\partial \hat{z}(x, a)}{\partial \theta} \tag{E.21}$$

Now note that in the proof of the Proposition 1 we showed

$$\frac{d\hat{z}(x, a)}{dx} = a + a - a\frac{n(x, a)}{\frac{dn(x,a)}{dx}}\frac{d^2n(x, a)}{dx^2} = 2a. \tag{E.22}$$

This implies

$$\frac{\partial}{\partial \theta}\hat{z}(x, a) = \frac{\partial}{\partial \theta}\int \frac{d\hat{z}(x, a)}{dx}dx = \frac{\partial}{\partial \theta}\int 2adx = \int \frac{\partial}{\partial \theta}2adx = 0. \tag{E.23}$$

It follows that

$$\frac{\partial G(x|a')}{\partial \theta} = i(\hat{z}(x, a))\frac{\partial \hat{z}(x, a)}{\partial \theta} = 0. \tag{E.24}$$

And so

$$\frac{dn}{d\theta} = -\Lambda p'(\theta)\int[1 - G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')]dF(a') + q'(\theta)\int G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a'). \tag{E.25}$$

Then, equation E.18 simplifies to

$$\begin{aligned}(z - (b + \epsilon^* a))(\Lambda p'(\theta) + q'(\theta))\int(\frac{a}{a'})g((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a')d\theta \\ - a[-\Lambda p'(\theta)\int[1 - G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')]dF(a') + q'(\theta)\int G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a')]d\theta \\ = 2a(\Lambda p(\theta) + q(\theta))\int\frac{a}{a'}g((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a')d\epsilon^*. \end{aligned} \tag{E.26}$$

It follows that

$$\begin{aligned}\frac{d\epsilon^*}{d\theta} = &\frac{(z - (b + \epsilon^* a))(\Lambda p'(\theta) + q'(\theta))\int(\frac{a}{a'})g((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a')}{2a(\Lambda p(\theta) + q(\theta))\int\frac{a}{a'}g((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a')} \\ &+ \frac{-a[-\Lambda p'(\theta)\int[1 - G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')]dF(a') + q'(\theta)\int G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a')]}{2a(\Lambda p(\theta) + q(\theta))\int\frac{a}{a'}g((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a')}\end{aligned} \tag{E.27}$$

Now note that the amount of people retained must equal the amount of people poached and so

$$\Lambda p(\theta)\int[1 - G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')]dF(a') = q(\theta)\int G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a') \tag{E.28}$$

The above implies

$$\Lambda p'(\theta)\int[1 - G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')]dF(a') = q'(\theta)\int G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a') \tag{E.29}$$

$$\Lambda p'(\theta) = (\Lambda p'(\theta) + q'(\theta))\int G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a'). \tag{E.30}$$

Since $\Lambda p'(\theta) > 0$ the above implies $(\Lambda p'(\theta) + q'(\theta))\int G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a') > 0$. And so it follows that

$$\begin{aligned}\frac{d\epsilon^*}{d\theta} = &\frac{(z - (b + \epsilon^* a))(\Lambda p'(\theta) + q'(\theta))\int(\frac{a}{a'})g((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a')}{2a(p(\theta) + q(\theta))\int\frac{a}{a'}g((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a')} \\ &+\frac{-a[-\Lambda p'(\theta)\int[1 - G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')]dF(a') + q'(\theta)\int G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a')]}{2a(\Lambda p(\theta) + q(\theta))\int\frac{a}{a'}g((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a')} > 0.\end{aligned} \tag{E.31}$$

□

Proof of Proposition 4. Average utility across all firms is given by

$$E[u] = \frac{\int\int (b + (\epsilon^* - \epsilon)a)\Lambda(1 - p(\theta)\int[1 - G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')]dF(a'))dF(a)dI(z)}{D} + \frac{\int\int (b + (\epsilon^* - \epsilon)a)q(\theta)\int G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a')dF(a)dI(z)}{D} \quad \text{(E.32)}$$

where

$$D \equiv \int\int \Lambda(1 - p(\theta)\int[1 - G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')]dF(a'))dF(a)dI(z) + \int q(\theta)\int G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a')dF(a) \quad \text{(E.33)}$$

Note that in aggregate the total amount of people poached has to equal the total amount of people not retained such that

$$\int\int p(\theta)\Lambda\int[1 - G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')]dF(a')dF(a)dI(z) = \int\int q(\theta)\int G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a')dF(a)dI(z). \quad \text{(E.34)}$$

And so average utility in the economy is given by

$$E[u] = \frac{1}{\int\int \Lambda dF(a)dI(z)} \cdot [\int\int (b+(\epsilon^*-\epsilon)a)\Lambda(1-p(\theta)\int[1-G((\epsilon^*-\epsilon)\frac{a}{a'}+\epsilon|a')]dF(a') + q(\theta)\int G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a'))dF(a)dI(z)] \quad \text{(E.35)}$$

Note that $\int\int \Lambda dF(a)dI(z) = \Lambda$, and so

$$E[u] = \int\int (b + (\epsilon^* - \epsilon)a)\Lambda(1 - p(\theta)\int[1 - G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')]dF(a') + q(\theta)\int G((\epsilon^* - \epsilon)\frac{a}{a'} + \epsilon|a')dF(a'))\frac{dF(a)dI(z)}{\Lambda} \quad \text{(E.36)}$$

Taking a derivative with respect to θ we get

$$\begin{aligned}\frac{dE[u]}{d\theta} = \int\int \frac{d\epsilon^*}{d\theta}\Lambda(1-p(\theta)\int[1-G((\epsilon^*-\epsilon)\frac{a}{a'}+\epsilon|a')]dF(a') \\ + q(\theta)\int G((\epsilon^*-\epsilon)\frac{a}{a'}+\epsilon|a')dF(a'))\frac{dF(a)dI(z)}{\Lambda} \\ \frac{1}{\Lambda}\int\int(b+(\epsilon^*-\epsilon)a)(p(\theta)\Lambda+q(\theta))\int\frac{a}{a'}g((\epsilon^*-\epsilon)\frac{a}{a'}+\epsilon|a')\frac{d\epsilon^*}{d\theta}dF(a')dF(a)dI(z) \\ \frac{1}{\Lambda}\int\int(b+(\epsilon^*-\epsilon)a)[-p'(\theta)\Lambda+(p'(\theta)\Lambda+q'(\theta))\int G((\epsilon^*-\epsilon)\frac{a}{a'}+\epsilon|a')dF(a')]dF(a)dI(z)\end{aligned} \tag{E.37}$$

Defining $n(a) = \Lambda(1-p(\theta)\int[1-G((\epsilon^*-\epsilon)\frac{a}{a'}+\epsilon|a')]dF(a'))+q(\theta)\int G((\epsilon^*-\epsilon)\frac{a}{a'}+\epsilon|a')dF(a')$, we get

$$\frac{dE[u]}{d\theta} = \int\int\frac{d\epsilon^*}{d\theta}n(a)\frac{dF(a)dI(z)}{\Lambda} + \int\int(b+(\epsilon^*-\epsilon)a)(\frac{dn(a)}{d\theta})\frac{dF(a)dI(z)}{\Lambda}. \tag{E.38}$$

□