Labor Market Tightness, Wage Inequality and Workplace Amenities

Anikó Bíró[*] João G. da Fonseca[†] Attila Lindner[‡] Tímea Laura Molnár[§]

September 2025

Abstract

Workplace-specific pay premiums and their dispersion rise with labor market tightness. We examine the role of compensating wage differentials in this relationship: as competition for labor intensifies, firms are compelled to offer higher pay for undesirable job attributes. Using administrative data from Hungary, we construct a novel measure of workplace-specific injury rates and study how workers are compensated for this negative attribute over the business cycle. We find that the wage premium associated with hazardous working conditions increases with market tightness, with compensation for workplace-specific injuries accounting for roughly 7% of the rise in wage dispersion. Nonetheless, despite offering higher wages, firms with poor amenities face increasing challenges in retaining workers in tight labor markets. We interpret these findings through the lens of a job search model with amenities, showing that while tighter labor markets can raise overall wage dispersion through compensating differentials, the dispersion in worker utilities across jobs declines.

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

[*]ELTE Centre for Economic and Regional Studies, Hungary. Email: biro.aniko@krtk.elte.hu.
[†]University of Montreal, Canada. Email: ja.galindo.da.fonseca@gmail.com.
[‡]University College London, UK. Email: a.lindner@ucl.ac.uk.
[§]Central European University, Austria. Email: molnartl@ceu.edu.

Acknowledgments: Bíró was supported by the National Research, Development and Innovation Office of Hungary (grant number: OTKA K 146309). Lindner acknowledges financial support from the ESRC Centre for the Microeconomic Analysis of Public Policy (ES/T014334/1), from the European Research Council under the European Union's Horizon 2020 research and innovation program (949995) and from the Economic and Social Research Council (ES/T008474/1). We thank István Boza, and seminar participants at University of Naples Federico II, Princeton University, IFS, LSE, Swedish Institute for Social Research, ROCKWOOL Foundation Berlin, Bergen Labor Workshop, and ELTE CERS for helpful comments.

1 Introduction

Persistent and high within-country wage inequalities are of major economic concern in many countries (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 inequality. For example, recent evidence highlighted the positive relationship between labor market tightness and wage growth (Katz and Krueger, 1999; Autor et al., 2023),[1] especially in competitive labor markets (Burya et al., 2023).

A significant share of wage inequality arises from differences in wages paid by firms to similar workers (Card et al., 2013, 2015, 2018; Kline, 2024; Di Addario et al., 2023). These firm-level components appear to strongly respond to labor market tightness. For example, in Hungary, we find that as local unemployment declines (i.e., tightness increases in a given local labor market), both the growth of firm-specific wage premiums and their *dispersion* increases. 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)'s 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, which has been documented in numerous surveys (e.g., Mas and Pallais, 2017; Wiswall and Zafar, 2018; Maestas et al., 2023). However, it is less clear whether these preferences are consistently reflected in wage determination, as predicted by theory (Mas, 2025). Several studies have documented positive correlation between wages and workplace amenities (e.g., Hotz et al., 2018; Sockin, 2022; Bana et al., 2023; Lachowska et al., 2023b; Bíró and Elek, 2025), which relation can be explained by variation in amenity costs across firms (Hwang et al., 1998). Moreover, the extent to which workers are compensated for poor working conditions likely depends on broader labor market conditions and the extent of competition for workers between firms. 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 theoretically investigating how a key implication of tighter labor markets, a higher rate at which workers find firms, affects compensating wage differentials. Our theoretical framework closely follows the canonical model of Burdett and Mortensen (1998) while allowing for amenities and decreasing returns to scale. The search for jobs is random and there is on the job search. We show that in equilibrium, lower amenity firms under-compensate workers for the lower amenity level, since high amenity firms also provide higher utility to their workers. Next, we show that as the

[1] In Hungary in 2003–2017, a one standard deviation tightness implies, on average, 2.1% additional annual wage growth, whereas the corresponding estimate of Autor et al. (2023) is very close at 2.6%.

economy approaches the perfectly competitive frictionless market (all workers immediately find all firms), compensating wage differentials converge to the full compensation result such that all workers receive the same utility. Interestingly, as the economy approaches the maximum amount of search frictions, compensating wage differentials also converge to the full compensation result. This is because firms in that case can extract all the rent from the workers, and simply pay their outside option. This leads to a low utility level (at the outside option), but compensation for amenities.

Between these two extremes, compensation will be less than full. To further explore the relationship between market tightness and compensating wage differentials, we conduct a numerical simulation of the model. The results confirm a U-shaped relationship between compensating differentials and the intensity of competition for workers. As the labor market transitions from a state of very high frictions, compensating differentials initially decline and eventually play only a minor role. However, as market tightness continues to increase and competition for workers intensifies, compensating differentials again become more important. Moreover, when compensating differentials rise with competition, wage dispersion increases, while the dispersion in utilities across jobs decreases.

In sum, whether compensating wage differentials vary with labor market conditions is ultimately an empirical question, with important implications for dispersion in utilities. Our model also shows that rising compensating differentials can be consistent with increasing voluntary separation rates from low-amenity firms. Intuitively, because workers are undercompensated for poor amenities in equilibrium, such firms continue to lose workers as competition intensifies, as long as the undercompensation persists. Our model gives a one-to-one mapping between the contact rate of workers and firms and the unemployment rate, which allows us to use unemployment as an empirical measure of search frictions—or, equivalently, the degree of competition for workers—in the labor market.

To study empirically whether compensating wage differentials vary with labor market tightness, we start 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.[2]

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 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

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

low-injury firms affects injury rates, and these effects are symmetric—suggesting a limited role for Roy-type selection based on workers' susceptibility to injury. We also show that change in injury rate for movers between firms with high and low injury risk are not driven by pre-trends – suggesting that mobility is not reflecting permanent or transitory shocks affecting workers' injury rate.[3]

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 percent 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, the rise in compensation for risk does not reflect changes in injury rates with market tightness. We find no evidence that tightness influences firm-specific injury risks, which remain acyclical to business cycle fluctuations. In addition, the correlation between injury risk and other job amenities is stable over the cycle, and revealed-preference measures of workers' willingness to pay to avoid workplace risks are likewise acyclical.

We present a battery of robustness checks to the main findings. We show that the results are robust to using alternative injury and tightness measures, and to including numerous firm-specific variables and their interaction with tightness and time effects in the main specification. 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 also present an event study specification, where we directly study the evolution of wages for movers to high risk firms and low-risk firms in high and low-marker tightness environment. Finally, we show that the result that the compensation for firm-level disamenities increases with labor market tightness also holds if we use revealed preference measures (retention rates) to capture disamenities, instead of our baseline disamenity measure of firm-specific injury risk. Following Sorkin (2018), we also provide evidence that the dispersion of compensating differentials increases with tightness.

Our findings highlight that the economy is currently on the upward-sloping part of the U-shaped relationship between market tightness and compensating wage differentials. Furthermore, 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

[3]Since our measure of injury rates is available at the monthly level and is not subject to rigidity, examining pre-trends is likely more informative for workplace injury rates than for wages, which may adjust more sluggishly to negative shocks.

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, separation rates are likely to increase with tightness, leading to higher worker turnover. This latter is precisely what we find: as market tightness increases, separation rate at high-risk firms rises, and worker turnover also rises. In sum, viewed through the lens of our search model, these findings suggest that higher market tightness not only contributed to greater wage dispersion through a stronger role for compensating differentials, but also reduced the dispersion of workers' utilities between high- and low-risk firms.

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; Wiswall and Zafar, 2018; Maestas et al., 2023), yet evidence on how preferences for amenities are priced in equilibrium is scarce (Mas, 2025). 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 (Brunello and Gambarotto, 2007; Rzepka and Tamm, 2016; 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 work pressure, as in Nagler et al., 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; Lehmann, 2023). In this literature, Mas (2025) presents the most important application of compensating wage differentials to fatality risk. Our similar, albeit less radical, injury risk measure has several advantages. First, it is a relatively common event, so that we can study firm-specific injury rates. Second, we can control for person effects since, unlike fatality events, injuries are not absorbing states. By borrowing the diagnostic

tests developed in the literature of AKM[4] 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, finding mixed evidence (Dorman and Hagstrom, 1998; Bender and Mridha, 2011; Mridha and Khan, 2013; Mridha, 2022). This literature typically relies on occupation- or sector-specific measures of injury risk rather than firm-specific ones. Our richer data allow us to estimate firm-specific injury risk while netting out worker sorting based on injury susceptibility. This not only strengthens identification but also enables us to focus on firms that contribute more to rising wage inequality than industries or occupations as a whole (see Card et al., 2013).

Fourth, our paper also relates to the literature studying search models with amenities. In the canonical paper by Hwang et al. (1998), the authors study an extension of the Burdett and Mortensen (1998) framework which incorporates amenities. The framework we consider is similar but differs in that firms face decreasing returns to scale.[5] Decreasing returns to scale allows us to obtain an equilibrium in which firms of different amenity levels still co-exist in the limit case of perfect competition, as opposed to only the highest amenity firms operating as is the case under constant returns to scale. Gronberg and Reed (1994) develop a method to estimate workers' marginal willingness to pay for amenities (MWTP) under the presence of search frictions. We use their method to test and verify the theoretical prediction that the MWTP for amenities does not vary with market conditions.

Finally, in addition to documenting the effect on wages, we examine changes in separation rates. Interestingly, despite higher compensation, we find that high-risk firms experience a rise in separation rates as labor market tightness increases. This provides evidence that workers were not fully compensated in slack labor markets—a novel finding in the literature and one consistent with our theoretical framework. The results also highlight that while greater compensation in tight labor markets increases the dispersion of wages across firms, it is accompanied by lower utility dispersion across firms.

In what follows, Section 2 presents the theoretical framework (a job search model with amenities). Then, Section 4 presents the data and measurement, focusing on our novel firm-specific injury risk measure, Section 5 presents our empirical strategies, and Section 6 presents evidence for compensating wage differentials and on the extent to which they depend on labor market tightness; it also presents results that link our empirical findings to our model. Section 7 shows evidence for firms' under-compensation for poor amenities, Section 8 provides evidence on external validity of our results and Section 9 concludes.

[4]Throughout the paper, we use the AKM abbreviation for the authors of Abowd et al. (1999): Abowd, Kramarz, and Margolis.

[5]While in our baseline we consider amenities to be exogenous characteristics of the firm, in an extension in Section 2.1 we allow for endogenous amenity choice focusing on the same amenity cost function used by Hwang et al. (1998).

2 Model

In this section, we extend the standard Burdett and Mortensen (1998) framework to study the relationship between market tightness and compensating wage differentials. We introduce two key modifications to the baseline model. First, we incorporate amenities. In the benchmark specification, amenities are treated as an exogenous firm characteristic —an assumption consistent with the empirical patterns we observe for workplace injury risks. In Section 2.1, we relax this assumption and allow firms to choose amenities endogenously. Second, firms operate with decreasing returns to scale technology

Consider there is a continuum of identical workers. There are two types of firms, one that provides amenity a_2 to its workers and one that provides amenity a_1 to its workers, where $a_2 > a_1$. A worker employed at firm of type i receiving wage w gets utility $w + a_i$. Denote the fraction of type-1 firms (firms with amenity a_1) as σ and the fraction of type-2 firms as $1 - \sigma$. At any moment in time, each worker is either unemployed (state 0) or employed (state 1). At random time intervals, a worker receives information about a new or alternative job opening. Let λ be the arrival rate of jobs for both employed and unemployed individuals. Let s be the exogenous rate at which a job is destroyed. It will be useful to define the object $k = \lambda/s$. In particular, k captures the degree of competition for workers. For example, in Burdett and Mortensen (1998), the authors show that as $k \to \infty$ the economy approaches the limit of a perfectly competitive frictionless economy. Stronger competition for workers is represented by a larger λ, hence, a larger k. Considering labor market tightness θ, we can think of $\lambda(\theta)$ with $(d\lambda/d\theta) > 0 \Rightarrow (dk/d\theta) > 0$. Through the remainder of this section, we focus on k as the parameter capturing the degree of search frictions with the understanding that in the background it is an increasing function of labor market tightness, θ.

From the point of view of workers, all they care about is the utility $x = w + a$ associated with a job; if two jobs give the same x the worker is indifferent between them. So, when looking for jobs, the worker draws different jobs with different values of $x = w + a$. Just as in Burdett and Mortensen (1998) firms commit to paying the worker the posted wage. Firms will choose optimally which wage w to post, which leads to an endogenous distribution of $x = w + a$ given the share of firms of type-1 and type-2 and the endogenous distribution of wages. Let such endogenous distribution of x be denoted by $F(x)$. Because there are two types of firms, the distribution function of utility offers, $F(x)$, is the weighted average of the x offered by the two types of firms:

$$F(x) = \sigma F_1(x) + (1 - \sigma)F_2(x). \tag{1}$$

While unemployed an individual receives utility b. Let U denote the value function associated with being unemployed, and $W(x)$ the value function associated with being

employed with $x = w + a$, then,

$$rU = b + \lambda \int_R (W(x) - U) dF(x) \tag{2}$$

where R is the reservation x of the worker, the lowest utility the worker is willing to accept to work. Once employed, a job is exogenously destroyed at rate s, and so

$$rW(x) = x + \lambda \int_x (W(x') - W(x)) dF(x') + s(U - W(x)). \tag{3}$$

By standard arguments, we can show that $R = b$.[6] In steady state, the flow of workers out of unemployment is given by $\lambda[1 - F(R)]u$, where R is the reservation utility and u is the unemployment rate. Note that $F(R) = 0$ as no firm would offer utility lower than the reservation utility. Therefore, the probability that the offer is high enough is $1 - F(R) = 1$. The flow of workers into unemployment is given by $s(1 - u)$. Thus, the equilibrium condition for the flow of workers in and out of unemployment is:

$$s(1 - u) = \lambda u \quad \Rightarrow \quad u = \frac{s}{s + \lambda}. \tag{4}$$

Let $G(x)$ denote the distribution of x among employed workers. The flow of workers out of jobs with utility less than or equal to x is given by $s(1 - u)G(x) + \lambda[1 - F(x)](1 - u)$. The flow of workers into jobs with utility less than or equal to x is $\lambda F(x)u$. Then, the steady-state condition for the flow of workers into and out of jobs is

$$s(1 - u)G(x) + \lambda[1 - F(x)](1 - u)G(x) = \lambda F(x)u.$$

After some algebra[7], and using the expression for the unemployment rate, u, we get the usual expression for the size of a firm making an offer x

$$l(x) = \frac{k}{[1 + k(1 - F(x))]^2} \tag{5}$$

where $k \equiv \dfrac{\lambda}{s}$.

A firm of size $l(x)$ has revenue $pl(x)^\alpha$ with $0 < \alpha < 1$. Hence, firms of type i solve the problem

$$\max_{x,w} pl(x)^\alpha - wl(x) \tag{6}$$

subject to

$$x = a_i + w \tag{7}$$

[6] To see this just evaluate $W(x)$ at $x = R$ and subtract it from U using the fact that by definition $W(R) = U$.

[7] See Appendix G for the step-by-step derivation of $l(x)$.

which is equivalent to

$$\max_x pl(x)^\alpha - (x - a_i)l(x). \tag{8}$$

The equilibrium is defined by profits π_1 for firms of type 1, π_2 for firms of type 2, offer distributions $F_1(x)$ and $F_2(x)$ such that for all $i = 1, 2$

$$\begin{aligned} pl(x)^\alpha - (x - a_i)l(x) &= \pi_i \quad \text{for all } x \text{ in the support of } F_i(x) \\ pl(x)^\alpha - (x - a_i)l(x) &\leq \pi_i \quad \text{for all } x \text{ not in the support of } F_i(x). \end{aligned} \tag{9}$$

Proposition 1. *High amenity firms (a_2) always deliver utility at least as high as low amenity firms (a_1), i.e, $x_2 \geq x_1$. For all w_1 offered by low amenity firms a_1 and all w_2 offered by high amenity firms a_2,*

$$w_1 - w_2 \leq a_2 - a_1. \tag{10}$$

We provide the proof of each proposition in Appendix H. The above proposition tells us that in equilibrium low-amenity firms do not fully compensate workers for the lower amenity. In other words, firms deliver lower compensating differential than the full compensation result obtained in Rosen (1986).[8]

Proposition 2. *As the economy approaches the perfectly competitive frictionless market ($k \to \infty$), the distribution of wages among workers employed by firms of type 1 converges to a single wage point, w_1, the distribution of wages among workers employed by firms of type 2 converges to a single wage point, w_2, and*

$$(w_1 - w_2) \to (a_2 - a_1). \tag{11}$$

As the economy approaches the maximum amount of friction, ($k \to 0$), the distribution of wages among workers employed by firms of type 1 converges to the single wage point: $w_1 = b - a_1$, the distribution of wages among workers employed by firms of type 2 converges to the single wage point, $w_2 = b - a_2$, and

$$(w_1 - w_2) \to (a_2 - a_1). \tag{12}$$

Proposition 2 above tells us that as the economy approaches the extremes of no friction ($k \to \infty$) or maximum friction ($k \to 0$), compensating differentials converge to full compensation. Intuitively, at the limit of perfect competition, all workers meet all firms simultaneously and instantaneously, leading firms to perfectly compete against each other recovering the Rosen result of perfect compensation. At the other extreme, as frictions become arbitrarily large, firms do not need to worry about losing workers to other firms,

[8] Full compensation à la Rosen (1986) corresponds here to having $w_1 - w_2 = a_2 - a_1$.

allowing them to offer the lowest utility that gets workers to choose employment over unemployment, b. This leads to $w_1 = b - a_1$ and $w_2 = b - a_2$, recovering Hwang et al. (1998) results where limited competition leads to an equilibrium with full compensating wage differentials. In summary, the above proposition highlights the non-linear relationship between competition for workers and compensating differentials.

To better map this result into empirical objects, it is useful to note that

$$1 - u = \frac{k}{1+k} \Rightarrow \frac{d(1-u)}{dk} > 0 \Rightarrow \frac{d(1-u)}{d\theta} > 0. \tag{13}$$

In other words, there is a direct mapping between k, and labor market tightness, θ, to $1 - u$. As a result, when investigating our model results empirically we can use $(1 - u)$ as a measure of labor market tightness, rather than needing to construct a direct measure of k or θ. With this in mind, for the remainder of this Section we use the term labor market tightness and $(1 - u)$ interchangeably.

To further investigate the relationship between market conditions and compensating wage differentials, we proceed to a numerical simulation of the model. In line with estimates by Cooper et al. (2007) and Cooper et al. (2015), we consider $\alpha = 0.64$. We normalize productivity p to 1. We interpret the two types of amenities as being the empirical equivalent of below and above median amenities. In line with this interpretation we set the share of low amenity firms, σ, to 0.5. Next, note that in the model, what matters is the difference in amenity levels $a_2 - a_1$ rather than their levels themselves. With this in mind, we set $a_1 = 0$. To normalize the full compensating differential to 1, we set $a_2 = 1$. Finally, we choose b such that the utility while unemployed equals the average amenity value in the market, $b = \sigma a_1 + (1 - \sigma)a_2$. We also consider sensitivity analysis to evaluate how our results vary for different values of b (see Appendix Section J).

Panel (a) of Figure 1 illustrates the relationship between market tightness $(1 - u)$ and wages. As competition between firms intensifies through higher job-offer arrival rates, wages rise, resembling the standard Phillips curve relationship between employment and wages. Panel (b) shows the relationship between wage dispersion and market tightness, which follows a more complex U-shape. The intuition, as highlighted in Proposition 2, is that compensating differentials are largest at the two extremes of market tightness—very high frictions and near-perfect competition—while they are smaller at intermediate levels.

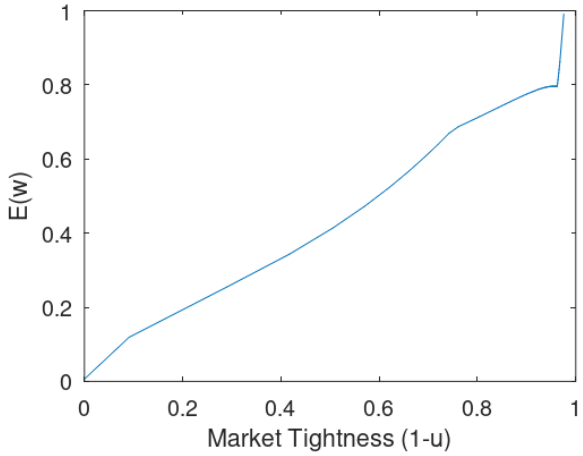
The variance of wages reflects the interaction of two offsetting forces, which can be seen from the following decomposition, based on the law of total variance:

$$Var(w) = E[Var(w|a)] + Var(E[w|a]), \tag{14}$$

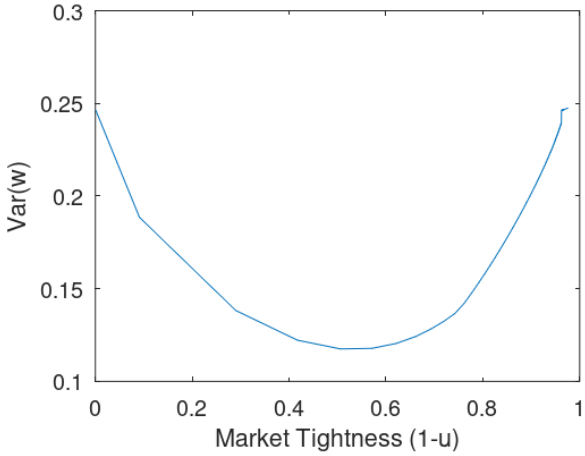
where $E[Var(w|a)]$ captures within–firm-type wage variation, and $Var(E[w|a])$ captures variance across firm types, i.e., compensating wage differentials.

Figure 1: Wages versus Tightness $(1-u)$

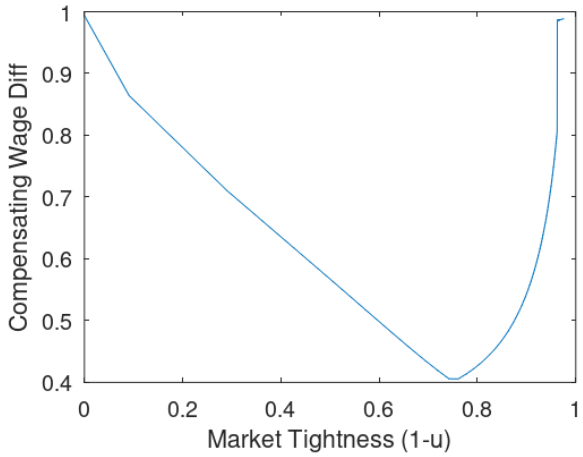
(a) Expected Wage $(E(w))$



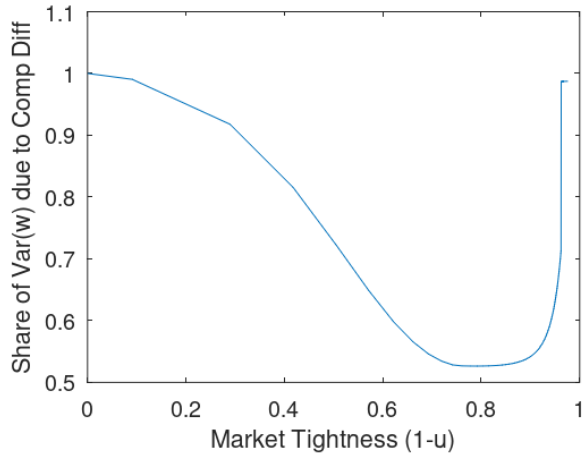
(b) Variance of Wages $(Var(w))$



(c) Compensating wage differential



(d) Share $Var(w)$ due to Comp Diff $(Var(E(w|a)))$



When frictions are maximal (the probability of receiving an offer approaches zero, $(1-u) \to 0$), all variation stems from between-firm compensating differentials, as shown in Proposition 2. Reducing frictions (i.e., increasing market tightness) from this point raises within–firm-type variance, as firms compete more actively for workers, but simultaneously lowers between-firm compensating variation (see Figure 1). Since the latter effect dominates initially, overall wage variance declines.

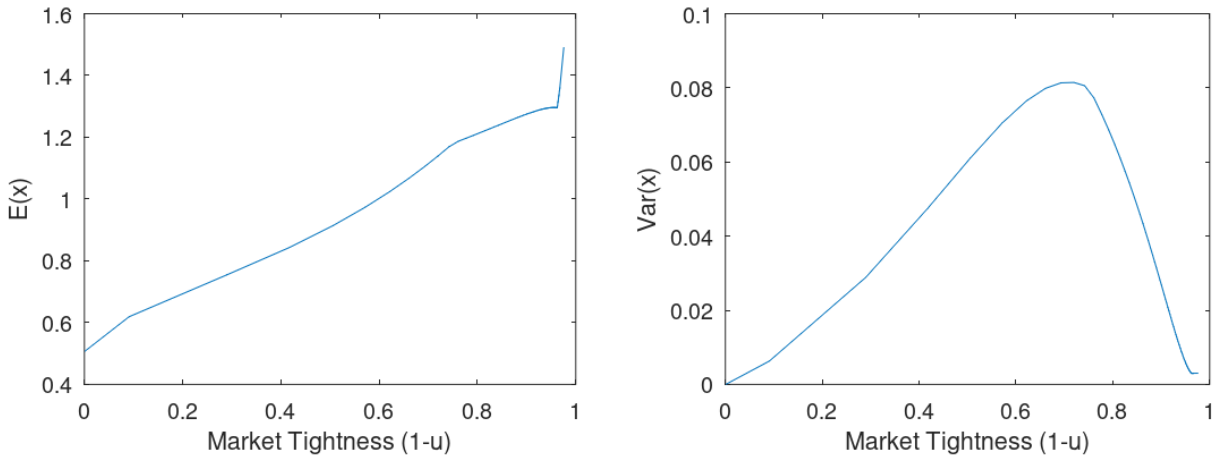
As market tightness continues to rise, however, increased competition gradually reduces the scope for within–firm-type wage dispersion, while compensating differentials once again expand. These opposing forces offset each other, but eventually the latter dominates, leading wage variance to increase.

Panels (c) and (d) directly illustrate compensating variation. Panel (c) shows that at the two extremes of market tightness, we obtain full compensation for amenities, i.e.,

$w_2 - w_1 = a_2 - a_1 = 1$. Between these extremes, compensation for poor amenities is incomplete. Panel (d) depicts the share of compensating variation in total wage variance, which follows a U-shaped pattern: its importance initially declines as market tightness increases, but then rises again as competition intensifies further.

Figure 2: Utility Versus Tightness $(1 - u)$

(a) Expected Utility $(E(x))$ (b) Variance of Utility $(Var(x))$



Together, these dynamics generate a U-shaped relationship between wage variance and market tightness. In contrast, utility dispersion follows an inverted U-shape, as shown in Panel (b) of Figure 2. Under maximal frictions, utility dispersion is close to zero because firms extract nearly all rents and workers are compensated for poor amenities only at their outside option b. In this case, workers' average utility is also close to zero, as illustrated in Panel (a) of Figure 2. As market tightness increases, the role of compensating differentials diminishes, increasing utility dispersion even as average utility rises. In the frictionless limit, compensating differentials regain importance, once again lowering utility dispersion while raising overall utility, as workers capture the full rents of the employment relationship.

Our main goal in the empirical section is to test the key prediction of the proposed framework, namely that compensating differentiation changes over the business cycle. We will study if compensating wage differentation increases over the business cycle, meaning that we are at the upward sloping part of the U-shaped relationship. By documenting an increasing role for compensating wage differentation, we can also infer a declining dispersion in utilities. In addition to these key predictions, we can also use our theoretical framework to derive further predictions of the model that we can test.

Voluntary separation. A key prediction of our framework is that workers are undercompensated in equilibrium at all levels of market tightness, except in the limit of perfect competition. As a consequence, voluntary separation can rise even when firms

with poor amenities increase compensation. In the Appendix (Section I), we show that, except under very high market tightness (e.g., when the unemployment rate falls below 3.8%), voluntary separation rates at low-amenity firms increase despite these firms offering higher wages.

This result stands in stark contrast to the classic insight of Rosen (1986), which emphasizes preference-based sorting. In Rosen's framework, all but the marginal worker—who is indifferent across firms—are overcompensated. With such inframarginal workers, an increase in compensating differentials (e.g., higher wages at high-risk firms) should strengthen retention, reducing voluntary separations. In our setting, however, workers are homogeneous, and thus no inframarginal workers exist. While this is admittedly a strong assumption, our empirical finding—that voluntary separations increase at low-amenity firms even as these firms raise wages—is consistent with our framework but difficult to reconcile with the preference-based sorting emphasized by Rosen (1986).

Market tightness and change in amenities. So far we have assumed that amenity choice is fixed over the business cycle. This is arguable a strong assumption as the increased competition could lead to firms changing their amenities, if they can. In our empirical set-up we focus on a workplace specific risks that might not be a choice of the firm. It is also possible that there is a change in the correlation with other amenities. Our framework, nevertheless, can be used to develop a testable prediction of changes in amenities (or the correlation with other unobserved amenities).

The key assumption in our model is that the utility of workers depends only on the wage they are paid w and the amenity level of their employer a or putting it differently that the marginal willingness to pay (MWTP) for the amenity is constant over the business cycle. By definition, the MWTP is defined as the marginal contribution of amenity to worker utility divided by the marginal contribution of wages to worker utility. Then, intuitively, if the utility of a worker depends only on amenities and wages, the same is true for the marginal contribution of both amenity and wages to utility, which implies the MWTP does not depend on market conditions. Importantly, this implication is present regardless of the functional form of the utility function.

Formally, let the utility of a worker employed at firm with amenity level a paying wage w be given by $V(w, a)$ where V is a continuous function increasing in a and w, then, the marginal willigness to pay for amenities (MWTP) is defined as

$$MWTP \equiv \frac{\dfrac{\partial V(w,a)}{\partial a}}{\dfrac{\partial V(w,a)}{\partial w}}, \tag{15}$$

which is independent of $1-u$ because V does not directly depend on $1-u$.

To test this prediction, we apply the MWTP estimation of Gronberg and Reed (1994)

(recently summararized by Mas (2025)). Let RR denote retention rates, then, following Mas (2025),

$$MWTP \equiv \frac{\frac{\partial V(w,a)}{\partial a}}{\frac{\partial V(w,a)}{\partial w}} = \frac{\frac{\partial RR}{\partial a}}{\frac{\partial RR}{\partial w}}. \tag{16}$$

The above gives us a way to measure MWTP by using data on retention rates, wages, and amenities. Importantly, the above prediction is independent on whether a is changing or not with $1-u$ and whether a is chosen endogenously or not by firms. The above test is all the more meaningful given that it is robust to any concern of unobserved amenities. To see this, consider the now the possibility that firms provide two types of amenities, a, that is observable to the econometrician and a vector ϕ of unobserved amenities. In particular, consider

$$V(w,a,\phi) = h(w,a) + g(\phi) \tag{17}$$

where h and g are increasing functions in their respective arguments.

Then, the marginal willingness to pay for amenity a is given by

$$MWTP \equiv \frac{\frac{\partial h(w,a)}{\partial a}}{\frac{\partial h(w,a)}{\partial w}} \tag{18}$$

which implies that that the MWTP for amenity a is independent of $1-u$ regardless of the correlation between a and the elements of vector ϕ and how it may change with $1-u$.

To summarize, our theoretical framework clarifies that whether compensating wage differentials increase with competition for workers, as captured by one minus the unemployment rate, is an empirical question. Furthermore, understanding this relationship informs us whether the variance of wages and the variance of utility are expected to be decreasing or not with the amount of competition for workers. Finally, since workers are under compensated in equilibrium, it is possible for compensating wage differentials and the voluntary separation rate from low amenity firms to simultaneously increase.

2.1 Endogenous Amenity Choice

In this subsection, we relax the assumption that amenities are an exogenous characteristic of the firm. We start by considering the cost function common in the literature and used in the seminal paper by Hwang et al. (1998) in which the cost of amenity provision depends on the firm size. The result are amenities that are chosen endogenously but do not vary with market conditions. Next, we consider how our results change if we instead consider the cost of amenity provision still depends on the amenity level but does not depend on the size of the firm.

Following the seminal paper by Hwang et al. (1998), let $c_i(a)$ represent the per-worker cost of providing job amenity level a for firms of type i, where $i = 1, 2$. In particular, consider the formulation of $c_i(a)$ adopted in the numerical analysis done in Hwang et al. (1998), that is, $c_i(a) = c_i \frac{a^2}{2}$, where $c_1 > c_2$.

The problem of a firm of type i becomes

$$\max_{x,w,a} pl(x)^\alpha - (w + \frac{c_i}{2}a^2)l(x) \tag{19}$$

subject to

$$x = a + w, \tag{20}$$

which is equivalent to

$$\max_{x,a} pl(x)^\alpha - (x - a + \frac{c_i}{2}a^2)l(x). \tag{21}$$

Note that besides this modification in the problem of the firm, everything else remains the same, since the problem of the worker did not change.

Proposition 3. *In the extension with endogenous amenity choice,*

$$a_i(c_i) = \frac{1}{c_i}, \quad \forall i = 1, 2. \tag{22}$$

Then, for values of c_i the choice of x by each firm coincides with a model of exogenous amenity where amenities of each firm is $a_i' = \frac{1}{2c_i} = \frac{1}{2}a_i(c_i)$.

The above proposition tells us that the endogenous amenity choice a_i by a firm of type i is independent of the market conditions and depends exclusively on the exogenous amenity cost function. Furthermore, the model with endogenous amenities always has a mapping to a model with exogenous amenities. Intuitively, under endogenous amenities the choice of the firm can be broken into two, the choice of how much utility to provide x, and the composition of that utility in terms of amenity a and wage w. The choice of this composition depends solely on the marginal cost of providing a higher amenity level, $c_i a$ and the marginal benefit for the utility of the worker, $\frac{dx}{da} = 1$. The firm chooses the amenity level that equals this marginal cost to the marginal benefit $1 = c_i a$.[9]

In line with this result, Propositions 4 and 5 below show that the results of undercompensation by low amenity firms and the convergence to full compensation as the economy converges to a perfectly competitive market or the maximum amount of frictions still all hold under endogenous amenity choice. Finally, we also consider a numerical simulation of this extension of the model to further highlight this point. In particular, to make the

[9] In Hwang et al. (1998), the utility x of the worker with wage w and amenity a is given by $x = w + h(a)$, and the cost function is parametrized in their numerical exercises as $\frac{\sigma_i}{2}a^2$ and so the above optimal condition is $\sigma_i a = h'(a)$, where σ_i is the equivalent of c_i here. More importantly, even with such a formulation the result of the above proposition continues to hold since the endogenous amenity choice is still just a function of the exogenous parameter σ_i and the exogenous function h.

endogenously chosen amenity values coincide with the values in the numerical simulation with exogenous amenities we set the $c_1 = \infty$ and $c_2 = 1$. All other parameters are set to the same values as in our baseline calibration. Figure 3 below once again confirms the U-shaped relationship between compensating wage differentials and our measure of friction in the labor market, one minus the unemployment rate.

Proposition 4. *Lower amenity cost firms (c_2) always deliver higher amenity level and higher utility than higher amenity cost firms (c_1), i.e, $x_2 \geq x_1$. For all w_1 offered by higher amenity cost firms (c_1) and all w_2 offered by lower amenity cost firms (c_2),*

$$w_1 - w_2 \leq a_2(c_2) - a_1(c_1), \text{ with } a_2(c_2) > a_1(c_1). \tag{23}$$

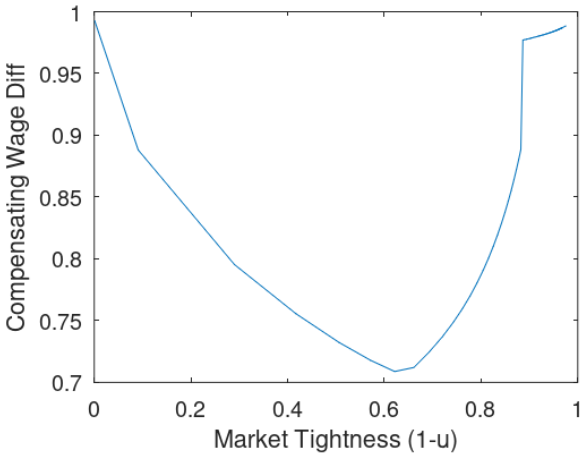
Proposition 5. *As the economy approaches the perfectly competitive frictionless market ($k \to \infty$), the distribution of wages among workers employed by firms of type 1 converges to a single wage point, w_1, the distribution of wages among workers employed by firms of type 2 converges to a single wage point, w_2, and*

$$(w_1 - w_2) \to (a_2(c_2) - a_1(c_1)). \tag{24}$$

As the economy approaches the maximum amount of friction, ($k \to 0$), the distribution of wages among workers employed by firms of type 1 converges to the single wage point: $w_1 = b - a_1(c_1)$, the distribution of wages among workers employed by firms of type 2 converges to the single wage point, $w_2 = b - a_2(c_2)$, and

$$(w_1 - w_2) \to (a_2(c_2) - a_1(c_1)). \tag{25}$$

Figure 3: Compensation Wage Differentials Versus 1-Unemployment Rate for the Case of Endogenous Amenity Choice



In the above formulation of the cost function there is an implicit assumption that the cost of providing a certain level of amenity a is increasing in the firm number of employees, $l(x)$. Of course this might not necessarily be the case. If the cost of amenity provision depends only on the level of amenity but not on the size of the firm, the problem of a firm of type i becomes

$$\max_{x,a} pl(x)^{\alpha} - (x-a)l(x) - c_i\frac{a^2}{2}, \tag{26}$$

where we have used the fact that $w = x + a$.

Proposition 6. *In the extension with endogenous amenity choice with the amenity cost independent of firms size $l(x)$,*

$$a_i(c_i) = \frac{l(x)}{c_i}, \quad \forall i = 1, 2. \tag{27}$$

We see that with this modified cost function, the amenity choice now varies with the size of the firm. Since in equilibrium there is wage dispersion among firms of the same type, there is dispersion in amenity levels even among firms with a same cost function.

The endogenous choice of amenity is derived by the level that equates the benefit of a marginal increase in amenities to the marginal cost. The marginal benefit of an amenity increase is given by the benefit to each individual worker $\frac{dx}{da} = 1$ multiplied by the number of workers $l(x)$, while the marginal cost is given by the $c_i a$ which does not depend on $l(x)$. It follows that as the size of the firm $l(x)$ increases so does the marginal benefit relative to marginal cost of amenities, leading the firm to choose a higher amenity level. In this sense, this formulation of the cost function effectively generates increasing returns in firm size $l(x)$.

Proposition 7. *Under an amenity cost function that does not depend on firm size, lower amenity cost firms (c_2) always deliver higher amenity level and higher utility than higher amenity cost firms (c_1), i.e, $x_2 \geq x_1$. For all w_1 offered by higher amenity cost firms (c_1) and all w_2 offered by lower amenity cost firms (c_2),*

$$w_1 - w_2 \leq a_2(c_2) - a_1(c_1), \text{ with } a_2(c_2) > a_1(c_1). \tag{28}$$

The above proposition tells us that even with this formulation of the cost function, firms under compensate workers for poor amenities, with high-cost (c_1) firms always offering amenities levels lower than or equal to those of low-cost (c_2) firms.

The above propositions have important implications for how an increase in market tightness influences compensating wage differentials. First, in order to talk about compensating wage differentials in a context of changing amenity values we need to talk about the difference in wages between low amenity and high amenity firms adjusting for the change in amenity levels. Intuitively, if low amenity firms increase their wages but also

lower their amenity levels it is not clear whether compensating wage differentials increase or decrease. Such a dynamic is exactly what takes place in this formulation of the model.

Just as we had previously, as frictions decrease (market tightness increases), the average size of good amenity firms increases while that of bad amenity firms decreases, leading to an increase in the marginal product of bad firms which translates into higher wages. Under exogenous amenity levels or a fixed endogenous choice of amenity, this mechanism translates to higher compensating wage differentials. However, when the provision of amenity increases in firm size, $l(x)$, the decrease in the size of the bad amenity firms leads them to worsen the amenity they provide. As a result, whether compensating wage differentials increases or decreases with market tightness depends on how much wages of bad amenity firms increase relative to the decrease in their amenity levels. This ambiguity in the relationship between compensating wage differentials and market tightness explains why we no longer obtain a proposition in the same spirit as Propositions 2 and 5.

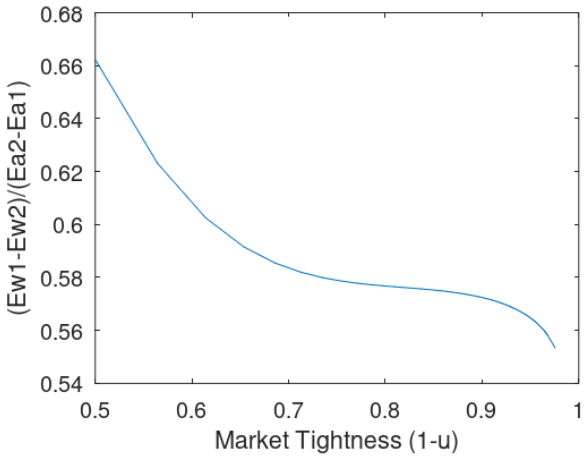
Another implication of this mechanism of changing amenity provision is that any increase in the wage difference paid by bad amenity and good amenity firms without taking into account changes in amenity provision should be interpreted as an upper bound to changes in compensating wage differentials, understood as wage changes adjusted by changes in amenity levels.

In the following, we consider a numerical simulation to further investigate the issue, we consider $c_1 = 2$ and $c_2 = 1$, with other parameters set to the same values as in our baseline numerical model simulation. As we see from Figure 4, in our numerical exercise, compensating wage differential defined as the differences in averages wages of bad and good amenity divided by the difference in amenity levels, $(E[w_1] - E[w_2])/(E[a_2] - E[a_2])$, decreases when market tightness $(1 - u)$ increases for high levels of market tightness $(1 - u)$. Furthermore, panel (b) clarifies this is despite the increase in the difference in wages $E[w_1] - E[w_2]$. In panel (b) we see that even as $E[w_1] - E[w_2]$ increases, the difference in amenity levels, $E[a_2] - E[a_1]$ increases by even more, pushing compensating differentials downward.

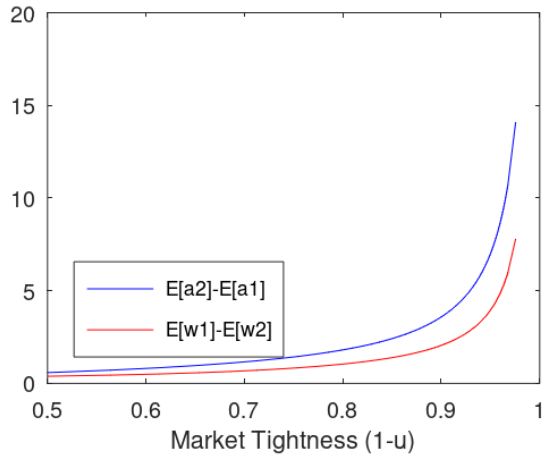
To summarize, the relationship between compensating wage differentials and market tightness under endogenous amenity choice is heavily dependent on the choice of cost function used. In particular, as long as the endogenous amenity choice does not vary with market tightness $(1 - u)$ we get back the results obtained under exogenous amenity provision. As it turns out, this is exactly what we find for our empirical measure of amenity. Taken together, these results further highlight that whether or not compensating wage differentials increase or decrease with market tightness $(1 - u)$ is an empirical question that we tackle in the remainder of the paper.

Figure 4: Patters for endogenous amenity choice when cost independent of size $l(x)$

(a) Compensating wage differential



(b) Wage difference across types



3 Labor Market Tightness, the Wage Phillips Curve, and Inequality

Prior to directly testing the empirical predictions of the model on compensating variation, it is instructive to characterize the relationship between market tightness and wage growth as well as wage inequality. To do so, we follow the standard approach in the literature (see, e.g., Autor et al., 2023), which studies the link between wage growth and the unemployment rate — the Phillips curve. However, we go beyond the standard focus on wage levels by also examining the evolution of wage dispersion and the change in firm-level wage premium.

We use Hungary, which the rest of the analysis relies on, and study labor market trends across and within its 20 counties (average size is 500 thousands people). We asses the relationship between tightness and growth of individual wages – the standard 'wage Phillips curve' – with the regression of Autor et al. (2023).[10] The vector of X incudes variables capturing the share of each one-digit industry in county c in year t.

Panel (a) of Figure 5 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,

[10]Our equation (29) corresponds to equation (5) on page 20 in Autor et al. (2023) using the following regression:

$$\Delta \ln w_{ct} = \beta(1 - UR_{c,t-1}) + X'_{ct}\gamma + \alpha_c + \delta_t + \varepsilon_{ct}, \tag{29}$$

where c indicates counties, t indicates years. The UR is the unemployment rate, which 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.

where the corresponding estimate of Autor et al. (2023) is very close at 2.6%.

In Panel (b) of Figure 5 we document a novel relationship between wage dispersion and market tightness. The figure reveals a clear positive association: a 10% increase in the unemployment rate corresponds to a 0.4 increase in the standard deviation of wages.

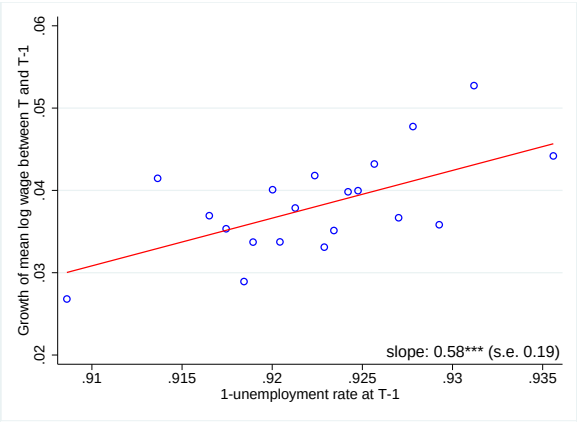
Next, we add new evidence for the relationship between market tightness and the *level* and *dispersion* of firm-specific wage premium. For this, we estimate firm-specific wage premia using the time-varying AKM approach (TV-AKM) of Lachowska et al. (2023a).[11] Panel (c) of Figure 5 shows that the positive relationship observed in panel (a), the 'wage Phillips curve' is partly due to firms: not only the individual-level wage, but also the firm wage premium grows faster in tighter labor markets. Panel (d) if Figure 5 shows a clear growth of the standard deviation of the firm-specific wage premium. This highlights that market tightness contributes to rising wage inequality, in part through firm-specific wage premiums.[12] The observed increase in firm-specific wage dispersion may stem from various sources. In our paper, we focus on one key source: the growing role of compensating variation, as demonstrated in the previous section. We now turn to assess this particular source by studying changes in compensation over the business cycle for one specific amenity: the workplace injury risk.

[11]This AKM regression is an extension of the original AKM model that allows for unrestricted interactions of year and firm indicators. Our estimation here is similar to the one estimated in (30), except we allow AKM varying at yearly level instead of the three-year period.

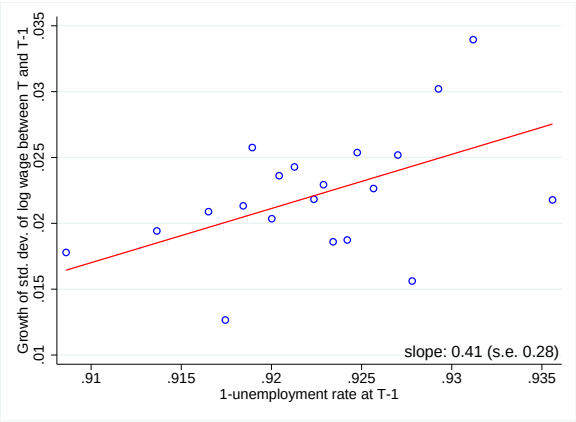
[12]Since workplace injury risk is mainly relevant for blue collar workers, we focus on them in the main analysis. In Appendix Figure E.1 we show that the relationships observed on Figure 5 also holds when we restrict the sample to our main empirical analysis.

Figure 5: Wage Phillips Curves

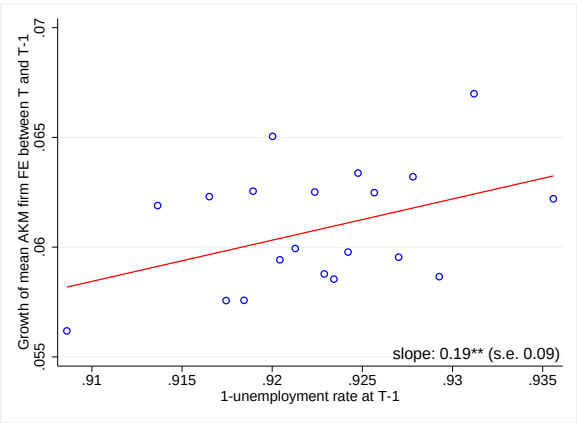
(a) Mean Log-Wage



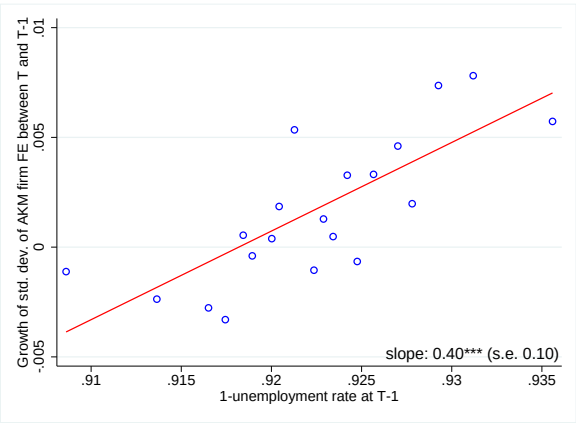
(b) Std. Dev. of Log-Wage



(c) Mean AKM Firm FE



(d) Std. Dev. of 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.

4 Data and Measurement

4.1 Data Sources

We rely on high-quality administrative data that allows us to study the link between (firm-specific) wage premium and injury rate. Our main data is an employer-employee linked panel dataset, covering a 50 percent random sample of the Hungarian population in 2003. Crucially, we do not only have information on workers' labor outcomes for 2003–2017, our data also contains their administrative health records for 2009–2017.[13] The health

[13]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 ELTE Centre for Economic and Regional Studies.

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.[14] Healthcare at public outpatient clinics and hospitals is funded by the social security, and no out-of-pocket payment is required.

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. Since workplace injury risks are mostly relevant for blue-collar workers, throughout the analysis we focus on blue collar workers aged 20–60 in the private sector.

To measure market tightness, we use the yearly county-specific unemployment statistics used for constructing our labor market tightness measure stems from the Hungarian Central Statistical Office. We also explore alternative measures taking into account job to job flows, and underemployment, following Autor et al. (2023) and Bell and Blanchflower (2013).

4.2 Firm-Specific Wage Premium

We are interested in the relationship between firm-level (dis)amenity and the change in firm-specific wage premium over the business cycle. We estimate the firm-specific wage premium for full-time workers using the following model of log wages:[15]

$$\ln w_{it} = X'_{it}\beta^w + \alpha_i^w + \phi^w_{j(i,t),T} + \varepsilon_{it}, \tag{30}$$

where i denotes individuals, j denotes firms. The $\phi^w_{j(i,t),T}$ represent firm fixed effects, estimated separately for three time intervals (2009–2011, 2012–2014, 2015–2017), with T denotes time periods. Our wage measure, w, 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, 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 follows Lachowska et al. (2023a). Note that we assume that the individual fixed effect is constant over time, allowing comparison of firm fixed effects over-time. Furthermore, relative to the traditional AKM model of Abowd et al. (1999), which is identified solely from movers between firms within a given period T, the time-varying AKM firm effects are identified from both workers who remain at the same

[14] The role of private care in the treatment of injuries – which is in the focus of our paper – is small (see e.g. Hüttl and Nagy, 2017 who estimate less than 10 percent of hospital care was provided by private hospitals).

[15] We exclude workers after the injury to make sure they do not bias our estimates.

firm across periods and from movers between firms.[16]

4.3 Firm-Specific Injury Risk

Our principal measure of firm-level (dis)amenity is workplace-specific injury risk, which we construct from administrative health record data. Injury risk has been a central focus in the amenity literature (see Mas, 2025, for a review). A key advantage of our approach is that it permits the calculation of injury risk for a large set of firms and across all periods, thereby enabling an analysis of within-firm wage premium dynamics over the business cycle.

Injury definition. We first identify if an individual is injured at a given month. Using diagnosis codes (ICD-10 codes) recorded at public outpatient clinics and hospitals, we flag individuals who suffer an injury.[17] To exclude minor cases, we restrict our attention to injuries that result in at least one day of sickness absence. In Hungary, workers who are unable to work for health-related reasons are entitled to sickness leave. The eligibility and the length of the leave depends on the injury and the workers' job and it is certified by a physician at an outpatient clinic.[18] Note that our injuries include all types of injuries, including those that took place outside of the workplace. As we will see later, we use a regression model to separate injuries to worker specific vs. firm specific component.[19]

This procedure yields a binary indicator of *injury diagnosis*. We define $S_{it} = 1$ if individual i is injured and on sickness leave in month t. For example, if an individual is injured in month t and the physician at the outpatient clinic certifies four months of sickness leave, then $S_{it} = 1$ for months t through $t + 3$.

In our sample, the chance of injury in a given month is 2.1% and 38% of those certified for a sickness leave. On average, injured people are on sickness leave for 39 days (with

[16] We show the variance decomposition of log wage in Appendix Table E.2. The variance shares of firm and person effects is around 30% each. The larger role of firms explaining wage variation comes from the fact that we focus here on blue-collar workers.

[17] Note, that ICD stands for International Classification of Diseases. We include all S and T ICD-10 diagnosis codes, making up the diagnosis 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. See Table E.1 for detailed list of ICD-10 codes and their share in injuries in our sample.

[18] The first 15 days of sickness leave are financed by the employer, during which employees receive 70% of their wage. After this period, the benefit is paid by the state at a replacement rate of 50–60%, depending on the worker's earnings history, for a maximum duration of one year.

[19] We conduct several robustness checks regarding injury definitions in Figure 9, for example by relaxing the requirement that an injury must result in at least one day of sickness absence, or by estimating standard, not time-varying AKM effects. Our data also allows us to directly identify injuries that occurred specifically at the workplace, in which case the sickness benefit equals 100% of the worker's previous wage. This measure, however, is prone to reporting bias: employees at lower-quality firms are more likely to under-report the workplace link when examined at outpatient clinics. To address this concern, our benchmark measure includes all injuries, while we report robustness results using the workplace-specific definition.

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.

Firm-specific risk of injury. Injuries may arise from a combination of personal and workplace-related factors. Some personal characteristics are observable (e.g., age, occupation), while others remain unobserved to us (e.g., dangerous hobbies, risk-taking behavior). Workplace conditions can also contribute to injuries, either directly on the job site or indirectly outside of work (e.g., through stress-related accidents). In addition, there are idiosyncratic components that cannot be attributed to either source.

Our baseline measure of workplace injuries assumes additive separability across these components. Specifically, in analogy to our wage equations, we consider the following model:

$$S_{it} = X_{it}'\beta^S + \alpha_i^S + \phi^S_{j(i,t),T(t)} + \varepsilon_{it}, \tag{31}$$

where t denotes monthly dates, 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, and $\phi^S_{j(i,t),T}$ is the three-year specific firm effect. To alleviate the noise in the estimation of $\phi^S_{j(i,t),T}$, we restrict the sample to those firm-year pairs in which, on average, we observe at least 20 (blue-collar) workers and apply empirical Bayes shrinkage a la Walters, 2024(details are in Appendix D, following). Finally, we standardize the estimated values of $\phi^S_{j(i,t),T}$ to have mean zero and standard deviation 1, as the firm-specific indicator of injury risk.

Basic descriptives. Appendix Figure E.2 shows the histogram of the firm-specific injury risk before standardization, it follows a normal distribution. Table 1 shows the variance decomposition of injury (S_{ijt}). 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. We also find some evidence for negative sorting: high risk firms tend to attract low risk prone individuals – making it harder to identify workplace effects in absence of controlling unobserved person effects.

Table 2 presents descriptive statistics on the relationship between firm-specific injury risk (column 1) or wage premium (column 2) and observable firm characteristics.

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 (31). Xb includes dummies of three-year groups, and the square and cube of (age − 40).

Larger firms, firms located outside Budapest (the capital of Hungary), and more productive firms appear to be more risk-prone. These firms also pay a higher wage premium, consistent with the prediction that workers receive some compensation for such risks. Nevertheless, the positive association between these firms characteristics and the wage premium is likely to be influenced by other factors (e.g. firms face upward sloping labor supply).

A more striking source of heterogeneity emerges across industries, as shown in Panel D. As expected, manufacturing (the reference category) and construction are more risk-prone than other sectors, while services and retail appear to be the least risk-prone. Interestingly, this pattern closely mirrors the observed wage premium, suggesting that compensating differentials may play a role in explaining industry wage premia.

Diagnostic Tests. A key assumption in measuring work-place specific injury risk based on equation 31 is the additivity between person and workplace effects. These assumptions is arguably strong. To provide empirical support for underscoring that this assumption holds, we can apply the same test developed to test the additivity assumption of log wages in the AKM literature (see Card et al. (2013)). We provide three diagnostic test here.

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 (31) 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 E.3 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.

Second, the additivity assumption implies that, conditional on person and firm effects, mobility is close to random. This rules out Roy-type selection based on unobserved

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	0.021***	0.059***
	[0.004]	[0.009]
250+	0.022***	0.125***
	[0.003]	[0.010]
Panel B: Location		
Budapest commuting zone	-0.017***	0.036***
	[0.004]	[0.009]
Panel C: Firm productivity		
Above median TFP	0.025***	0.241***
	[0.003]	[0.007]
Panel D: Industry (ref.: manufacturing)		
Wholesale and retail	-0.043***	-0.054***
	[0.005]	[0.011]
Construction	-0.002	-0.056***
	[0.008]	[0.019]
Transportation	-0.031***	-0.068***
	[0.006]	[0.016]
Services	-0.043***	-0.104***
	[0.004]	[0.010]
Other	-0.014**	-0.020*
	[0.006]	[0.012]
Number of observations	11,070	11,070
Number of firms	5,319	5,319
Mean	-0.004	0.097
Std. dev.	0.120	0.324

Notes: Table shows OLS regression results for the relation of firm-specific injury risk (estimated by equation (31), not standardized) and firm-specific wage premium (estimated by equation (30)) 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.

idiosyncratic components. Following Card et al. (2013), we test for such selection by examining the symmetry of injury rate changes among workers who move from high-risk to low-risk firms or vice versa. We present the results following the approach of Chetty et al. (2014) and Sorkin (2017), who applied this test to support teacher value-added and AKM firm wage-premium effect estimates, respectively. Specifically, we regress the three-year change in individual injury rates on the three-year change in firm-specific injury risk for movers. If firm-specific injury risk is not driven by Roy-selection (or some match effects), the slope of this regression should be close to 1, and the relationship should be approximately linear. The estimated slope, shown in Appendix Figure E.5: the slope is 0.95 and the relationship is linear. We find no indication for assymetric change in risk for those who move higher or lower risk firms.

Third, we test whether mobility driven by idiosyncratic shocks could bias the estimates. To do so, we examine the injury rates of workers who move between firms, distinguishing by the risk categories of the origin and destination firms. Two key patterns emerge.

First, we find no evidence of transitory changes in injury rates prior to firm transitions, regardless of mover type. Second, injury rates decline for workers who move from high-risk to low-risk firms, while the opposite holds for those moving from low-risk to high-risk firms. These patterns suggest that moving to a higher- or lower-risk firm affects injury risk in an additive manner.

Cyclicality of firm-specific injury risk. Our primary objective is to examine how compensating variation changes over the business cycle. In the ideal case, amenities are fixed, allowing us to directly study whether the compensation associated with a given (dis)amenity varies with labor market tightness. In practice, however, amenities may not be entirely fixed but may fluctuate for reasons unrelated to market conditions. This would still allow us to test for compensating varion.

A more problematic scenario would arise if workplace injury risk itself were cyclical. For instance, tighter labor markets might be associated with higher workloads, increased time pressure, or staffing shortages, all of which could adversely affect worker health and safety. However, we find no evidence of such a relationship: the correlation between changes in labor market tightness and changes in firm-specific injury risk is essentially zero (see Appendix Figure E.6).We also find no evidence of a relationship between changes in market tightness and healthcare utilization following injuries. This suggests that neither injury incidence nor severity exhibits cyclical behavior.[20]

In Appendix Table E.3, we further test whether market tightness systematically affects changes in risk across high- and low-risk firms. Specifically, we regress firm-specific injury risk on labor market tightness, its lag, and their interaction. While we find a strong correlation between current and lagged firm-specific risk, this relationship does not vary with changes in market tightness. This result reinforces the conclusion that changes in firm-level injury risk are not systematically related to fluctuations in market tightness."

Correlation with other amenities.An important question is how firm-specific injury risk relates to other workplace amenities, and whether this relationship is cyclical. Unfortunately, our administrative data do not allow us to measure other amenities directly. To address this, we draw on the European Working Conditions Survey (EWCS; see Appendix A for details), which contains information on a range of workplace amenities, including health risks at work. In Appendix A, we show that health risk at work (a "bad" amenity) is negatively correlated with "good" amenities, such as working hours that fit family life, the absence of abuse at work, high perceived quality of management, and overall satisfaction with working conditions. This negative correlation implies that our

[20]There is evidence in the literature that workplace injury rates are pro-cyclical, although the magnitude of this relationship varies across industries (Davies et al., 2009; Asfaw et al., 2011). Boone et al. (2011) argue, however, that the observed cyclicality largely reflects differences in reporting practices rather than actual variation in injury incidence. Importantly, our measure of firm-specific injury risk – based on including all injuries and estimating a person and firm effects – is not subject to such reporting biases.

firm-level injury risk measure reflects not only that specific amenity but also a broader bundle of unfavorable job attributes.[21]

Importantly, the EWCS also allows us to examine whether this correlation varies over the business cycle. We find no evidence that the correlation changes with rising unemployment, suggesting that the relationship is stable over time. While this constitutes only indirect evidence of stability, we later provide a more direct test. Motivated by our model, we estimate the marginal willingness to pay (MWTP) for firm-specific injury risk over the business cycle and show that it remains constant. Viewed through the lens of our model, this proves that the amenity bundle proxied by our firm-level injury risk measure does not vary systematically over the business cycle.

5 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.

5.1 Baseline Specification

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

$$y_{jt} = \beta \text{tight}_{r(j),t} \times \text{risk}_{jt} + \gamma_{1t} \text{tight}_{r(j),t} + \gamma_{2t} \text{risk}_{jt} + \theta X_{jt} + \mu_j + \delta_t + \varepsilon_{jt}, \tag{32}$$

where the outcome variable, y_{jt}, is either the firm-specific wage premium (AKM firm FE) or one of the separation rate measures. risk_{jt} is the standardized firm-specific injury risk (i.e., the standardized value of $\phi^S_{j(i,t),T}$ from equation (31)). 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 controls X_{jt} includes the mean age, sex, person fixed effect of the injury (mean of α^S_i from equation (31)), and occupation composition of the workers (with one-digit occupations). μ_j are firm fixed effects and δ_t are time effects (2009-2011, 2012-2014, 2015-2017) .

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

[21] The positive correlation of amenities is well documented in the literature (see Sockin (2022)).

Appendix Table E.4, in which we extend the X's with county and industry effects.

In equation (32), the γ's are t-specific. This specification avoids a potential concern that the coefficient estimate on the interaction term ($\hat{\beta}$) may otherwise be driven by aggregate time trends either in risk or in tightness. We also estimate an alternative 'with net-of-time variables' specification, in which we first net-out the time period effects from the firm-specific injury risk and labor market tightness measures (risk^D_{jt} and $\text{tight}^D_{r(j),t}$) and include these variables in the regression with time-invariant coefficients:

$$y_{jt} = \tilde{\beta}\text{tight}^D_{r(j),t} \times \text{risk}^D_{jt} + \tilde{\gamma}_1\text{tight}^D_{r(j),t} + \tilde{\gamma}_2\text{risk}^D_{jt} + \tilde{\theta}X_{jt} + \tilde{\mu}_j + \tilde{\delta}_t + \tilde{\varepsilon}_{jt}. \tag{33}$$

5.2 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:

$$z_{r(j)t} = \sum_{k=1}^{K} s^0_{r(j)tk} g_{tk}, \tag{34}$$

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 (32) with $z_{r(j)t}$.[22]

5.3 Event Study Approach

As an alternative specification, we conduct an event study analysis to estimate the relationship between firm-specific risk and wages, and its heterogeneity by tightness. This approach takes a step towards estimating the causal effect of firm-specific injury risk on wages, while still focusing on the heterogeneity of this effect by labor market tightness.

Here, we focus on blue-collar workers moving between firms, and look at their wages and injury rates ±2 years around the move. To identify likely voluntary moves, we use

[22] Specifically, we predict $\text{tight}_{r(j)t}$ with $z_{r(j)t}$, $z_{r(j)t} \times \text{risk}_{jt}$, risk_{jt}, $z_{r(j)t} \times D_t$ and D_t, 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 $\widehat{\text{tight}}_{r(j)t} \times D_t$.

monthly data, and focus on workers who work at different firms in two consecutive months. We define high (low) labor market tightness as above- (below-) median tightness (one minus unemployment rate) both before and after the move, where the median is calculated by three-year periods. We categorize firms to bottom vs. top third of the firm-specific injury risk (estimated in equation (31)). We exclude workers in the middle category and confirm that results are robust to categorizing firms to below vs. above median injury risk.

We estimate the following event study regression model, separately for tight labor markets and for slack labor markets:

$$y_{ith} = \sum_{k=-2}^{1} \alpha_k \mathbb{1}[e_{ith} = k] + \sum_{k=-2}^{1} \beta_k \mathbb{1}[e_{ith} = k] \times \text{HighRisk}_{j(i)th} + \mu_{ih} + \delta_{th} + u_{ith}, \quad (35)$$

where i denotes individuals, t denotes monthly date, h denotes the monthly date of the move, $\mathbb{1}[e_{ith} = k]$ are event dummies indicating ± 2 years around the move (with event time 0 indicating the first twelve-month period after the move), and $\text{HighRisk}_{j(i)t}$ captures the risk category of the destination firm at the time of the move. The outcome variable y_{it} is the log wage, the binary indicator of having an injury, or the firm-specific injury risk. Our focus is on the β_k coefficients, and their difference between high- and low-tightness environments. We cluster standard errors by person by date of move.

This specification follows the stacked event study estimator of Cengiz et al. (2019). As explained by Cengiz et al. (2019), this approach aligns events by event-time, and is equivalent to a setting where the events happen all at once and are not staggered, avoiding negative weighting of some events that may occur under a staggered design. This is achieved by including in equation (35) person by date of move fixed effects (μ_{ih}), and calendar time (monthly date) by date of move fixed effects (δ_{th}).

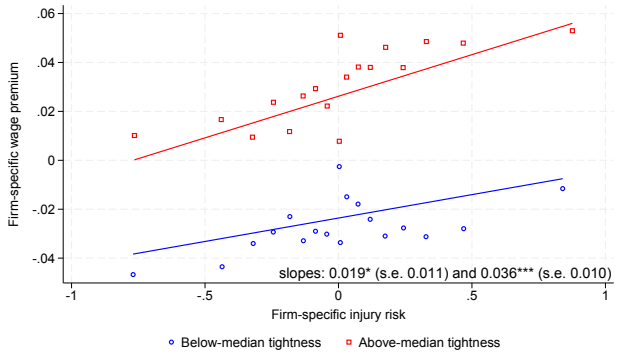
6 Evidence for Compensating Wage Differentials

In this Section, we first present our baseline estimates for the relationship between the firm-specific injury risk and the firm-specific wage premium, and to what extent this relationship depends on the level of labor market tightness in a county (in Section 6.1), by estimating models (32) and (33) from Section 5.1 . Next, in Section 6.2, we present the results of numerous robustness checks and responses to various threats to identification: we present the results of the shift-share Instrumental Variable strategy, the Event Study strategy, and estimates if using alternative measures of tightness and risk. We slso show reassuring evidence that marginal willingness to pay does not vary with labor market tightness. Finally, in Section 6.3, we quantify the share of Compensating Wage Differentials in explaining the larger dispersion of the firm-specific wage premium in tighter markets.

6.1 Baseline Results for the Firm-Specific Wage Premium

Figure 6 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 6: 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, and firm effects.

Main Estimates. We present the estimates from equation (32) in the top panel of Table 3.[23] 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).[24] In the bottom panel, we report the results without time effects or time-varying coefficients, stemming from equation (33). The baseline coefficient estimates on the interaction term (column (1)) are very similar under specifications (32) and (33). We consider the model with time-varying coefficients (32) as our preferred specification because that takes aggregate time trends into account in a single regression.

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 2.1 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.[25]

In columns (2)-(5) of Table 3, we present four robustness checks to estimates in column (1): (i) in column (2), we exclude the control variables (vector X_{jt} in equation (32)); (ii)

[23] We report the full set of coefficients in column (1) of Appendix Table E.6.

[24] We present OLS regression results (without firm fixed effects) in Appendix Table E.4.

[25] We show in Appendix B that our results are robust to estimating the relation of injury risk and labor market tightness to individual-level wage.

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 sample of 2009–2017. Our estimates, especially the estimated coefficient on the interaction between labor market tightness and firm-specific injury risk, are very similar across the robustness checks around the baseline estimate of 0.021.

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	(6) IV
Baseline						
tight × risk	0.021***	0.021***	0.020**	0.020***	0.023***	0.023**
	[0.007]	[0.007]	[0.008]	[0.007]	[0.008]	[0.010]
With net-of-time variables						
tight × risk	0.021***	0.021***	0.018**	0.020***	0.023***	0.024**
	[0.007]	[0.007]	[0.008]	[0.007]	[0.008]	[0.010]
tight	0.078***	0.079***	0.043**	0.079***	0.087***	0.093***
	[0.014]	[0.014]	[0.020]	[0.014]	[0.016]	[0.019]
risk	0.014**	0.013**	0.012	0.013**	0.016**	0.015*
	[0.006]	[0.006]	[0.007]	[0.006]	[0.007]	[0.008]
observations	9,208	9,208	7,014	8,733	6,842	9,208

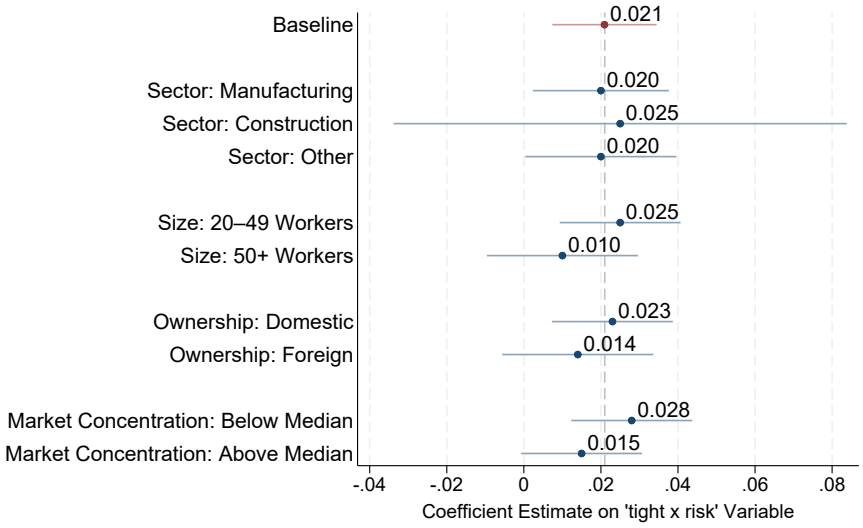
Notes: Table shows estimated coefficients of equations (32)-(33). In column (6), we instrument labor market tightness with the shift-share instrument $z_{r(j)t}$. Variable "tight" is the county-level labor market tightness, "risk" is the firm-specific injury risk. Control variables: mean age, sex, and 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.

Heterogeneities. To analyze heterogeneities in the relation of injury risk and labor market tightness to firm-specific wage premium, we extend equation (32) 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 Figure 7. We estimate a separate regression for each subgroup.

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[26] being below vs. above its median.

Figure 7: Heterogeneity: Relation of Risk and Tightness to Firm-Specific Wage Premium



Notes: Figure shows the estimated β coefficients on the tight $\times$ risk variable, with 95% confidence interval, stemming from equation (32), for various subgroups. The baseline point estimate is 0.02093 with SE estimate of 0.006905.

6.2 Robustness and Threats to Identification

Shift-Share Instrument for Labor Market Tightness. First, we apply the shift-share IV strategy introduced in Section 5.2, and report the IV estimates of the interaction coefficient between firm-specific risk and tightness in column (6) of Table 3. 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.[27]

Event Study Results. Next, we turn to the event study approach introduced in Section 5.3, and present the β_{ik} coefficients of equation (35) in Figure 8. This approach aims to estimate a causal effect of firm-specific injury risk on wages, while focusing on its heterogeneity by labor market tightness. Panel (a) shows the effect of moving to a high-risk firm on the yearly measure of firm-specific injury risk. Note, that here we do not standardize the firm-specific injury risk, in order to visualize the magnitude of the actual injury rate. The estimated effect on the firm-specific injury risk is close to 10 percentage

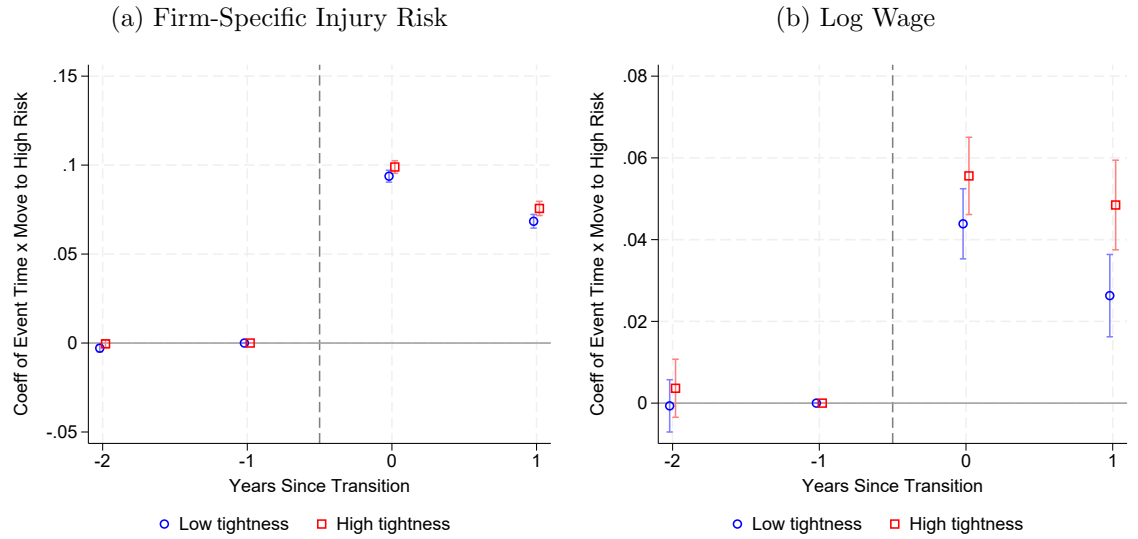
[26]We calculate the Herfindahl–Hirschman index at the county and three-year level as $\sum_j p_j^2$, where p_j is the employment share of firm j in the given county in the given three-year period.

[27]When forming our IV, the prediction for $\text{tight}_{r(j)t}$ with $z_{r(j)t}$, $z_{r(j)t} \times \text{risk}_{jt}$, risk_{jt}, $z_{r(j)t} \times D_t$ and D_t yields an F statistics of $1,240$; then, the first-stage F statistics for $\text{tight}_{r(j)t}$ is 639, indicating a very strong first-stage relationship, and no concerns of weak instruments.

points in the first year after move and around 7 percentage points in the second year, with little heterogeneity by labor market tightness. Panels (b) of the figure shows that moving to a high-risk firm, as opposed to a low-risk firm, leads to around 5% higher wage growth, and this wage growth increases with labor market tightness.

The event study estimates can be compared to our baseline estimates. In the sample of movers, the standard deviation of the firm-specific injury risk is 0.09. Therefore, the estimated event study results imply that if the firm-specific injury risk increases by one standard deviation then wages grow about 1.8 percent more in tight labor markets than in slack labor markets, over a two-year horizon after the move.[28] The average difference in unemployment rate between tight vs. low labor markets is 4.6 percentage points. Assuming linear relationships, it follows that a one standard deviation increase in firm-specific injury risk is estimated to lead to around 3.9 percent higher wages if labor market tightness increases by 10 percentage points (we obtain the 3.9 percent result from $1.8 \times 10/4.6$). This estimated effect is higher than but still comparable to the estimated 2.1 percent increase in the wage premium under the baseline specification.

Figure 8: Stacked Event Study Estimates for the Effect of Moving to High-Risk Firm



Notes: Figure shows estimated β parameters of equation (35) with 95% confidence intervals, following the stacked event study estimator of Cengiz et al. (2019). The move takes place between the last month of event year -1 and the first month of event year 0. High (low) tightness indicates above- (below-) median labor market tightness, measured by one minus unemployment rate at the county level.

Change in Amenity Valuations (MWTP Test). In Section 2, following Mas (2025), we showed that the marginal willingness to pay (MWTP) for amenities can be estimated using voluntary work separations and that such marginal willingness to pay

[28]The average estimated increase in the firm-specific injury risk in the first two years after move is 0.084. The average gap in the estimated wage effects between high and low tightness markets is 1.7 percent. We then calculate $1.7 \times 0.09/0.084 = 1.8$.

should not vary with one minus the unemployment rate.

To obtain the MWTP value of equation (16), we use the one minus the voluntary separation rate as a measure of retention rate (RR), use the firm-specific wage premium measure for w. We measure (dis)amenities (a) with the firm-specific injury risk.

We obtain the partial effects from the following model for firm j at time t:

$$RR_{jt} = \alpha X_{jt} + \beta_1 risk_{jt} + \beta_2 risk_{jt} \times tight_{jt} + \gamma_1 w_{jt} + \gamma_2 w_{jt} \times tight_{jt} + \delta_t + u_{jt}, \quad (36)$$

where vector X includes industry, county, and worker composition measures (occupation, sex, age, and worker risk composition). We cluster the standard errors on the firm level. The labor market tightness measure is either continuous or binary, indicating above-median tightness. When working with the continuous measure, we calculate the MWTP value (from equation (16)) at the 10th and 90th percentile of the tightness distribution.

Appendix Table E.5 indicates that the MWTP for the injury risk is around -0.05 both in low and high tightness labor markets. While the MWTP estimates are significantly different from zero, the estimates do not differ statistically between low and tight labor markets. The estimated MWTP of around -0.05 indicates that workers are willing to pay around 5% of their wages to decrease the firm-specific injury risk by 1 standard deviation, which corresponds to a one percentage point decrease in the monthly probability of injury (using that the standard deviation of annual, non-standardized injury risk is 0.121).

Robustness to Alternative Injury Risk Measures. In the upper panel of Figure 9, we report the coefficient of the interaction term in equation (32) with eight alternative 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 injuries not conditional on sick leave absence afterwards; (5) 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); (6) injury rate at the firm; (7) baseline risk measured at the first three-year period (i.e., 2009–2011), and (8) constant risk throughout 2009-2017.[29] All firm-specific risk measures are standardized values, and, except for the injury rate at firm, are based on the estimation of equation (31).[30] We do no use definition (5) as our base baseline risk definition because it is known that there is substantial under-reporting of workplace accidents[31], whereas our baseline definition is not subject to such reporting issues because

[29]The correlation coefficient of the baseline firm-specific injury risk with measures (1), (2), (3), (4), (5), (6), (7), and (8), respectively, is 1,00, 0.87, 0.83, 0.80, 0.65, 0.51, 0.86, and 0.91.

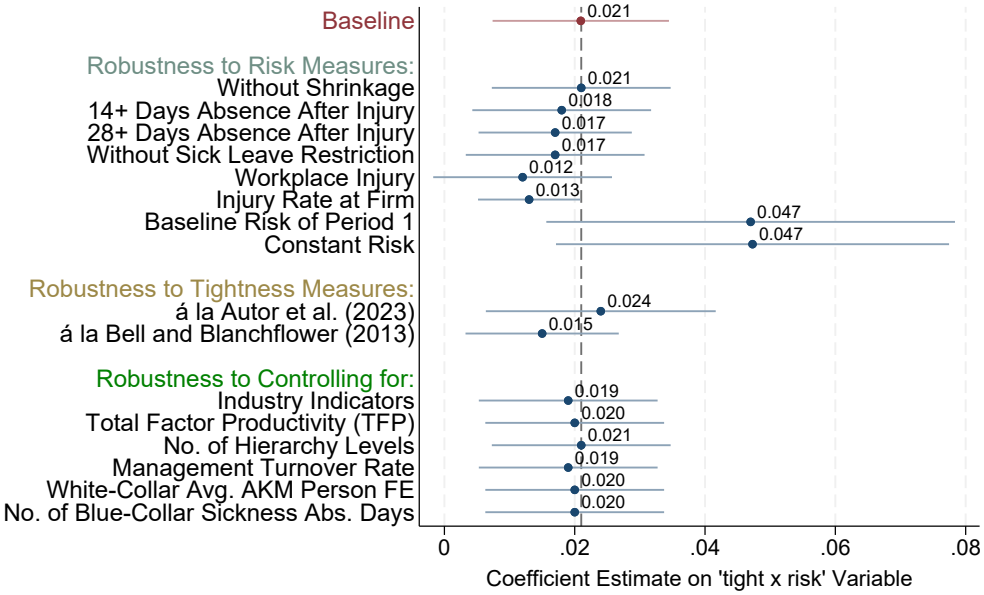
[30]For the risk indicators (2) and (3), we apply the empirical Bayes shrinkage, using the bootstrap estimate of the variance of the estimated baseline risk.

[31]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.

it is based on diagnosis codes and all categories of sickness absence.

Figure 9 shows 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 with stricter definitions of the injury risk and under the specification using the injury rate at firm as risk measure (except for the coefficient in the log size model, which is statistically insignificant under all specifications except for the specification with the injury rate). Finally, when we use the baseline risk of period 1 or a constant risk measure, the point estimates of the interaction term are about twice as big as the baseline estimate but with larger standard error.

Figure 9: Robustness: Relation of Risk and Tightness to Firm-Specific Wage Premium



Notes: Figure shows the estimated β coefficients on the tight $\times$ risk variable, with 95% confidence interval, stemming from equation (32), under various robustness checks. The baseline point estimate is 0.02093 with SE estimate of 0.006905.

Robustness to Alternative 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 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 ($\sum h$):

$$\text{underemployment} = \frac{U\bar{h} + \sum \tilde{h}}{U\bar{h} + \sum h}. \tag{37}$$

We define tightness measured based on the underemployment indicator as ten times the negative underemployment rate. We report in Figure 9 the coefficient of the interaction term in equation (32) using the two alternative definitions of tightness. Although there are some variations in the point estimates, the results are qualitatively robust.

Robustness to Including Further Firm-Level Variables as Controls. 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 market tightness. Because of this concern, we extend equation (30) 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)[32]; (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 (30) 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 Figure 9. The results are very robust to the analyzed extensions, indicating that our results are not driven by varying effects of labor market

[32]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.

tightness across industries, by productivity, management structure and quality, quality of white-collar workers, or sickness absence of blue-collar workers.

In Appendix Table E.7 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-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.

6.3 Back-Of-The-Envelope Estimates

Next, we quantify what our baseline estimate of 0.021 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,[33] 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 (32) 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.

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)	(9)	(10)
			$\hat{\beta} = 0.021$		$\hat{\beta} = 0.00739$		$\hat{\beta} = 0.03446$		$\hat{\beta} = 0.04729$	
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	SD $\tilde{y}^{CF}_{jt}$	CWD
D2	0.2104									
D9	0.2417	6.60 pp	0.2394	7.28%	0.2408	2.79%	0.2383	10.96%	0.2374	13.67%
D10	0.2489	7.85 pp	0.2462	7.03%	0.2478	2.76%	0.2450	10.23%	0.2442	12.27%

Using our baseline $\hat{\beta} = 0.021$, 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 0.0022 units lower, implying a Compensating Wage Differential (CWD) share of

[33] We describe these steps in detail in Appendix C.

7.28 (7.03) percent (column (4) in Table 4). With the upper bound of $CI^{95}_{\hat{\beta}}$, these shares are 10.96 and 10.23 percents, respectively (columns (7)-(8)). Finally, if we use the point estimate of β using constant risk as shown in the robustness check in Figure 9, then the CWD shares increase to 13.67 and 12.27 percents, respectively (columns (9)-(10)).

7 Evidence for Under-Compensation for Disamenities

7.1 Baseline Results for Separation Rates

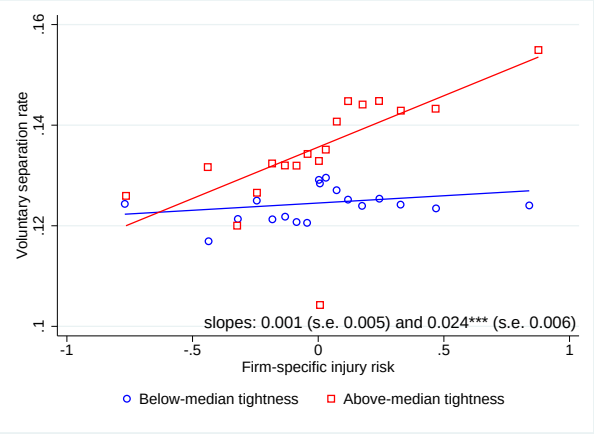
Figure 10 illustrates the relation between firm-specific injury risk and separation rates[34] We use the three-yearly average of monthly employer-to-employer transition rate, multiplied by 12, to capture annual rates. The so defined employer-to-employer transition rate is then our measure for *voluntary separation rate (VSR)*.

Separation Rate. Our second measure of separation rate of blue collar workers is broad *separation rate (SR)*. 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 voluntary separation rate measure. We use the three-yearly average of monthly separation rate, multiplied by 12. , 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 in the labor market, suggesting that negative preferences for high-risk firms increase with tightness.

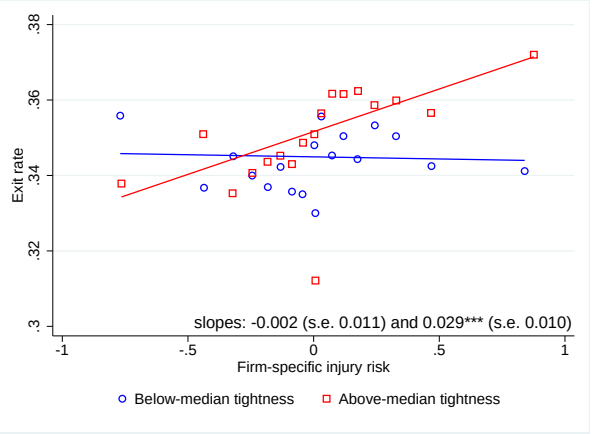
[34]We define voluntary separation rate as an employer-to-employer transition where the worker does not return to the firm within three month. To make sure that a change of the firm identifier does not lead to a false move, we apply the worker-flow method of detecting firm identifier changes as in Saygin et al. (2021). Separation rate is calculated without those who ever suffered an injury to ensure that injuries do not have mechanical effect separation rate (as during sickness leave workers cannot be laid-off). Furthermore, we exclude workers who retire or go on parental leave.

Figure 10: Relation Between Injury Risk and Separation Rate

(a) Voluntary Separation Rate



(b) Separation Rate



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

Main Estimates. The main estimates stemming from equation (32) are in column (1) of Table 5,[35] and show that the effect of the firm-specific injury risk on separation rates increases with labor market tightness; thus, the negative preferences for high-risk firms increase with tightness. Specifically, a one standard deviation increase in firm-specific injury risk leads to 1.7 percentage points (s.e. 0.005) higher voluntary separation rate and 2.9 percentage points (s.e. 0.011) higher (broad) separation rate if labor market tightness increases (i.e., unemployment rate decreases) by 10 percentage points.

In columns (2)–(5) of Table 5, we perform the same robustness checks as for the firm-specific wage premium in Section 6.1. Overall, the results are robust. Note, that if we exclude the Budapest commuting zone from the sample (column (3)), then the coefficient estimate of the interaction becomes more imprecise, but the estimated patterns remain.

Heterogeneities. As Figure E.7 shows, there are no major and statistically significant heterogeneities for either of the separation rate outcomes.

[35]We report the full set of coefficients in columns (2)-(3) of Appendix Table E.6.

Table 5: Relation of Risk and Tightness to Separation Rates

	(1) Baseline	(2) No controls	(3) Excluding Budapest CZ	(4) Excluding construction	(5) Balanced sample	(6) IV
Dependent variable: Voluntary Separation Rate						
tight × risk	0.017***	0.016***	0.013**	0.016***	0.017***	0.017**
	[0.005]	[0.005]	[0.006]	[0.005]	[0.005]	[0.007]
Dependent variable: Separation Rate						
tight × risk	0.029***	0.028**	0.019	0.031***	0.026**	0.029**
	[0.011]	[0.011]	[0.014]	[0.011]	[0.011]	[0.014]
observations	9,208	9,208	7,014	8,733	6,842	9,208

Notes: Table shows estimated β coefficients of equations (32). 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.

7.2 Robustness and Threats to Identification

In Table 5, we also apply the shift-share IV strategy introduced in Section 5.2, and report the IV estimates of the interaction coefficient between firm-specific risk and tightness in column (6) of Table 5. The IV estimates are very close to the baseline ones.

In Figure E.8, we show evidence that the results for separation rates are robust to the use of other firm-specific injury risk definitions, to alternative tightness measures, and to the addition of further firm-level outcomes as control variables.

8 External Validity

Revealed preferences capturing amenities. So far we used the firm-specific injury risk measure as a proxy for bad amenities. Also, in Figure 10, we have seen that voluntary separation rate and (broad) separation rate are positively correlated with the firm-specific injury risk.

In this section, we take a broader perspective, and capture amenities provided by the firm by the firm-specific separation rate ("revealed preference"). More specifically, we capture revealed preference with the voluntary and broad separation rate from the firm. Note, that for both measure, a higher value indicates lower preference for the firm. We net each revealed preference measure of AKM firm FE, mean age, sex, and occupation composition of workers, county, industry, and time effects, although we also check the sensitivity of our results to not netting out AKM firm FE. To reduce simultaneity problems, we consider the lagged residualized revealed preference measure (measured in the previous three-year period), and use its standardized version in the following regression:

$$y_{jt} = \beta \text{tight}_{r(j),t} \times \text{RP}_{jt-1} + \gamma_{1t} \text{tight}_{r(j),t} + \gamma_{2t} \text{RP}_{jt-1} + \theta X_{jt} + \mu_j + \delta_t + \varepsilon_{jt}, \qquad (38)$$

where y_{jt} is the firm-specific wage premium (AKM firm FE), and we use the same notation and include the same control variables as in equation (32), and RP denotes the standardized residual revealed preference measure.

The estimates in Table 6 are in line with our baseline estimates (Table 3): the marginal effect of workplace disamenity (captured by higher Revealed Preference values) on the firm-level wage premium increases with labor market tightness. This result is robust to the two Revealed Peference measures, and to netting out the AKM firm FE.

Table 6: Relation of Lagged Revealed Preference Measures to Firm-Specific Wage Premium

	(1) AKM firm FE	(2) AKM firm FE
Panel A: AKM Firm FE Netted Out From Revealed Preference Measures		
tight × std lagged RP	0.010***	0.008**
	[0.004]	[0.004]
Panel B: AKM Firm FE Not Netted Out From Revealed Preference Measures		
tight × std lagged RP	0.011***	0.010**
	[0.004]	[0.004]
RP measure	VSR	SR
observations	7,767	7,767

Notes: Table shows estimated coefficients of equation (38). Variable "tight" refers to the county-level labor market tightness. RP denotes revealed preference, with a higher value indicating lower preference for the firm. VSR abbreviates voluntary separation rate, SR abbreviates (broad) separation rate. 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.

Relationship between revealed preferences and wage premium. Next, we turn to the relation of revealed preferences (captured by the retention rate), and the mean and dispersion of firm-specific wage premium, separately for labor markets that are characterized by tightness below- and above the median. In this approach, we follow Figure V of Sorkin (2018), with the extension of heterogeneity by labor market tightness. Our main results presented so far suggest that as labor market tightness increases, the variation of compensating differentials increases – firms with worse amenities need to provide higher wage compensations at tighter markets. In Figure 11, we generalize this concept to the relation between revealed preferences (instead of the firm-specific risk measure we used so far) and the firm-specific wage premium.

Similarly to the results of Sorkin (2018), the upward slope in the fitted lines on panels (a) to (d) of Figure 11 show that higher firm-specific earnings are reflected in higher revealed preferences (higher retention rate). We also see that on average, the firm-level wage premium has a closer relation to the revealed preference proxies at tighter markets.[36]

The dispersion of compensating differentials is higher at above-median tightness than

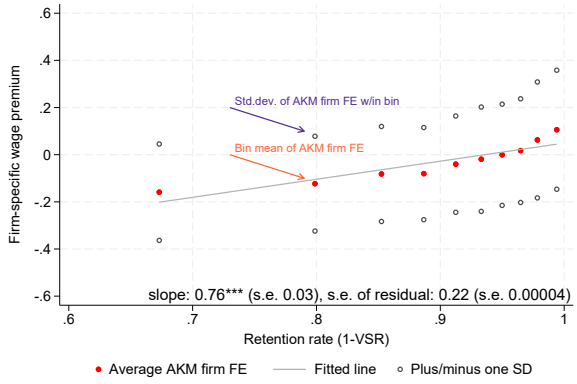
[36]Our focus here is on the standard deviation of the firm-specific wage premium. As this dispersion measure is not scale-invariant, to ensure that the dispersion measures are not driven by aggregate trend in the three-yearly firm-specific wage premium, we net out time effects from the firm-specific wage premium in this exercise.

at below-median tightness labor markets. We display the average value of the within-bin standard deviation of the firm-specific wage premium in the bottom right corner of each panel of Figure 11, and show the standard deviation in Appendix Figure E.9.

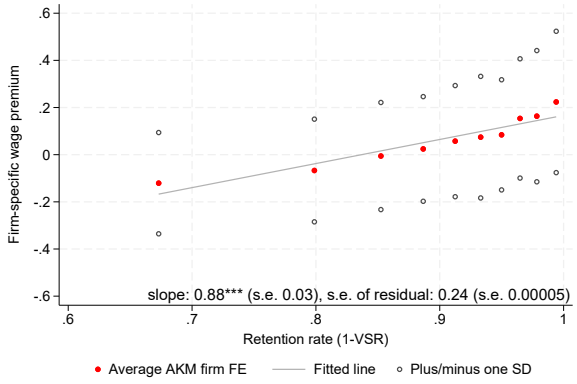
In Appendix F shows that we obtain similar results if instead of retention rates, we use the Sorkin index (following Sorkin (2018)) as a measure of revealed preferences for the firm.

Figure 11: Relation Between Retention Rates and Firm-Specific Wage Premium

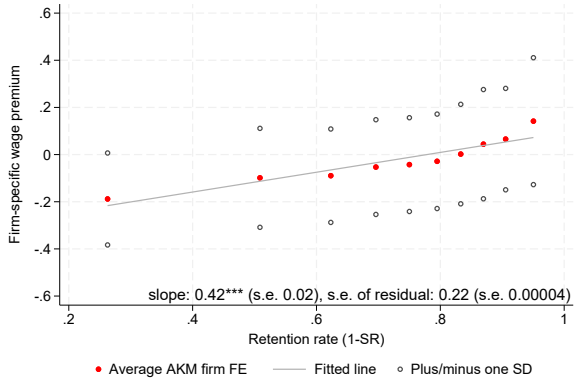
(a) Firm-Specific Wage Premium and Retention Rate (1-VSR), Below-Median Tightness



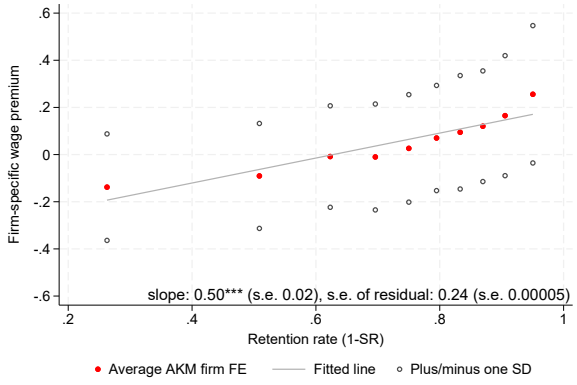
(b) Firm-Specific Wage Premium and Retention Rate (1-VSR), Above-Median Tightness



(c) Firm-Specific Wage Premium and Retention Rate (1-SR), Below-Median Tightness



(d) Firm-Specific Wage Premium and Retention Rate (1-SR), Above-Median Tightness



Notes: Figure shows binscatter plots (with fitted lines) of firm-specific wage premium with 10 equal sized bins of the firm dynamics measure indicated on the x-axis. The dashed lines show the bin-specific mean plus and minus one standard deviation of the firm-specific wage premium within the bin. Left-hand-side panels show these patterns for low (below-median) tightness labor markets, right-hand-side panels show these patterns for high (above-median) tightness labor markets. VSR abbreviates voluntary separation rate.

9 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 higher separation rate than in slack labor markets.

Our results, through the lens of our search model 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 for workers increases compensation for risk, leading to more dispersion in wages, but not necessarily to higher dispersion in utility.

References

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High Wage Workers and High Wage Firms. *Econometrica*, 67(2):251–333.

Adams-Prassl, A., Le Barbanchon, T., and Marcato, A. (2022). On-The-Job Training and Labor Market Competition. *SSRN WP 4477642*.

Asfaw, A., Pana-Cryan, R., and Rosa, R. (2011). The Business Cycle and the Incidence of Workplace Injuries: Evidence From the USA. *Journal of Safety Research*, 42(1):1–8.

Autor, D., Dube, A., and McGrew, A. (2023). The Unexpected Compression: Competition at Work in the Low Wage Labor Market. *National Bureau of Economic Research*, WP 31010.

Bana, S., Bedard, K., Rossin-Slater, M., and Stearns, J. (2023). Unequal Use of Social Insurance Benefits: The Role of Employers. *Journal of Econometrics*, 233(2):633–660.

Bartik, T. J. (1991). Who Benefits From State and Local Economic Development Policies. *Kalamazoo, MI: WE Upjohn Institute for Employment Research*.

Bell, D. N. and Blanchflower, D. G. (2013). Underemployment in the UK Revisited. *National Institute Economic Review*, 224:F8–F22.

Bender, K. A. and Mridha, H. (2011). The Effect of Local Area Unemployment on Compensating Wage Differentials for Injury Risk. *Southern Economic Journal*, 78(2):287–307.

Bíró, A. and Elek, P. (2025). Firm Quality and Health Maintenance. *Journal of Health Economics*, 103:103045.

Bonhomme, S., Holzheu, K., Lamadon, T., Manresa, E., Mogstad, M., and Setzler, B. (2023). How Much Should We Trust Estimates of Firm Effects and Worker Sorting? *Journal of Labor Economics*, 41(2):291–322.

Boone, J., Van Ours, J. C., Wuellrich, J.-P., and Zweimüller, J. (2011). Recessions Are Bad for Workplace Safety. *Journal of Health Economics*, 30(4):764–773.

Borusyak, K., Hull, P., and Jaravel, X. (2024). A Practical Guide to Shift-Share Instruments. *National Bureau of Economic Research*, WP 33236.

Brunello, G. and Gambarotto, F. (2007). Do Spatial Agglomeration and Local Labor Market Competition Affect Employer-Provided Training? Evidence From the UK. *Regional Science and Urban Economics*, 37(1):1–21.

Burdett, K. and Mortensen, D. T. (1998). Wage Differentials, Employer Size, and Unemployment. *International Economic Review*, 39(2):257–273.

Burya, A., Mano, R., Timmer, Y., and Weber, A. (2023). The Wage Phillips Curve under Labor Market Power. *AEA Papers and Proceedings*, 113:110–13.

Caliendo, L., Monte, F., and Rossi-Hansberg, E. (2015). The Anatomy of French Production Hierarchies. *Journal of Political Economy*, 123(4):809–852.

Card, D., Cardoso, A. R., Heining, J., and Kline, P. (2018). Firms and Labor Market Inequality: Evidence and Some Theory. *Journal of Labor Economics*, 36(S1):S13–S70.

Card, D., Cardoso, A. R., and Kline, P. (2015). Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women. *The Quarterly Journal of Economics*, 131(2):633–686.

Card, D., Heining, J., and Kline, P. (2013). Workplace Heterogeneity and the Rise of West German Wage Inequality. *The Quarterly Journal of Economics*, 128(3):967–1015.

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The Effect of Minimum Wages on Low-Wage Jobs. *The Quarterly Journal of Economics*, 134(3):1405–1454.

Chetty, R., Friedman, J. N., and Rockoff, J. E. (2014). Measuring the Impacts of Teachers I: Evaluating Bias in Teacher Value-Added Estimates. *American Economic Review*, 104(9):2593–2632.

Cooper, R., Haltiwanger, J., and Willis, J. L. (2007). Search Frictions: Matching Aggregate and Establishment Observations. *Journal of Monetary Economics*, 54:56–78.

Cooper, R., Haltiwanger, J., and Willis, J. L. (2015). Dynamics of Labor Demand: Evidence From Plant-Level Observations and Aggregate Implications. *Research in Economics*, 69(1):37–50.

Davies, R., Jones, P., and Nuñez, I. (2009). The Impact of the Business Cycle on Occupational Injuries in the UK. *Social Science & Medicine*, 69(2):178–182.

Di Addario, S., Kline, P., Saggio, R., and Sølvsten, M. (2023). It Ain't Where You're From, It's Where You're At: Hiring Origins, Firm Heterogeneity, and Wages. *Journal of Econometrics*, 233(2):340–374.

Dorman, P. and Hagstrom, P. (1998). Wage Compensation for Dangerous Work Revisited. *Industrial and Labor Relations Review*, 52(1):116–135.

EURES (2024). *Report on Labour Shortages and Surpluses 2023*. Publications Office of the European Union.

European Commission (2023). *Labour Market and Wage Developments in Europe 2023*. European Commission, Directorate-General of Employment, Social Affairs and Inclusion.

Friedrich, B. U. (2022). Trade Shocks, Firm Hierarchies, and Wage Inequality. *Review of Economics and Statistics*, 104(4):652–667.

Gronberg, T. J. and Reed, W. R. (1994). Estimating Workers' Marginal Willingness to Pay for Job Attributes Using Duration Data. *Journal of Human Resources*, pages 911–931.

Hotz, V. J., Johansson, P., and Karimi, A. (2018). Parenthood, Family Friendly Workplaces, and the Gender Gaps in Early Work Careers. *National Bureau of Economic Research*, WP 24173.

Hüttl, A. and Nagy, Á. (2017). Organisational Capital and Hospital Performance in Hungary. *Hungarian Statistical Review*, 95(K21):128–146.

Hwang, H.-s., Mortensen, D. T., and Reed, W. R. (1998). Hedonic Wages and Labor Market Search. *Journal of Labor Economics*, 16(4):815–847.

James, W. and Stein, C. (1961). Estimation With Quadratic Loss. In *Proceedings of the Berkeley Symposium on Mathematical Statistics and Probability*, page 361. University of California Press.

Katz, L. F. and Krueger, A. B. (1999). The High-Pressure U.S. Labor Market of the 1990s. *Brookings Papers on Economic Activity*, 30(1):1–88.

Kline, P. (2024). Firm Wage Effects. *Handbook of Labor Economics*, 5:115–181.

Lachowska, M., Mas, A., Saggio, R., and Woodbury, S. A. (2023a). Do Firm Effects Drift? Evidence From Washington Administrative Data. *Journal of Econometrics*, 233(2):375–395.

Lachowska, M., Mas, A., Saggio, R., and Woodbury, S. A. (2023b). Work Hours Mismatch. *National Bureau of Economic Research*, WP 31205.

Lamadon, T., Mogstad, M., and Setzler, B. (2022). Imperfect Competition, Compensating Differentials, and Rent Sharing in the US Labor Market. *American Economic Review*, 112(1):169–212.

Lavetti, K. (2020). The Estimation of Compensating Wage Differentials: Lessons From the Deadliest Catch. *Journal of Business & Economic Statistics*, 38(1):165–182.

Lavetti, K. and Schmutte, I. M. (2023). Gender Differences in Sorting on Wages and Risk. *Journal of Econometrics*, 233(2):507–523.

Lee, J. M. and Taylor, L. O. (2019). Randomized Safety Inspections and Risk Exposure on the Job: Quasi-Experimental Estimates of the Value of a Statistical Life. *American Economic Journal: Economic Policy*, 11(4):350–374.

Lehmann, T. (2023). Non-Wage Job Values and Implications for Inequality. *SSRN WP 4373816*.

Maestas, N., Mullen, K. J., Powell, D., Von Wachter, T., and Wenger, J. B. (2023). The Value of Working Conditions in the United States and Implications for the Structure of Wages. *American Economic Review*, 113(7):2007–2047.

Mas, A. (2025). Non-Wage Amenities. *National Bureau of Economic Research*, WP 33643.

Mas, A. and Pallais, A. (2017). Valuing Alternative Work Arrangements. *American Economic Review*, 107(12):3722–3759.

Mridha, H. and Khan, F. (2013). Does Unemployment Affect Compensating Wage Differentials for Work-Related Fatal Injuries? Empirical Evidence from Occupational Data. *Applied Economics Letters*, 20(14):1283–1287.

Mridha, H. A. (2022). Compensating Wage Differentials for Workplace Risks and Local Unemployment: New Evidence for Gender, Union, and Nonunion Workers in the USA. *The Journal of Developing Areas*, 56(2):65–75.

Nagler, M., Rincke, J., and Winkler, E. (2023). High-Pressure, High-Paying Jobs? *Review of Economics and Statistics*, pages 1–45.

Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy*, 82(1):34–55.

Rosen, S. (1986). The Theory of Equalizing Differences. *Handbook of Labor Economics*, 1:641–692.

Rzepka, S. and Tamm, M. (2016). Local Employer Competition and Training of Workers. *Applied Economics*, 48(35):3307–3321.

Saygin, P. O., Weber, A., and Weynandt, M. A. (2021). Coworkers, Networks, and Job-Search Outcomes Among Displaced Workers. *ILR Review*, 74(1):95–130.

Sockin, J. (2022). Show Me the Amenity: Are Higher-Paying Firms Better All Around? *CESifo Working Paper Series*, 9842.

Sorkin, I. (2017). Ranking Firms Using Revealed Preference. *National Bureau of Economic Research*, WP 23938.

Sorkin, I. (2018). Ranking Firms Using Revealed Preference. *The Quarterly Journal of Economics*, 133(3):1331–1393.

Taber, C. and Vejlin, R. (2020). Estimation of a Roy/Search/Compensating Differential Model of the Labor Market. *Econometrica*, 88(3):1031–1069.

Walters, C. R. (2024). Empirical Bayes Methods in Labor Economics. In *Handbook of Labor Economics*, volume 5, pages 183–260. Elsevier.

Wiswall, M. and Zafar, B. (2018). Preference for the Workplace, Investment in Human Capital, and Gender. *The Quarterly Journal of Economics*, 133(1):457–507.

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).[37]

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.[38]

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

[37] 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.

[38] 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 Individual-Level Wage Regressions

In this specification check, instead of estimating firm-level regressions with the firm-specific wage premium as dependent variable as in Section 6.1, we estimate individual-level wage regressions.

Our individual-level specification includes time effects and time-varying coefficients:

$$\log(w_{it}) = \beta \text{tight}_{r(i),t} \times \text{risk}_{j(i)t} + \gamma_{1t}\text{tight}_{r(i),t} + \gamma_{2t}\text{risk}_{j(i)t} + \theta X_{it} + \mu_i + \delta_t + \varepsilon_{it}, \quad \text{(B.1)}$$

where the outcome variable, $\log(w_{it})$, is the logarithm of the average wage of individual i at three-year period t. $\text{risk}_{j(i)t}$ is the standardized firm-specific injury risk of firm j. Labor market tightness is $\text{tight}_{r(i)t}$, defined as $(10 \times (-\text{unemployment rate}))$, where unemployment rate is the three-year average of the country-specific unemployment rate. The vector of control variables X_{it} includes occupation and age effects. Finally, μ_i are person effects and δ_t are time effects.

We present the estimated β coefficients in Table B.1. In the first column we include all blue-collar workers, in the second column we include only those who work at firms with at most 5,000 blue-collar workers observed in our data.

Table B.1: Relation of Risk and Tightness to Individual-Level Wage

	(1) Log wage Full sample	(2) Log wage Firm size (blue-c. workers) $\leq$ 5000
tight × risk	0.017* [0.009]	0.018** [0.009]
observations	1,583,578	1,487,186

Notes: Table shows estimated coefficients of equation (B.1). Variable "tight" refers to the county-level labor market tightness, "risk" refers to the firm-specific injury risk. Control variables: age, occupation, person and time effects. Standard errors in brackets, clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

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

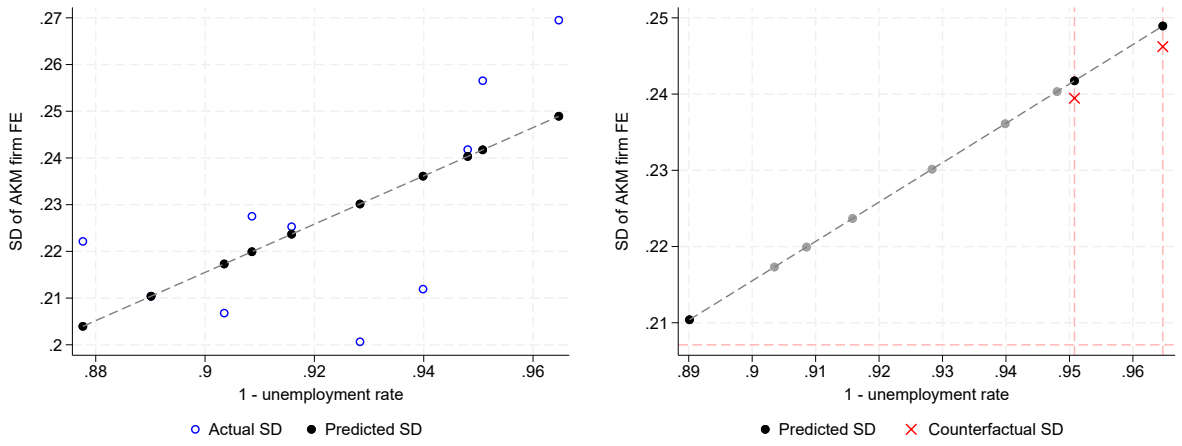
In this section, the specific question we ask: *how much do Compensating Wage Differentials ('CWDs') account for the difference in Standard Deviations (SDs) of the firm-specific wage premium between tight and slack labor markets?* To answer it, we connect two results: (1) firms in tighter labor markets 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 (32), 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 C.1:

Figure C.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 C.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 (32) 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 (32). Then, using our baseline estimate, $\hat{\beta} = 0.021$, 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 C.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)
			$\hat{\beta} = 0.021$		$\hat{\beta} = 0.00739$		$\hat{\beta} = 0.03446$	
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	0.2104							
Decile 9	0.2417	6.60 pp	0.2394	7.28%	0.2408	2.79%	0.2383	10.96%
Decile 10	0.2489	7.85 pp	0.2462	7.03%	0.2478	2.76%	0.2450	10.23%

In Table C.1, the predicted SD of $\tilde{y}_{jt}$ in column (1) is the same as in Figure C.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 18 percent or by $0.2489 - 0.2104 = 0.0385$ 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., $\frac{0.2417}{0.2565}$ 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 C.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 0.2417 to 0.2394, and the difference in SDs would be by 0.00224 units lower, implying a CWD share of 7.28 percent.[39] Moving to Columns (7)–(8) and using the upper bound of the 95 percent CI, $\hat{\beta} = 0.03446$, if firms in Decile 9 compensated for risk as firms in Decile 2, the SD of the $\tilde{y}_{jt}$ would decrease from 0.2417 to 0.2383, implying a CWD share of 10.96 percent. The analogous CWD shares in Decile 10 are 7.03 and 10.23 percent, respectively.

[39] The exact calculation is $0.0735 = \frac{0.2417-0.2394}{0.2397-0.2103} = \frac{0.0022}{0.03134}$.

D 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:

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

where $\hat{\phi}^S_{jT}$ is the noisy estimate based on the estimation method described in Section 4.3, 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:

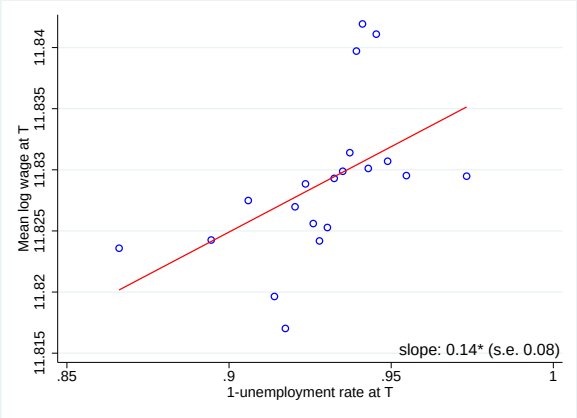
$$\sigma^2_T = \frac{1}{J}\sum_{j=1}^{j=J}\left[(\hat{\phi}^S_{jT} - \hat{\mu}_\phi)^2 - s^2_{jT}\right]. \tag{D.2}$$

In equation (D.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).

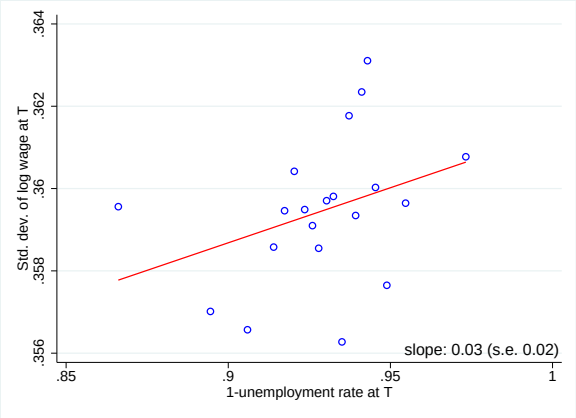
E Further Figures and Tables

Figure E.1: 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

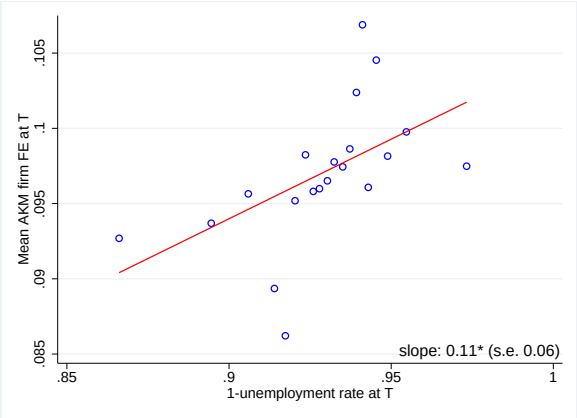
(a) Mean log wage



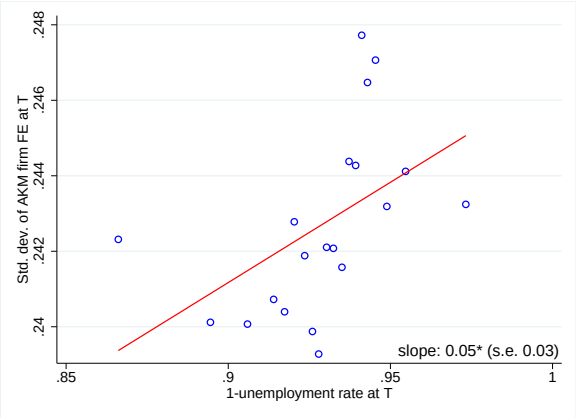
(b) Std. dev. log wage



(c) Mean AKM firm FE

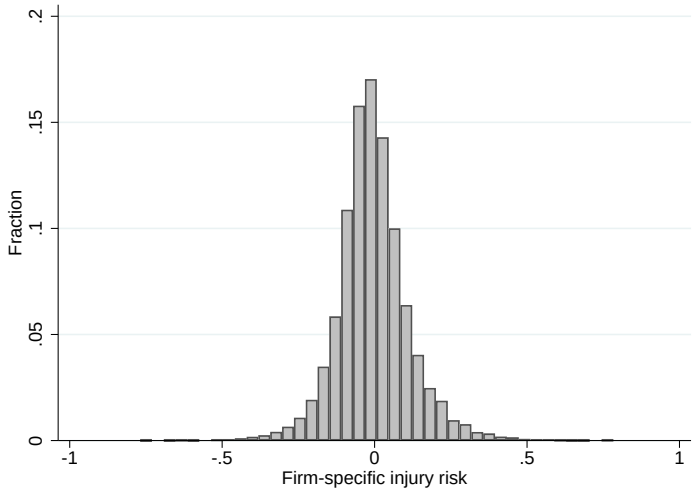


(d) Std. dev. AKM firm FE



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.

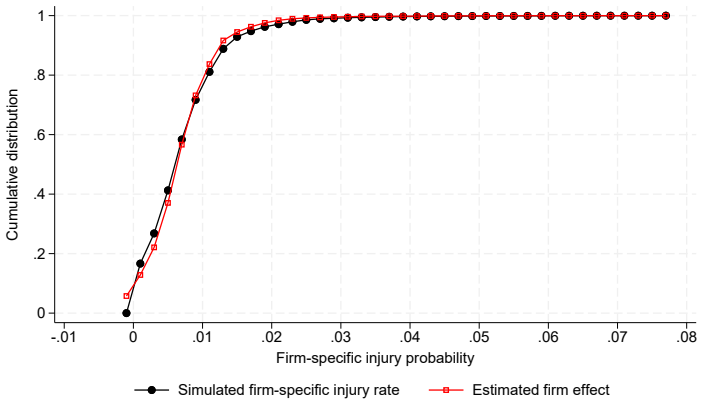
Figure E.2: Distribution of Firm-Specific Injury Risk



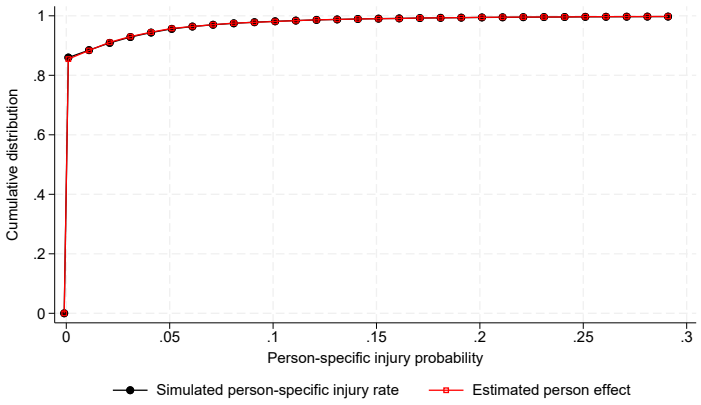
Notes: Figure shows the distribution of firm-specific injury risk, without standardizing the risk indicator. Mean: -0.004, standard deviation: 0.123.

Figure E.3: Firm and Person Effects on Simulated Data

(a) Firm effects

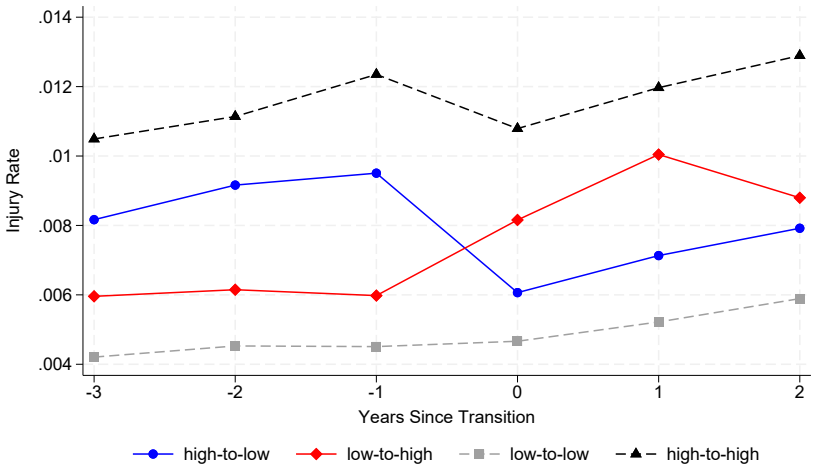


(b) Person effects



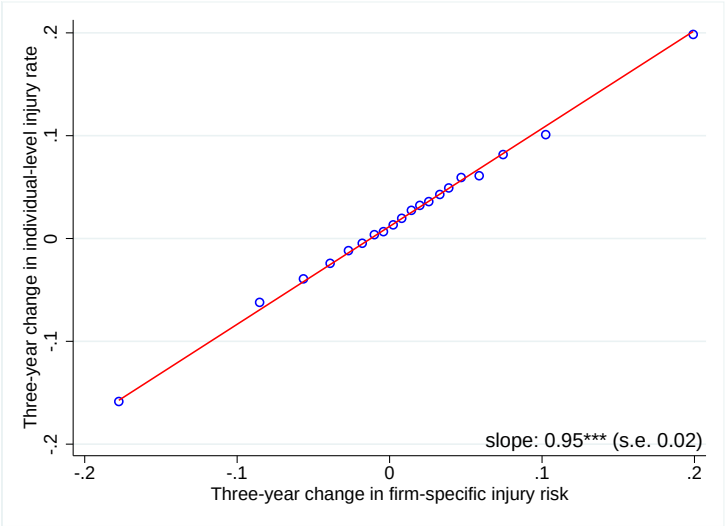
Notes: Figure shows with back line and dots the cumulative probability of three-yearly firm-specific injury rate and person specific injury rate in the simulate data, as is explained in Section 4.3. Figure shows with red line and squares the cumulative probability of the estimated firm effect and person effect, based on equation (31).

Figure E.4: 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.

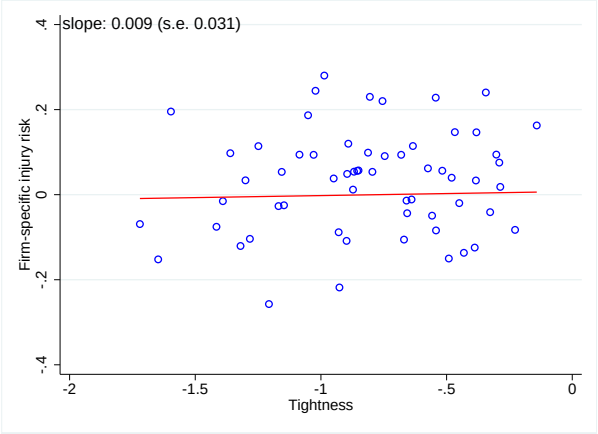
Figure E.5: Change in Injury Rate Related to Change in Firm-Specific Injury Risk



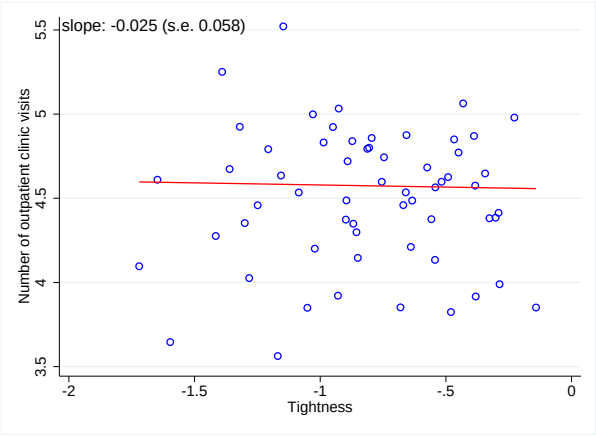
Notes: Figure shows how the person-level injury rate changes between three-year periods relate to the three-year change in firm-specific injury risk. The change in firm-specific injury risk can originate both from movers between firms and from within-firm changes of injury risk. Figure shows a binscatter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

Figure E.6: Cyclicality of Injury Risk

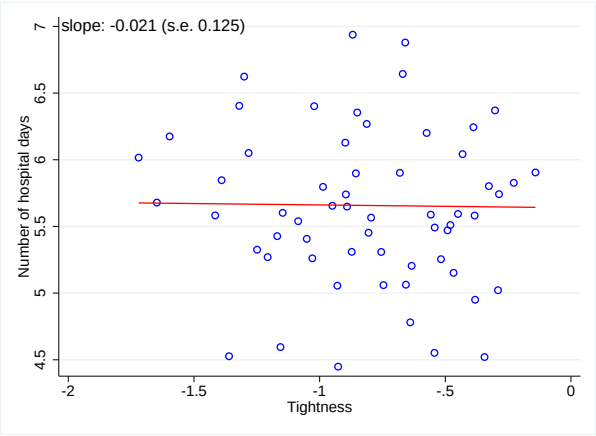
(a) Firm-specific injury risk



(b) Monthly outpatient clinic visits



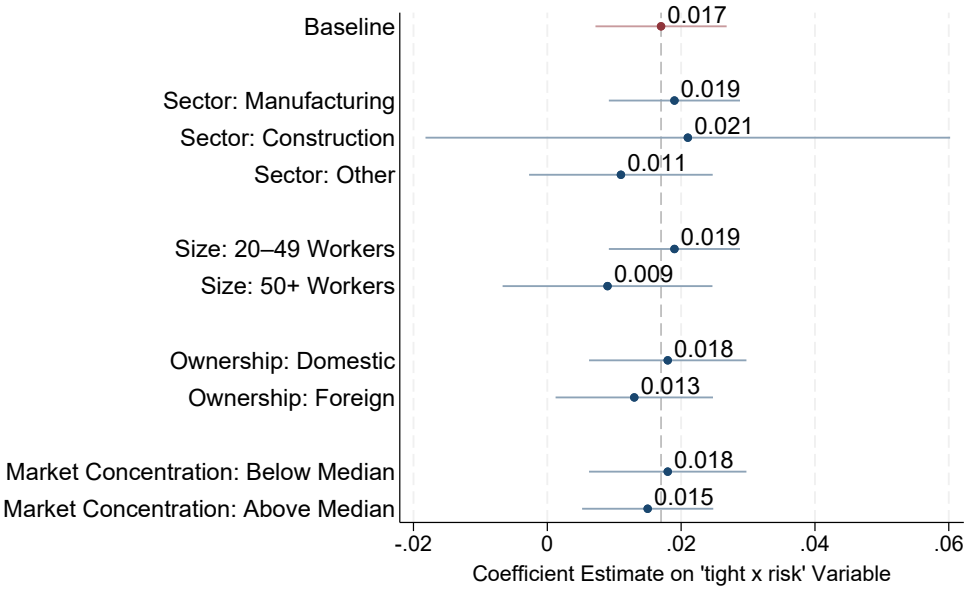
(c) Monthly hospital days



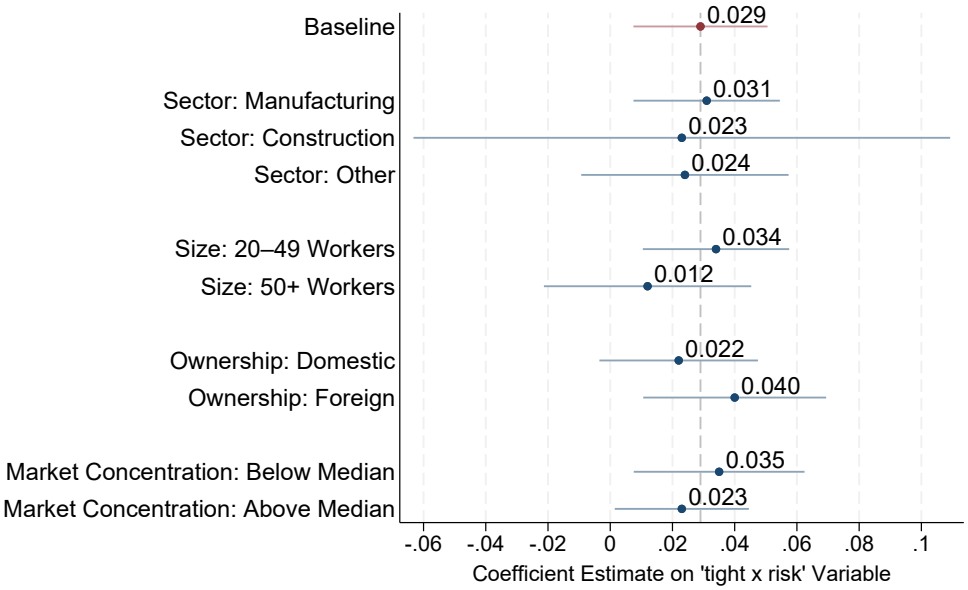
Notes: Figure shows binscatter plots with tightness rate on the x-axis (which is $(-10)\times$ unemployment rate on the level of county and three-year interval), and firm-specific injury risk, and monthly outpatient specialist visits and hospital days on the y-axis. The healthcare use measures are conditional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

Figure E.7: Heterogeneities: Relation of Risk and Tightness to Separation Rates

(a) Voluntary Separation Rate



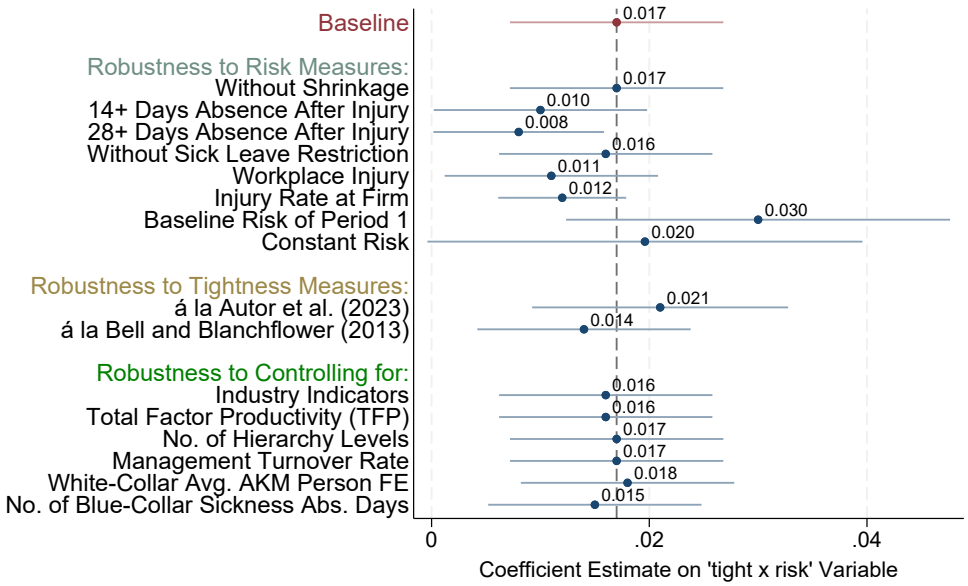
(b) Separation Rate



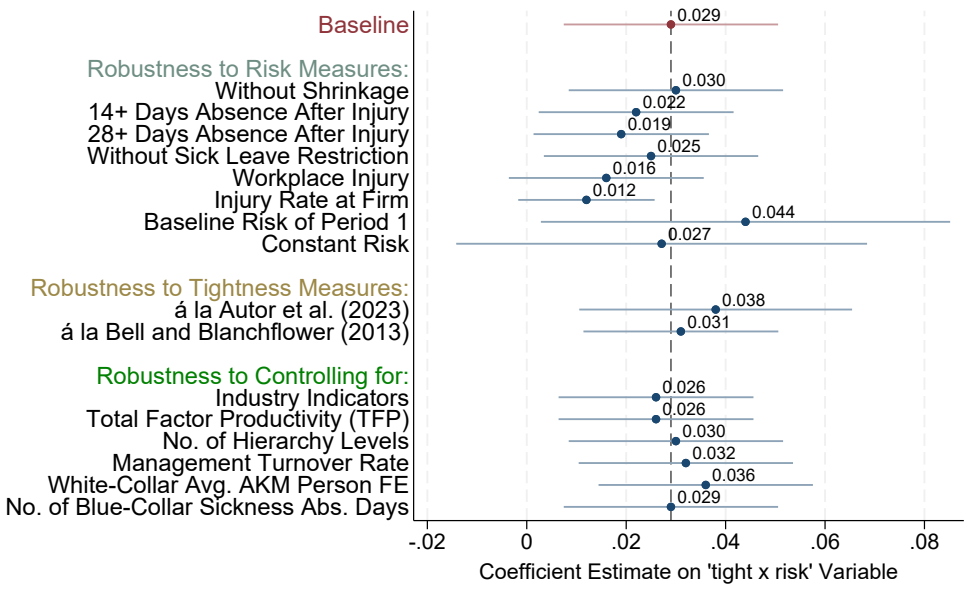
Notes: Figure shows the estimated β coefficients on the tight $\times$ risk variable, with 95% confidence interval, stemming from equation (32), for various subgroups. The baseline point estimate for the voluntary separation rate is 0.0217 with SE estimate of 0.005. The baseline point estimate for the separation rate is 0.029 with SE estimate of 0.011.

Figure E.8: Robustness Checks: Relation of Risk and Tightness to Separation Rates

(a) Voluntary Separation Rate



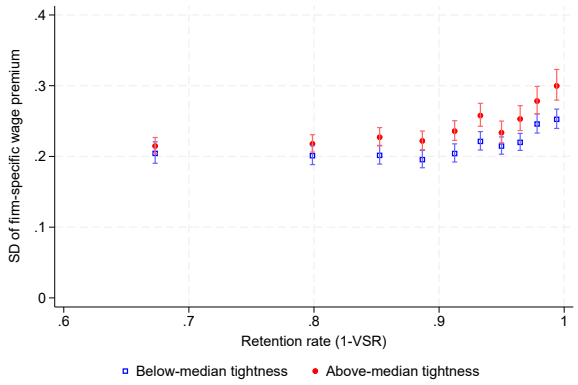
(b) Separation Rate



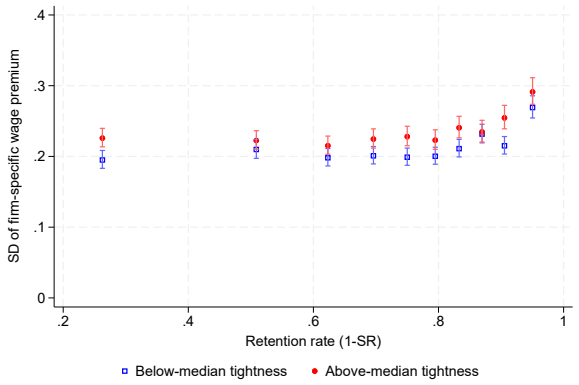
Notes: Figure shows the estimated β coefficients on the tight $\times$ risk variable, with 95% confidence interval, stemming from equation (32), under various robustness checks. The baseline point estimate for the voluntary separation rate is 0.0217 with SE estimate of 0.005. The baseline point estimate for the separation rate is 0.029 with SE estimate of 0.011.

Figure E.9: Relation Between Retention Rates and Dispersion of Firm-Specific Wage Premium

(a) SD by Retention Rate (1-VSR)



(b) SD by Retention Rate (1-SR)



Notes: Figure shows the standard deviation (SD) with 95% confidence interval of firm-specific wage premium within 10 equal sized bins of the firm dynamics measure indicated on the x-axis at tight and slack labor markets. VSR abbreviates voluntary separation rate, SR abbreviates separation rate.

Table E.1: Share of ICD-10 Codes in Injuries

ICD-10 code	Share
S00 Superficial injury of head	0.29%
S01 Open wound of head	**1.38%**
S02 Fracture of skull and facial bones	0.94%
S03 Dislocation and sprain of joints and ligaments of head	0.00%
S04 Injury of cranial nerve	0.01%
S05 Injury of eye and orbit	0.47%
S06 Intracranial injury	0.84%
S07 Crushing injury of head	**1.56%**
S08 Avulsion and traumatic amputation of part of head	0.00%
S09 Other and unspecified injuries of head	0.08%
S10 Superficial injury of neck	0.02%
S11 Open wound of neck	0.02%
S12 Fracture of cervical vertebra and other parts of neck	0.20%
S13 Dislocation and sprain of joints and ligaments at neck level	0.26%
S14 Injury of nerves and spinal cord at neck level	0.06%
S15 Injury of blood vessels at neck level	0.00%
S16 Injury of muscle, fascia and tendon at neck level	0.00%
S17 Crushing injury of neck	0.00%
S19 Other specified and unspecified injuries of neck	0.01%
S20 Superficial injury of thorax	**1.81%**
S21 Open wound of thorax	0.05%
S22 Fracture of rib(s), sternum and thoracic spine	**1.75%**
S23 Dislocation and sprain of joints and ligaments of thorax	0.38%
S24 Injury of nerves and spinal cord at thorax level	0.01%
S25 Injury of blood vessels of thorax	0.00%
S26 Injury of heart	0.00%
S27 Injury of other and unspecified intrathoracic organs	0.17%
S28 Crushing injury of thorax, and traumatic amputation of part of thorax	0.01%
S29 Other and unspecified injuries of thorax	0.01%
S30 Superficial injury of abdomen, lower back, pelvis and external genitals	0.62%
S31 Open wound of abdomen, lower back, pelvis and external genitals	0.10%
S32 Fracture of lumbar spine and pelvis	**1.28%**
S33 Dislocation and sprain of joints and ligaments of lumbar spine and pelvis	0.20%
S34 Injury of lumbar and sacral spinal cord and nerves at abdomen, lower back and pelvis level	0.00%
S35 Injury of blood vessels at abdomen, lower back and pelvis level	0.00%
S36 Injury of intra-abdominal organs	0.12%
S37 Injury of urinary and pelvic organs	0.04%
S38 Crushing injury and traumatic amputation of abdomen, lower back, pelvis and external genitals	0.02%
S39 Other and unspecified injuries of abdomen, lower back, pelvis and external genitals	0.01%
S40 Superficial injury of shoulder and upper arm	**1.24%**
S41 Open wound of shoulder and upper arm	0.10%
S42 Fracture of shoulder and upper arm	**3.55%**
S43 Dislocation and sprain of joints and ligaments of shoulder girdle	**1.92%**
S44 Injury of nerves at shoulder and upper arm level	0.06%
S45 Injury of blood vessels at shoulder and upper arm level	0.02%
S46 Injury of muscle, fascia and tendon at shoulder and upper arm level	**1.08%**
S47 Crushing injury of shoulder and upper arm	0.00%
S48 Traumatic amputation of shoulder and upper arm	0.01%
S49 Other and unspecified injuries of shoulder and upper arm	0.05%
S50 Superficial injury of elbow and forearm	**1.13%**
S51 Open wound of elbow and forearm	0.87%
S52 Fracture of forearm	**6.91%**
S53 Dislocation and sprain of joints and ligaments of elbow	0.38%
S54 Injury of nerves at forearm level	0.12%
S55 Injury of blood vessels at forearm level	0.04%
S56 Injury of muscle, fascia and tendon at forearm level	0.21%
S57 Crushing injury of elbow and forearm	0.01%
S58 Traumatic amputation of elbow and forearm	0.01%
S59 Other and unspecified injuries of elbow and forearm	0.04%
S60 Superficial injury of wrist, hand and fingers	**4.54%**
S61 Open wound of wrist, hand and fingers	**9.13%**
S62 Fracture at wrist and hand level	**7.81%**
S63 Dislocation and sprain of joints and ligaments at wrist and hand level	**1.41%**
S64 Injury of nerves at wrist and hand level	0.29%
S65 Injury of blood vessels at wrist and hand level	0.10%
S66 Injury of muscle, fascia and tendon at wrist and hand level	**1.44%**
S67 Crushing injury of wrist, hand and fingers	0.06%

Table E.1: Share of ICD-10 Codes in Injuries, Continued

ICD-10 code	Share
S68 Traumatic amputation of wrist, hand and fingers	0.96%
S69 Other and unspecified injuries of wrist, hand and finger(s)	0.20%
S70 Superficial injury of hip and thigh	0.50%
S71 Open wound of hip and thigh	0.25%
S72 Fracture of femur	**1.51%**
S73 Dislocation and sprain of joint and ligaments of hip	0.08%
S74 Injury of nerves at hip and thigh level	0.00%
S75 Injury of blood vessels at hip and thigh level	0.02%
S76 Injury of muscle, fascia and tendon at hip and thigh level	0.26%
S77 Crushing injury of hip and thigh	0.01%
S78 Traumatic amputation of hip and thigh	0.01%
S79 Other and unspecified injuries of hip and thigh	0.01%
S80 Superficial injury of knee and lower leg	**3.07%**
S81 Open wound of knee and lower leg	**1.09%**
S82 Fracture of lower leg, including ankle	**10.53%**
S83 Dislocation and sprain of joints and ligaments of knee	**6.46%**
S84 Injury of nerves at lower leg level	0.04%
S85 Injury of blood vessels at lower leg level	0.03%
S86 Injury of muscle, fascia and tendon at lower leg level	**1.28%**
S87 Crushing injury of lower leg	0.02%
S88 Traumatic amputation of lower leg	0.01%
S89 Other and unspecified injuries of lower leg	0.04%
S90 Superficial injury of ankle, foot and toes	**2.95%**
S91 Open wound of ankle, foot and toes	0.88%
S92 Fracture of foot and toe, except ankle	**4.42%**
S93 Dislocation and sprain of joints and ligaments at ankle, foot and toe level	**5.90%**
S94 Injury of nerves at ankle and foot level	0.01%
S95 Injury of blood vessels at ankle and foot level	0.01%
S96 Injury of muscle and tendon at ankle and foot level	0.06%
S97 Crushing injury of ankle and foot	0.03%
S98 Traumatic amputation of ankle and foot	0.04%
S99 Other and unspecified injuries of ankle and foot	0.09%
T00 Superficial injuries involving multiple body regions	0.01%
T01 Open wounds involving multiple body regions	0.01%
T02 Fractures involving multiple body regions	0.03%
T03 Dislocations, sprains and strains involving multiple body regions	0.06%
T04 Crushing injuries involving multiple body regions	0.00%
T05 Traumatic amputations involving multiple body regions	0.01%
T06 Other injuries involving multiple body regions, not elsewhere classified	0.00%
T07 Unspecified multiple injuries	0.02%
T08 Fracture of spine, level unspecified	0.08%
T09 Other injuries of spine and trunk, level unspecified	0.01%
T10 Fracture of upper limb, level unspecified	0.00%
T11 Other injuries of upper limb, level unspecified	0.02%
T12 Fracture of lower limb, level unspecified	0.00%
T13 Other injuries of lower limb, level unspecified	0.02%
T14 Injury of unspecified body region	0.04%
T15 Foreign body on external eye	0.71%
T16 Foreign body in ear	0.02%
T17 Foreign body in respiratory tract	0.02%
T18 Foreign body in alimentary tract	0.01%
T19 Foreign body in genitourinary tract	0.01%
T20 Burn and corrosion of head, face, and neck	0.05%
T21 Burn and corrosion of trunk	0.04%
T22 Burn and corrosion of shoulder and upper limb, except wrist and hand	0.08%
T23 Burn and corrosion of wrist and hand	0.29%
T24 Burn and corrosion of lower limb, except ankle and foot	0.08%
T25 Burn and corrosion of ankle and foot	0.18%
T26 Burn and corrosion confined to eye and adnexa	0.12%
T27 Burn and corrosion of respiratory tract	0.00%
T28 Burn and corrosion of other internal organs	0.00%
T29 Burns or chemical burns of multiple body regions	0.01%
T30 Burn and corrosion, body region unspecified	0.02%
T31 Burns classified according to extent of body surface involved	0.58%
T32 Corrosions classified according to extent of body surface involved	0.01%
T33 Superficial frostbite	0.01%
T34 Frostbite with tissue necrosis	0.01%

Table E.1: Share of ICD-10 Codes in Injuries, Continued

ICD-10 code	Share
T66 Radiation sickness, unspecified	0.00%
T67 Effects of heat and light	0.00%
T68 Hypothermia	0.00%
T69 Other effects of reduced temperature	0.00%
T70 Effects of air pressure and water pressure	0.00%
T71 Asphyxiation	0.00%
T73 Effects of other deprivation	0.00%
T75 Other and unspecified effects of other external causes	0.06%
T78 Adverse effects, not elsewhere classified	0.25%
T79 Certain early complications of trauma, not elsewhere classified	0.50%
T80 Complications following infusion, transfusion and therapeutic injection	0.00%
T81 Complications of procedures, not elsewhere classified	0.07%
T83 Complications of genitourinary prosthetic devices, implants and grafts	0.00%
T84 Complications of internal orthopedic prosthetic devices, implants and grafts	0.00%
T85 Complications of other internal prosthetic devices, implants and grafts	0.00%
T86 Complications of transplanted organs and tissue	0.01%
T87 Complications peculiar to reattachment and amputation	0.02%
T88 Other complications of surgical and medical care, not elsewhere classified	0.01%
T90 Sequelae of injuries of head	0.03%
T91 Sequelae of injuries of neck and trunk	0.05%
T92 Sequelae of injuries of upper limb	0.16%
T93 Sequelae of injuries of lower limb	0.17%
T94 Sequelae of injuries involving multiple and unspecified body regions	0.01%
T95 Sequelae of burns, corrosions and frostbite	0.01%
T96 Sequelae of poisoning by drugs, medicaments and biological substances	0.00%
T97 Sequelae of toxic effects of substances chiefly nonmedicinal as to source	0.00%
T98 Sequelae of other and unspecified effects of external causes	0.00%

Notes: Table shows the share of injury codes in our analysis sample. Number of injuries: 245,739. We highlight with bold characters the injury codes representing at least 1% of injuries.

Table E.2: 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 (30). Xb includes dummies of three-year groups, and the square and cube of (age − 40).

Table E.3: 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.

Table E.4: Relation of Risk and Tightness to Firm-Specific Wage Premium and Separation Rates, OLS Estimates

	(1) AKM firm FE	(2) Voluntary separation rate	(3) Separation rate
Baseline			
tight × risk	0.028***	0.001	0.009
	[0.009]	[0.004]	[0.011]
With net-of-time variables			
tight × risk	0.028***	0.001	0.010
	[0.009]	[0.004]	[0.011]
tight	0.092***	-0.039**	-0.069**
	[0.023]	[0.015]	[0.033]
risk	0.042***	0.005	0.012
	[0.008]	[0.004]	[0.009]
observations	11,045	11,045	11,045

Notes: Table shows estimated coefficients of equations (32) and (33), 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.

Table E.5: MWTP for Injury Risk

	(1) MWTP, discrete tightness above/below median tightness	(2) MWTP, continuous tightness tightness at 10th and 90th percentile
low tightness	-0.045***	-0.057***
	[0.017]	[0.022]
high tightness	-0.050***	-0.043***
	[0.016]	[0.016]
p-value of equality test	0.771	0.564

Notes: Table shows MWTP for injury risk, as explained in Section 6.2. Standard errors in brackets, clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table E.6: Relation of Risk and Tightness to Firm-Specific Wage Premium and Separation Rates, All Estimated Coefficients

	(1) AKM firm FE	(2) Voluntary separation rate	(3) Separation rate
tight × risk	0.021***	0.017***	0.029***
	[0.007]	[0.005]	[0.011]
year 2009–2011 × tight	0.096***	-0.033*	-0.054*
	[0.021]	[0.018]	[0.032]
year 2012–2014 × tight	0.086***	-0.038*	-0.046
	[0.024]	[0.021]	[0.039]
year 2015–2017 × tight	0.103***	-0.033	-0.049
	[0.032]	[0.027]	[0.052]
year 2009–2011 × risk	0.023***	0.021***	0.034***
	[0.007]	[0.005]	[0.012]
year 2012–2014 × risk	0.013**	0.017***	0.026***
	[0.006]	[0.004]	[0.009]
year 2015–2017 × risk	0.006	0.010***	0.017**
	[0.004]	[0.003]	[0.007]
mean age of workers	-0.001	-0.007***	-0.022***
	[0.001]	[0.001]	[0.002]
share of men among workers	0.058**	-0.048*	-0.161***
	[0.026]	[0.026]	[0.057]
mean injury person FE of workers	0.030	0.062***	0.064
	[0.028]	[0.022]	[0.044]
share of skilled blue-collar workers	-0.027**	-0.025**	-0.056**
	[0.012]	[0.012]	[0.025]
share of assemblers, machine operators	-0.047***	-0.029**	-0.061**
	[0.012]	[0.013]	[0.027]
year 2012–2014	0.145***	0.035***	0.012
	[0.005]	[0.005]	[0.009]
year 2015–2017	0.274***	0.094***	0.065***
	[0.007]	[0.006]	[0.011]
constant	0.082*	0.383***	1.313***
	[0.044]	[0.044]	[0.091]
observations	9,208	9,208	9,208

Notes: Table shows estimated coefficients of equation (32). 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.

Table E.7: 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
Baseline					
tight × risk	0.018	0.036	0.030	0.010	-0.632*
	[0.026]	[0.029]	[0.068]	[0.009]	[0.377]
With net-of-time variables					
tight × risk	0.018	0.038	0.031	0.010	-0.597
	[0.026]	[0.029]	[0.068]	[0.009]	[0.380]
tight	-0.073	-0.038	-0.158	-0.029	0.553
	[0.060]	[0.057]	[0.117]	[0.018]	[0.661]
risk	0.012	0.051**	0.018	0.004	2.611***
	[0.020]	[0.024]	[0.048]	[0.006]	[0.315]
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 equations (32) and (33) 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.

F Sorkin Index Results

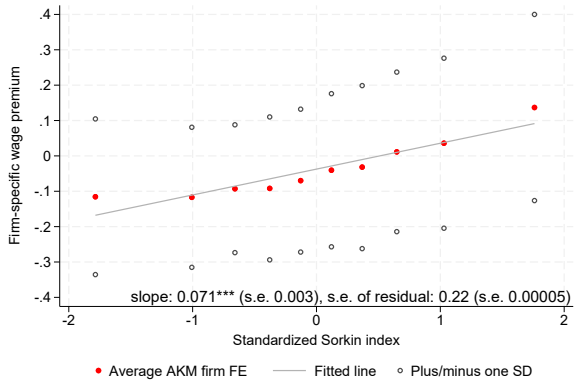
Following Sorkin (2018), we define a revealed preference estimator for the firm, which we call the Sorkin index. To estimate the Sorkin index, we work with quarterly-level data and apply the *PyTwoWay* package of Bonhomme et al. (2023). We estimate the index on the sample of blue-collar workers, separately for the three three-yearly periods we include in our analysis (2009–2011, 2012–2014, 2015–2017). We restrict the sample to the strictly connected set of firms and to firms that hire also from non-employment (as in Sorkin, 2018). We adjust the Sorkin index for offer distribution and firm size, as in equation (13) of Sorkin (2018). We drop those firm- and three-year-specific observations in the following exercise, where the number of poached workers or the number of workers moving to another firm exceed 100% of the average size of the firm. We standardize the Sorkin index by three-year periods.

We repeat the exercise we performed in Section 8 with using the Sorkin index instead of retention rates as proxies for revealed preferences for the firm. We analyze the relation of the Sorkin index and the mean and dispersion of firm-specific wage premium, separately for below- and above-median tightness labor markets. In this approach, we follow Figure V of Sorkin (2018), with the extension of heterogeneity by labor market tightness.

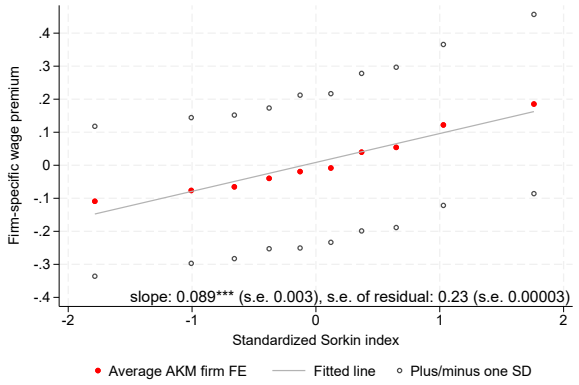
The dispersion of compensating differentials tends to be higher at above-median tightness than at below-median tightness labor markets. We display the average value of the within-bin standard deviation of the firm-specific wage premium in the bottom right corner of panels (a) and (b) of Figure F.1, and present the standard deviation in panel (c).

Figure F.1: Relation Between Sorkin Index and Firm-Specific Wage Premium

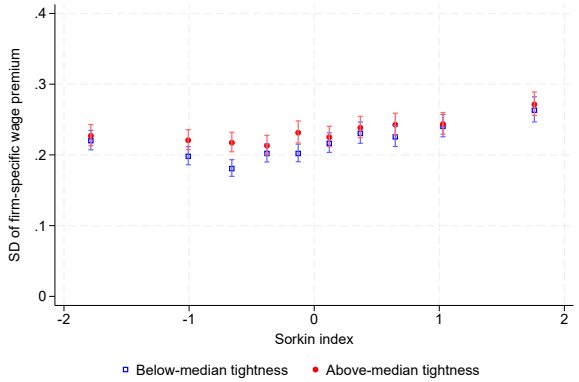
(a) Below-Median Tightness



(b) Above-Median Tightness



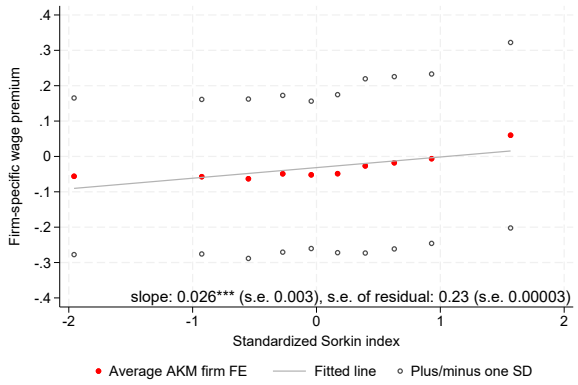
(c) SD of Firm-Specific Wage Premium



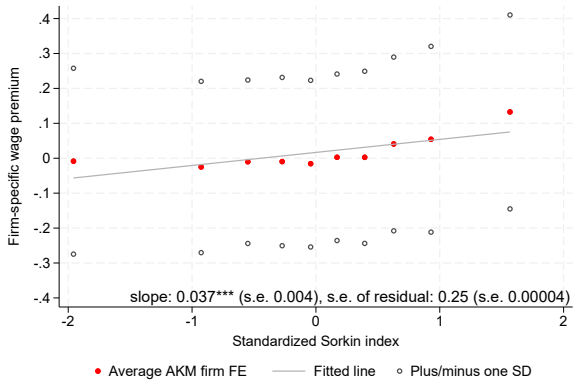
Notes: Panels (a) and (b) show binscatter plots (with fitted lines) of firm-specific wage premium with 10 equal sized bins of the adjusted Sorkin index indicated on the x-axis. The dashed lines show the bin-specific mean plus and minus one standard deviation of the firm-specific wage premium within the bin. Panel (a) shows these patterns for low (below-median) tightness labor markets, panel (b) for high (above-median) tightness labor markets. Bottom panel shows the standard deviation (SD) of firm-specific wage premium with 95% confidence interval within 10 equal sized bins of Sorkin index indicated on the x-axis at tight and slack labor markets

Figure F.2: Relation Between Non-Adjusted Sorkin Index and Firm-Specific Wage Premium

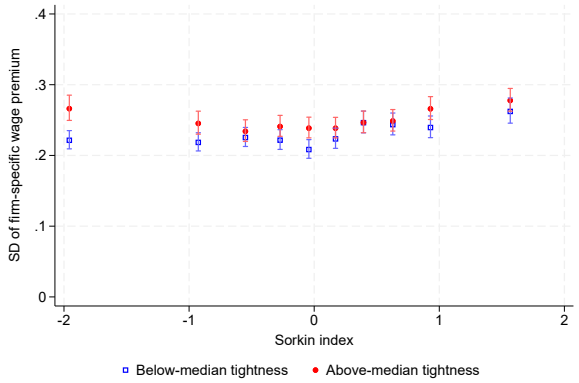
(a) Below-Median Tightness



(b) Above-Median Tightness



(c) SD of Firm-Specific Wage Premium



Notes: Panels (a) and (b) show binscatter plots (with fitted lines) of firm-specific wage premium with 10 equal sized bins of the Sorkin index indicated on the x-axis. The dashed lines show the bin-specific mean plus and minus one standard deviation of the firm-specific wage premium within the bin. Panel (a) shows these patterns for low (below-median) tightness labor markets, panel (b) for high (above-median) tightness labor markets. Bottom panel shows the standard deviation (SD) of firm-specific wage premium with 95% confidence interval within 10 equal sized bins of Sorkin index indicated on the x-axis at tight and slack labor markets

G Derivation of Expression for $l(x)$

Using the steady state condition for the flow of workers into and out of jobs we get

$$G(x) = \frac{\lambda F(x) u}{s(1-u) + \lambda[1-F(x)](1-u)} = \frac{kF(x)}{1+k[1-F(x)]} \frac{u}{1-u} \tag{G.1}$$

Now using the fact that

$$\frac{u}{1-u} = \frac{1}{k} \tag{G.2}$$

we get

$$G(x) = \frac{F(x)}{1+k[1-F(x)]} \tag{G.3}$$

Now taking a derivative with respect to x gives

$$g(x) = \frac{f(x)}{1+k[1-F(x)]} + \frac{F(x)kf(x)}{(1+k[1-F(x)])^2} = \frac{f(x)+kf(x)-kf(x)F(x)+kf(x)F(x)}{(1+k[1-F(x)])^2} \tag{G.4}$$

$$g(x) = \frac{f(x)(1+k)}{(1+k[1-F(x)])^2} \tag{G.5}$$

Next note that

$$l(x) = (1-u)\frac{g(x)}{f(x)} = \frac{k}{1+k} \frac{(1+k)}{(1+k[1-F(x)])^2} = \frac{k}{(1+k[1-F(x)])^2}. \tag{G.6}$$

H Proofs of Model Propositions

Proof of Proposition 1. In equilibrium no firm wants to deviate from their current wage policy. This implies that for any utility x_2 chosen by a firm of type 2 and utility x_1 chosen by a firm of type 1 we must have that

$$pl(x_2)^\alpha - (x_2 - a_2)l(x_2) \geq pl(x_1)^\alpha - (x_1 - a_2)l(x_1) > pl(x_1)^\alpha - (x_1 - a_1)l(x_1) \geq pl(x_2)^\alpha - (x_2 - a_1)l(x_2)$$

where the first inequality comes from the fact that a firm of type 2 must not want to deviate to offering the utility of a firm of type 1. The second inequality follows simply from $a_2 > a_1$. And the last inequality follows from the fact that a firm of type 1 must not want to deviate to offering the utility of a firm of type 2. The above inequalities imply

$$pl(x_2)^\alpha - (x_2 - a_2)l(x_2) - [pl(x_2)^\alpha - (x_2 - a_1)l(x_2)] \geq pl(x_1)^\alpha - (x_1 - a_2)l(x_1) - [pl(x_1)^\alpha - (x_1 - a_1)l(x_1)]$$

which implies

$$(a_2 - a_1)l(x_2) \geq (a_2 - a_1)l(x_1) \Rightarrow l(x_2) \geq l(x_1). \tag{H.1}$$

Since $l(x)$ is positively sloped, this implies

$$x_2 \geq x_1 \Rightarrow w_2 + a_2 \geq w_1 + a_1 \Rightarrow w_1 - w_2 \leq a_2 - a_1. \tag{H.2}$$

Next, to prove that $\overline{x}_1 = \underline{x}_2$, consider instead that $\overline{x}_1 > \underline{x}_2$, then, this implies there exists at least one x_1 for which $x_1 > x_2$ contradicting the above. Next, note that just as in Burdett and Mortensen (1998), there can be no gaps in the distribution $F(x)$. To see this, consider instead that there is a gap between points x and x' with $x' > x$. Then, the firm offering x' can lower their offered utility to $x + \epsilon$ with $\epsilon \approx 0$, without losing any workers, contradicting this being an equilibrium. It follows that there can be no gaps in the distribution of offers $F(x)$. It follows that we can not have $\overline{x}_1 < \underline{x}_2$. Hence, $\overline{x}_1 = \underline{x}_2$ □

Proof of Proposition 2. From the previous proposition we know that $\overline{x}_1 = \underline{x}_2$, it follows that $F(\overline{x}_1) = F(\underline{x}_2) = \sigma$. Next, note that from the indifference condition for each firm type i, we can write

$$x_2 = pl(x_2)^{\alpha-1} + a_2 - \frac{\pi(\underline{x}_2)}{l(x_2)}, \quad \forall x_2 \text{ in the support of } F_2(x) \tag{H.3}$$

where $\pi(\underline{x}_2)$ is the profit made by type 2 firms. It follows that if $F_2(x)$ is non-degenerate it must be that

$$\overline{x}_2 - \underline{x}_2 = R \equiv pl(\overline{x}_2)^{\alpha-1} - pl(\underline{x}_2)^{\alpha-1} - \pi(\underline{x}_2)\left[\frac{1}{l(\overline{x}_2)} - \frac{1}{l(\underline{x}_2)}\right] \tag{H.4}$$

Consider now the limit when $k \to \infty$. Suppose the equilibrium in this limit case is such that $F_2(x)$ is non-degenerate, that is, $\overline{x}_2 > \underline{x}_2$. Note that as $k \to \infty$

$$\lim_{k\to\infty} l(\underline{x}_2) = \lim_{k\to\infty} \frac{k}{(1 + k[1-\sigma])^2} = 0 \tag{H.5}$$

which implies

$$\lim_{k\to\infty} \pi(\underline{x}_2) = 0. \tag{H.6}$$

As a result,

$$\lim_{k\to\infty} \pi(\underline{x}_2)\left[\frac{1}{l(\overline{x}_2)} - \frac{1}{l(\underline{x}_2)}\right] = \lim_{k\to\infty} \pi(\underline{x}_2) \lim_{k\to\infty}\left[\frac{1}{l(\overline{x}_2)} - \frac{1}{l(\underline{x}_2)}\right] = 0. \tag{H.7}$$

Next note that that

$$\lim_{k\to\infty} l(\overline{x}_2) = \lim_{k\to\infty} k = \infty \Rightarrow \lim_{k\to\infty} pl(\overline{x}_2)^{\alpha-1} = 0 \tag{H.8}$$

and

$$\lim_{k\to\infty} l(\underline{x}_2) = 0 \Rightarrow \lim_{k\to\infty} pl(\underline{x}_2)^{\alpha-1} = \infty. \tag{H.9}$$

It follows that

$$\lim_{k\to\infty} \overline{x}_2 - \underline{x}_2 < 0, \tag{H.10}$$

which contradicts the definition of $\overline{x}_2$ and $\underline{x}_2$, which is that $\overline{x}_2 \geq \underline{x}_2$. It follows that in the limit case of $k \to \infty$, $F_2(x)$ mut be degenerate, so we have

$$\overline{x}_2 = \underline{x}_2 = \overline{x}_1. \tag{H.11}$$

Finally, note that as $k \to \infty$ workers meet all firms instantaneously and simultaneously, so only the firms paying the highest utility will have workers. Hence, as $k \to \infty$ all workers receive the same utility $\overline{x}_2 = \underline{x}_2 = \overline{x}_1 = x^*$ and are indifferent between firms of type 2 all offering x^* and the firm of type 1 offering the highest utility $\overline{x}_1 = x^*$. All other firms of type 1 offer a utility $x < x^*$ obtaining $l(x) = 0$. In order for these firms offering $x < x^*$ to not want to deviate the firm of type 1 offering the highest utility $\overline{x}_1 = x^*$ must be making zero profits. It follows that at the limit case of $k \to \infty$, workers employed at a firm of type 1 are paid their marginal product of labor. The wage of individuals employed by a firm of type 1 is

$$w_1 = x^* - a_1 \tag{H.12}$$

and the wage of individuals employed by a firm of type 2 is

$$w_2 = x^* - a_2. \tag{H.13}$$

It follows that the compensating differential in the economy is given by

$$w_1 - w_2 = a_2 - a_1. \tag{H.14}$$

Next, consider the case where k becomes arbitrarily small. When this happens, $l(x)$ no longer depends on x. Intuitively, for small enough k, firms do not need to worry about other firms poaching their workers. As a result, firms can offer their workers the minimum utility required to get them to work, b. As a result, firms of type 1 pay workers $w_1 = b - a_1$ and firms of type 2 pay workers $w_2 = b - a_2$. The compensating wage differential in this case is $w_1 - w_2 = a_2 - a_1$.

□

Proof of Proposition 3. From the first order condition for a we obtain

$$1 = c_i a \Rightarrow a_i = \frac{1}{c_i}. \tag{H.15}$$

Then, the profit maximization problem of a firm of type i becomes

$$\max_x p l(x)^\alpha - \left(x - \frac{1}{c_i} + \frac{c_i}{2}\left(\frac{1}{c_i}\right)^2 \right) l(x) = \max_x p l(x)^\alpha - \left(x - \frac{1}{2c_i} \right) \tag{H.16}$$

Then consider a model with exogenous amenity levels $a_i = \frac{1}{2c_i}$, the problem of the firm will be the same

$$\max_x pl(x)^\alpha - \left(x - \frac{1}{2c_i}\right) l(x) \tag{H.17}$$

and hence gives the same solution for x.

□

Proof of Proposition 4. First start by the fact that from the previous proposition we know that

$$a_2(c_2) = \frac{1}{c_2} > \frac{1}{c_1} = a(c_1). \tag{H.18}$$

$$pl(x_i)^\alpha - \left(x - a + \frac{c_i}{2}a^2\right) l(x) = pl(x)^\alpha - \left(x - \frac{1}{2c_i}\right) l(x). \tag{H.19}$$

Next, note that in equilibrium no firm wants to deviate from their current wage policy. This implies that

$$\begin{aligned} pl(x_2)^\alpha - \left(x_2 - \frac{1}{2c_2}\right) \geq pl(x_1)^\alpha - \left(x_1 - \frac{1}{2c_2}\right) l(x_1) > \\ > pl(x_1)^\alpha - \left(x_1 - \frac{1}{2c_1}\right) l(x_1) \geq pl(x_2)^\alpha - \left(x_2 - \frac{1}{2c_1}\right) l(x_2), \end{aligned} \tag{H.20}$$

where the first inequality follows from the fact that a firm of type 2 must not want to deviate from offering the utility of a firm of type 1. The second inequality follows simply from $c_2 < c_1$. And the last inequality follows from the fact that a firm of type 1 must not want to deviate to offering the utility of a firm of type 2. The above inequalities imply

$$\begin{aligned} pl(x_2)^\alpha - (x_2 - \frac{1}{2c_2})l(x_2) - \left[pl(x_2)^\alpha - \left(x_2 - \frac{1}{2c_1}\right) l(x_2)\right] \\ \geq pl(x_1)^\alpha - \left(x_1 - \frac{1}{2c_2}\right) l(x_1) - \left[pl(x_1)^\alpha - \left(x_1 - \frac{1}{2c_1}\right) l(x_1)\right] \end{aligned} \tag{H.21}$$

which implies

$$\left(\frac{1}{2c_2} - \frac{1}{2c_1}\right) l(x_2) \geq \left(\frac{1}{2c_2} - \frac{1}{2c_1}\right) l(x_1). \tag{H.22}$$

And so,

$$l(x_2) \geq l(x_1) \Rightarrow x_2 \geq x_1 \tag{H.23}$$

which implies

$$w_1 - w_2 \leq a_2(c_2) - a_1(c_1). \tag{H.24}$$

□

Proof of Proposition 5 . As in the case of exogenous amenity we will have $\overline{x}_1 = \underline{x}_2$, it follows that $F(\overline{x}_1) = F(\underline{x}_2) = \sigma$, since like before we have $x_2 \geq x_1, \forall x_2, x_2$ Next, note that

from the indifference condition for each firm type i, we can write

$$x_2 = pl(x_2)^{\alpha-1} + \frac{1}{2c_2} - \frac{\pi(\underline{x_2})}{l(x_2)}, \quad \forall x_2 \text{ in the support of } F_2(x) \tag{H.25}$$

Then, we can write the expression for $\overline{x}_2 - \underline{x}_2$ exactly as we did in the proof of Propostion 2. Following exactly the same steps we get the desired result.

□

Proof of Proposition 6. From the first order condition for a we obtain

$$a_i = \frac{l(x)}{c_i}. \tag{H.26}$$

□

Proof of Proposition 7. First start by the fact that from the previous proposition we know that

$$a_i(c_i, x) = \frac{l(x)}{c_i}. \tag{H.27}$$

$$pl(x_i)^\alpha - \left(x - \frac{l(x)}{c_i}\right) l(x) + \frac{c_i}{2}(\frac{l(x)}{c_i})^2 = pl(x)^\alpha - \left(xl(x) - \frac{l(x)^2}{2c_i}\right). \tag{H.28}$$

Next, note that in equilibrium no firm wants to deviate from their current wage policy. This implies that

$$\begin{aligned} pl(x_2)^\alpha - \left(x_2 l(x_2) - \frac{l(x_2)^2}{2c_2}\right) \geq pl(x_1)^\alpha - \left(x_1 l(x_1) - \frac{l(x_1)^2}{2c_2}\right) > \\ > pl(x_1)^\alpha - \left(x_1 l(x_1) - \frac{l(x_1)^2}{2c_1}\right) \geq pl(x_2)^\alpha - \left(x_2 l(x_2) - \frac{l(x_2)^2}{2c_1}\right), \end{aligned} \tag{H.29}$$

where the first inequality follows from the fact that a firm of type 2 must not want to deviate from offering the utility of a firm of type 1. The second inequality follows simply from $c_2 < c_1$. And the last inequality follows from the fact that a firm of type 1 must not want to deviate to offering the utility of a firm of type 2. The above inequalities imply

$$\begin{aligned} pl(x_2)^\alpha - \left(x_2 l(x_2) - \frac{l(x_2)^2}{2c_2}\right) - \left[pl(x_2)^\alpha - \left(x_2 l(x_2) - \frac{l(x_2)^2}{2c_1}\right)\right] \\ \geq pl(x_1)^\alpha - \left(x_1 l(x_1) - \frac{l(x_1)^2}{2c_2}\right) - \left[pl(x_1)^\alpha - \left(x_1 l(x_1) - \frac{l(x_1)^2}{2c_1}\right)\right] \end{aligned} \tag{H.30}$$

which implies

$$\left(\frac{l(x_2)^2}{2c_2} - \frac{l(x_2)^2}{2c_1}\right) \geq \left(\frac{l(x_1)^2}{2c_2} - \frac{l(x_1)^2}{2c_1}\right). \tag{H.31}$$

And so,

$$l(x_2) \geq l(x_1) \Rightarrow x_2 \geq x_1 \tag{H.32}$$

which implies

$$w_1 - w_2 \leq a_2(c_2) - a_1(c_1). \tag{H.33}$$

And since $l(x_2) \geq l(x_1)$ it follows that

$$a_2(c_2, x_2) = \frac{l(x_2)}{c_2} \geq \frac{l(x_1)}{c_1} = a_1(c_1, x_1), \forall x_2, x_1 \tag{H.34}$$

□

I Model Results on Voluntary Separations

Next, we look at the difference in the rate at which workers voluntarily leave the firm, i.e, voluntary separation rate, between low and high amenity firms. The voluntary separation rate for a firm offering utility x is given by $\lambda(1-F(x))$. As a result, the average voluntary separation rate (VSR_i) for firms of type i is given by

$$VSR_i \equiv \lambda \int_{\underline{x}_i}^{\overline{x}_i} (1 - F(x)) \frac{dG(x)}{G(\overline{x}_i) - G(\underline{x}_i)} \equiv sk \int_{\underline{x}_i}^{\overline{x}_i} (1 - F(x)) \frac{dG(x)}{G(\overline{x}_i) - G(\underline{x}_i)}, \tag{I.1}$$

where $G(x)$ is the endogenous distribution of x in the economy and $k \equiv \lambda/s$. Note that VSR is not bounded from above given that λ is an arrival rate and so can take values from 0 to ∞. The difference in these rates between low and high amenity firms is then given by

$$VSR_1 - VSR_2 \equiv sk[\int_{\underline{x}_1}^{\overline{x}_1} (1-F(x)) \frac{dG(x)}{G(\overline{x}_2) - G(\underline{x}_2)} - \int_{\underline{x}_2}^{\overline{x}_2} (1-F(x)) \frac{dG(x)}{G(\overline{x}_2) - G(\underline{x}_2)}], \tag{I.2}$$

From Proposition 2, we know that as $k \to 0$, the utility offers by all firms converge to b, as a result,

$$\lim_{k \to 0} VSR_1 - VSR_2 = 0. \tag{I.3}$$

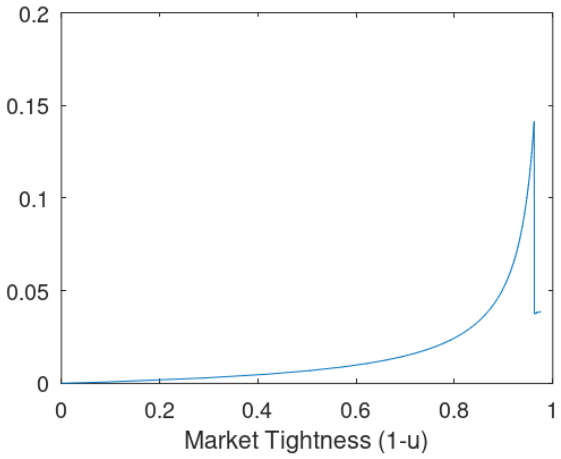
In contrast, the limit of $VSR_1 - VSR_2$ when λ becomes arbitrarily large is much less clear. In particular,

$$\begin{aligned} \lim_{k\to\infty} (VSR_1 - VSR_2) &= \lim_{k\to\infty} sk[\int_{\underline{x}_1}^{\overline{x}_1} (1-F(x)) \frac{dG(x)}{G(\overline{x}_2) - G(\underline{x}_2)} - \int_{\underline{x}_2}^{\overline{x}_2} (1-F(x)) \frac{dG(x)}{G(\overline{x}_2) - G(\underline{x}_2)}] \\ = s \lim_{k\to\infty} k \lim_{k\to\infty} [\int_{\underline{x}_1}^{\overline{x}_1} (1-F(x)) \frac{dG(x)}{G(\overline{x}_2) - G(\underline{x}_2)} - \int_{\underline{x}_2}^{\overline{x}_2} (1-F(x)) \frac{dG(x)}{G(\overline{x}_2) - G(\underline{x}_2)}] &= s \cdot \lim_{k\to\infty} \lambda \cdot 0, \end{aligned} \tag{I.4}$$

which is undefined. Next, we look numerically at how this difference in voluntary separate

rates $VSR_1 - VSR_2$ varies with one minus the unemployment rate through changes in k. We consider a monthly separation rate, s, of 0.03.[40] Importantly, the value of s only scales $VSR_1 - VSR_2$ without really changing the relationship between $VSR_1 - VSR_2$ and one minus the unemployment rate. In this sense, we see the choice of s as innocuous. Figure I.1 shows that the difference in voluntary separation rates between low and high amenity firms is monotonically increasing in one minus unemployment rate until the unemployment rate becomes equal or lower than 3.8%. Taken together with Figure **??**, these results indicate that even when compensating wage differentials start to increase with competition for workers (one minus unemployment rate), low amenity firms continue to lose more workers to competitors with increased competition. Intuitively, this happens because workers are under compensated for the lower amenity. As a result, even as the compensation for the low amenity increases, as long as workers are not fully compensated, increased compensation just leads to more workers leaving low amenity firms.

Figure I.1: Difference in Voluntary Separation Rates Between Low and High Amenity Firms Versus 1−Unemployment Rate

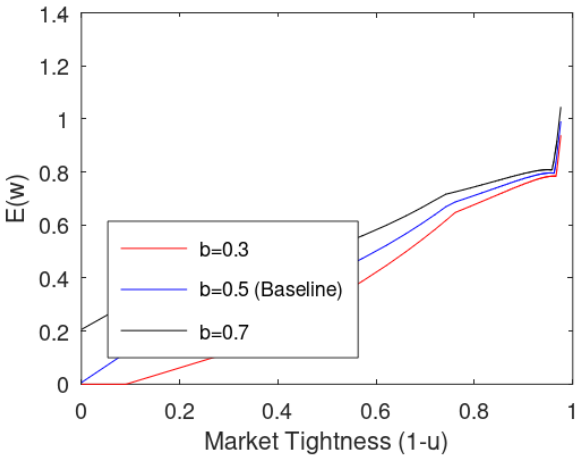


J Model Robustness for Varying Levels of Unemployment Utility b

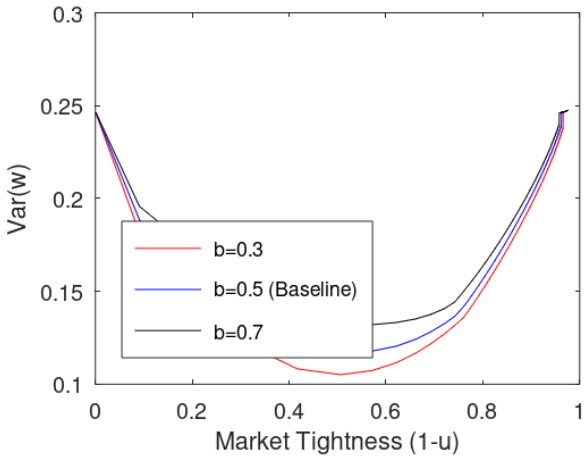
[40] This corresponds to jobs getting exogenously destroyed on average after 2.5 years.

Figure J.1: Wages versus Tightness $(1-u)$ for varying b

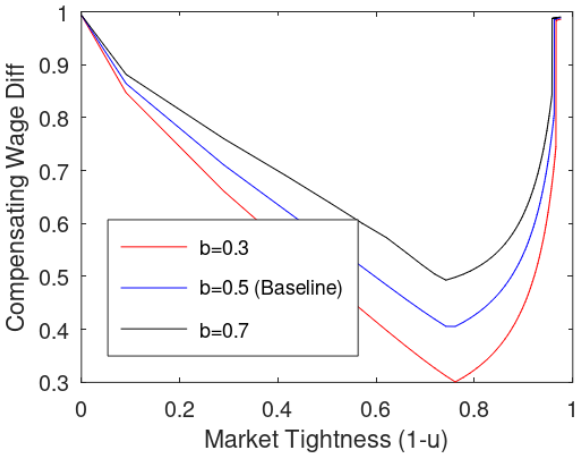
(a) Expected Wage $(E(w))$



(b) Variance of Wages $(Var(w))$



(c) Compensating wage differential



(d) Share $Var(w)$ due to Comp Diff $(Var(E(w|a)))$

