Domestic Outsourcing and Employment Security

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Abstract

Domestic outsourcing is robustly associated with lower transitions into unemployment among cleaners and security guards in Brazil during their first few years of tenure. This difference is not explained by worker characteristics or differential exposure to labor market conditions. We explain this novel fact by developing a search-theoretic model wherein intermediary firms can reassign outsourced workers across client firms when negative productivity shocks hit. The estimated model fits observed wage differentials and hazard profiles tightly. By easing reassignment across firms, domestic outsourcing had more positive welfare effects on workers upon job entry than implied by wage differentials alone.

Keywords: outsourcing, employment security, job search
JEL: J31, J62, L24

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1 Introduction

To focus on their "core competencies," firms have increasingly relied on outsourced workers to provide professional services once performed by direct employees, such as cleaning, security, IT, and HR. The rise of domestic outsourcing is widely believed to have fundamentally altered the structure of labor markets (Song et al. 2019; Stansbury and Summers 2020), but its precise effects remain controversial. The *efficiency* view suggests that domestic outsourcing helps firms and workers overcome labor market imperfections and therefore raises productivity and welfare (Abraham and Taylor 1996; Houseman 2001). The *rent-stripping* view instead emphasizes that outsourcing reduces the wages and benefits of low-wage workers, and thereby contributes to inequality (Weil 2014; Goldschmidt and Schmieder 2017).

To disentangle these views, it is necessary to investigate how domestic outsourcing has altered the nature of job search. A growing literature in economics shows that outsourcing is associated with lower wages and benefits for low-wage workers, especially for workers initially at high-wage firms (Dube and Kaplan 2010; Goldschmidt and Schmieder 2017; Drenik et al. 2023). Domestic outsourcing is also associated with increased employment, suggesting that outsourcing may bring aggregate efficiency benefits (Bertrand, Hsieh and Tsivanidis 2021; Bilal and Lhuillier 2021; Felix and Wong 2024). Yet, to date, there is very little evidence about the effects of domestic outsourcing on job transitions (Bernhardt et al. 2016). Such evidence is needed to understand how domestic outsourcing affects worker welfare and labor market structure and has implications for the proper design of labor regulations.[1]

In this paper, we present the first estimates of the effects of domestic outsourcing on worker employment security. We focus on cleaners and security guards in Brazil, since outsourced workers in these two occupations are cleanly identifiable from Brazil's administrative data. We find, to our surprise, that outsourcing is associated with *higher* employment security, especially during the first few years of employment spells. This finding is robust to controls for worker characteristics and local labor market conditions and contrasts with recent studies showing that

[1] In the past few years, Mexico and Peru instituted restrictions on domestic outsourcing (Jiménez and Rendon 2022; Estefan et al. 2024). Meanwhile, Brazil relaxed restrictions on outsourcing in 2017 in hopes of increasing the efficiency of labor markets.

outsourcing harms workers by reducing their wages and benefits. To explain the observed wage and hazard effects, we devise a search-theoretic model wherein outsourcing enables workers to be flexibly reassigned across firms without entering unemployment. The estimated model fits the data very well. Because of increased employment security, we estimate that outsourcing increased worker welfare in Brazil despite lowering wages.

We focus on data between 2003 and 2010, a period where precise employment spell start and end dates are available. We first estimate outsourcing wage differentials using a regression specification that includes controls for worker characteristics and fixed effects, following Dube and Kaplan (2010). We use an event study to confirm whether these wage differentials reflect the causal effect of outsourcing. We then estimate the effects of outsourcing on hazard into unemployment using a linear probability model. We control for observable worker selection and local labor market conditions. We also account for unobservable worker selection by investigating coefficient stability following Oster (2019).

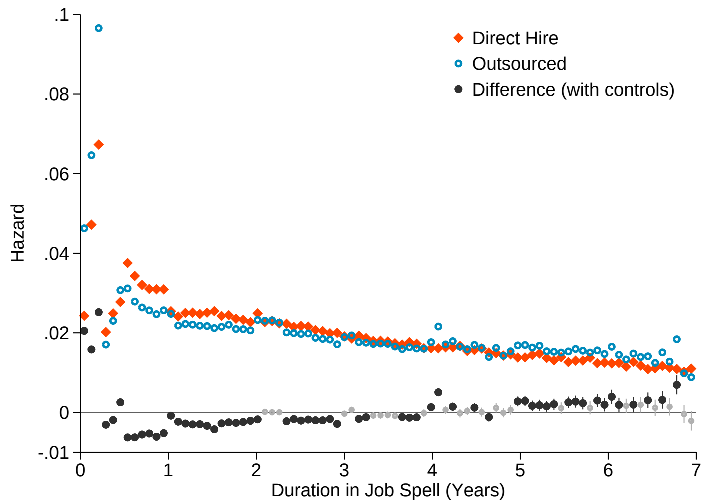
Our wage estimates are broadly consistent with recent literature, which suggests that outsourcing reduces worker wages for low-wage workers, but less so for high-wage workers (Dube and Kaplan 2010; Goldschmidt and Schmieder 2017; Spitze 2022; Drenik et al. 2023; Felix and Wong 2024). In the low-wage occupation of cleaners, outsourcing is associated with wages that are 11 percent lower. For the more professionalized and higher-wage occupation of security guards, outsourcing is associated with wages that are only 1.3 percent lower.

More strikingly, we find that outsourcing is associated with reduced transitions to unemployment. As shown in Figure 1, outsourced security guards have lower rate of hazard into unemployment than direct-hire guards for the first six years of their employment spells. During the first year of employment spells, the predicted hazard of direct-hire security guards is roughly 50 percent higher. It is only in the seventh year of employment that their predicted hazard rates become the same. For cleaners, the hazard rates of direct-hire workers are higher than that of outsourced workers during the first three years of employment, but fall below that of outsourced workers thereafter. These differences are not explained by local labor market conditions or worker selection.

To explain our findings, we develop a search-theoretic model with endogenous separations.

Figure 1: Hazard into Unemployment, Direct-hire and Outsourced Workers

(a) Cleaners



(b) Security guards

Notes: Each panel plots the raw probability of entering unemployment during each 30-day interval, separately for outsourced and direct-hire workers, conditional on being employed at the beginning of that interval. The sample includes the first full-time spells at each employer between 2003-2010. The black dots plot the estimated effect of being outsourced on entering unemployment using the linear probability model in Equation (2), without any controls. Vertical bars show 95% confidence intervals.

The model features *ex ante* identical workers, heterogeneous firms, and wage bargaining. A one-time shock to match-specific productivity occurs stochastically after a worker-firm pair is matched, as in Blanchard and Landier (2002). If the shock falls below some threshold, the match no longer generates a positive surplus, leading workers to separate from their employer.

We model outsourcing by introducing an intermediary who can facilitate the allocation of outsourced workers to different firms. In response to a negative shock, the intermediary can immediately reassign the worker to another firm with some probability. The involvement of the intermediary may also alter the bargaining power of workers. In addition, we allow outsourced and directly hired workers to have different match productivity distributions. This difference may reflect productivity differences between firms that outsource or directly employ. They may also arise from service fees, worker screening, and training by the intermediary.

A sharp theoretical prediction of the model is that when the reassignment rate is sufficiently large, the hazard rate of outsourced workers is lower than that of directly employed workers during the early period of employment spells. However, as time progresses, the hazard rate of outsourced workers becomes higher than direct-hire workers. This is because reassignment exposes the outsourced worker to the possibility of another match-specific shock at the new firm. Therefore, the hazard rates of outsourced workers decrease at a slower pace compared to those of directly employed workers, and the hazard rate of direct-hire workers "crosses" from above to below the hazard rate of outsourced workers over the employment spell.

We structurally estimate the model from the hazard rates and wage distributions of directly employed and outsourced workers using the Generalized Method of Moments (GMM). The estimates allow us to assess the fit of the model, evaluate the importance of the reassignment channel, and quantify the welfare effects of outsourcing on workers.

The estimated model fits the data very well. To match the observed hazard rates, the model infers that the reassignment rate is higher for cleaners compared to guards, with rates of 37% and 20%, respectively. The larger difference in reassignment rate for cleaners is consistent with the fact that hazard profiles exhibit a "crossing" pattern for cleaners but not for guards. To match the observed wage distributions, the model infers that the bargaining power of outsourced workers is lower than that of directly employed workers, and that outsourcing reduced bargaining power more for cleaners than for security guards.

Based on these estimates, we conclude that the effect of outsourcing on worker welfare is much more positive than implied by outsourcing wage differentials alone. Under a broad set of calibration assumptions, we find that outsourced workers had higher expected utility at the start of employment spells than directly employed workers.

To our knowledge, this paper is the first to estimate the effects of outsourcing on job hazards using administrative employment records (see surveys by Davis-Blake and Broschak 2009; Bernhardt et al. 2016). In related contributions, Batt, Doellgast and Kwon (2005) and Batt, Holman and Holtgrewe (2009) use a comparatively small sample of survey data, rather than a comprehensive employment registry, and show that outsourcing is associated with lower *perceived* job security among call center workers in the US. Our findings suggest that although outsourcing reduced wages in Brazil, it improved *actual* employment security and thereby brought benefits to workers.[2]

Our paper relates to a growing literature in macroeconomics that uses search-theoretic models to assess the aggregate effects of domestic outsourcing. In pioneering contributions, Bilal and Lhuillier (2021) use a model with wage posting and on-the-job search to analyze the effects of domestic outsourcing and argue that outsourcing increased both aggregate output and inequality in France. Spitze (2022) uses a search-and-matching model with constant match productivity and exogenous separations and argues that outsourcing disproportionately hurts low-wage workers in the U.S.. Neither of these models, however, features the possibility that outsourcing lengthens employment spells through flexible worker reassignment across firms. For this reason, they cannot explain our finding that outsourcing is associated with *higher* employment security and may understate the benefits of domestic outsourcing.

Our model builds on insights from Blanchard and Landier (2002), who study the effects of fixed-term contracts using a search model with a one-time productivity shock. The way that we model how intermediaries reassign workers across firms is similar to models of on-the-job search (Pissarides 1994; Cahuc, Postel-Vinay and Robin 2006).[3] By incorporating the reassignment

[2]Early work studies the determinants of outsourcing and suggests that firms outsource partly to overcome fluctuations in labor demand (Abraham and Taylor 1996; Houseman 2001). Many recent papers have focused on the effect of outsourcing on wage levels (Abraham 1990; Dube and Kaplan 2010; Goldschmidt and Schmieder 2017; Drenik et al. 2023). There is a growing literature that uses variation from policy changes to examine the effects of outsourcing in the labor market. For example, Felix and Wong (2024) use cross-regional variation to study the effects of Brazil's 1993 outsourcing legalization and find that outsourcing legalization increased the total employment of security guards in local labor markets. See also Bertrand, Hsieh and Tsivanidis (2021).

[3]Relatedly, Shimer (1999) and Prat (2006) study unemployment, worker turnover, and wage dispersion using models with match productivity shocks following Brownian motion. Arnold and Bernstein (2021) and Cahuc, Malherbet and Prat (2019) study the effects of discontinuities in severance pay schedules on worker hazard.

effect of labor market intermediaries, our model provides an explanation for the observed effects of domestic outsourcing on both worker hazard into unemployment and wage dispersion.

Our findings suggest that domestic outsourcing may have very different effects in the labor market than fixed-term contracts. Studies from Europe suggest that the rise of fixed-term contracts is associated with *reduced* employment security among young workers (Blanchard and Landier 2002; Bentolila and Saint-Paul 1992; Cahuc and Postel-Vinay 2002; García-Pérez, Marinescu and Vall Castello 2018; Daruich, Addario and Saggio 2020), while we find that domestic outsourcing *increases* employment security. The likely reason for this difference is that European regulations did not permit intermediation. Potential efficiency gains and benefits to workers from flexible reassignment by labor market intermediaries therefore could not be realized.[4]

The rest of the paper is organized as follows. Section 2 describes our empirical setting. Section 3 presents our hazard estimates. Section 4 describes our model. Section 5 presents a quantitative model. Section 6 concludes.

2 Background

2.1 Data and Sample Construction

We use Brazil's employee-employer matched administrative data, *Relação Anual de Informações Sociais* (RAIS), which cover the near universe of Brazil's formal-sector workers. The RAIS data include annual information on the start and end dates of employment spell, the average monthly wage over that period, and several demographic variables (such as education, gender, race, and age), which are collected through a mandatory survey administered by the Brazilian Ministry of Labor and Employment. These data are of high quality, since firms are fined for failure to report and workers cannot receive government benefits unless accurate information is reported.

We focus on data from 2003 to 2010, a period that is uncontaminated by the effects of Brazil's 1993 outsourcing legalization and has both consistent occupation codes and exact start

[4]In related work, Bertrand, Hsieh and Tsivanidis (2021) document that the use of contract workers who are employees of staffing firms enabled Indian firms to scale up and generated positive contributions to firm growth.

and end dates for employment spells. To identify direct-hire and outsourced workers, we use detailed industry and occupation codes.

Despite their richness, these data have two limitations. First, we do not observe worker-firm-intermediary linkages, so we cannot characterize the match between outsourced workers and client firms.[5] Second, there is a substantial informal sector in Brazil that is not covered by these data. Missing observations in our data could represent either unemployment or informal employment. We address this shortcoming by leveraging information on separation reasons.

For our hazard estimation, we construct employment histories for individual workers as follows. We restrict attention to workers aged 18-65 in full-time jobs (at least 35 hours per week) and exclude workers with temporary contracts.[6] We say that an employment spell ends in unemployment if there is more than one week between the spell's end and the start of the next full-time employment spell. We count all exits into unemployment towards the hazard except retirement, death, and quits. Since a large portion of Brazilian workers is in the informal sector, censoring quits reduces the likelihood of misclassifying transitions to informal jobs as exits to nonemployment. As shown in Appendix Figure B.5, our main results are highly similar when quits are not censored. Appendix A provides data definitions.

2.2 Our Focus: Cleaners and Security Guards

We focus on cleaners and security guards, for two reasons. First, both are large occupations where a substantial number of workers are employed by contract firms and within which the task requirements are relatively homogeneous. Second, there is a clear mapping from industry codes to contract firm status that does not exist in other occupations, so we confidently identify outsourced workers.[7]

Security guards in Brazil are highly professionalized, regulated, and well-paid. Because of

[5] This is a problem that plagues most administrative employment records with only one known exception (Drenik et al. 2023).

[6] These contracts are uncommon and subject to approval by the Ministry of Labor (MTE) to meet temporary increases in demand. Many of these contracts last for three months.

[7] It is not easy to sharply identify the effects of domestic outsourcing in other occupations using industry codes. For example, outsourced drivers work in the "road transport" industry, but this category also includes drivers who work for public transportation companies.

high crime rates and inadequate public provision of policing, security guards in Brazil undergo mandatory training administered by the Brazilian government and face regulatory requirements for gun carry licenses. The vast majority of security guards are in the formal sector.

Cleaners, by contrast, are an unlicensed occupation where many workers are in the informal sector. They are also the lowest-paid occupation in the formal sector. The mean monthly wage of cleaners in 2010 is roughly equal to one-half of the mean monthly wage of security guards.

Table 1 shows the characteristics of the employment spells of outsourced and direct-hire workers, including age, education, gender, and race at spell start. Anticipating our main result below, the employment spells for outsourced cleaners and security guards are *less* likely to end in unemployment than direct-hire cleaners and security guards, respectively.

2.3 Effect of Outsourcing on Wages

As a first look at the effects of outsourcing in these two occupations, we measure the effect of outsourcing on worker wages. Following Dube and Kaplan (2010), we estimate the following equation using yearly panels of security guards and cleaners, respectively:

$$\ln w_{it} = \gamma O_{it} + \theta_{omt} + X_{it}'\beta + \alpha_i + \epsilon_{imt}, \tag{1}$$

where t indexes year, i indexes the worker, w_{it} is the average real monthly wage, O_{it} indicates whether the worker is outsourced, θ_{omt} is a suboccupation-year-microregion fixed effect, $X_{it}'\beta$ are the effects of time-varying observable worker characteristics (such as education and age), α_i controls for individual fixed effects, and ϵ_{imt} is a composite error that may include idiosyncratic worker-firm match effects.[8] We then check whether estimated outsourcing wage differentials have a causal interpretation by plotting event studies for workers who change contractual arrangements, following the method of Card, Heining and Kline (2013).

[8] An alternative approach is to follow Goldschmidt and Schmieder (2017), who estimate wage differentials using "on-site outsourcing events." We do not follow this approach for two reasons. First, Brazilian labor law prohibits nominal wage reductions through the firing and rehiring of workers at an intermediary to perform the same job. As a consequence, estimates of wage differentials using such events are likely to be biased upward. Second, as documented by Felix and Wong (2024), on-site outsourcing is exceedingly rare in Brazil. Given the rarity, wage differentials estimated using this method necessarily use a highly selected population of workers.

Table 1: Summary Statistics of Employment Spells, Brazil, 2003-2010

	Cleaners		Security guards	
	Direct-hire	Outsourced	Direct-hire	Outsourced
Worker characteristics at spell start:				
Age	32.4	33.1	36.1	32.6
	[10.1]	[9.81]	[10.8]	[7.93]
Years of schooling	7.82	7.37	8.53	9.88
	[3.25]	[3.07]	[3.53]	[2.79]
Male	0.50	0.43	0.96	0.94
	[0.50]	[0.50]	[0.21]	[0.24]
Non-white	0.45	0.51	0.52	0.50
	[0.50]	[0.50]	[0.50]	[0.50]
Contract hours	43.6	43.7	43.3	43.7
	[1.49]	[1.29]	[2.12]	[1.52]
Share of spells that end within:				
one year	0.50	0.59	0.47	0.38
1-2 years	0.13	0.13	0.14	0.14
2-3 years	0.06	0.06	0.06	0.07
3-4 years	0.03	0.03	0.03	0.04
4-5 years	0.015	0.013	0.015	0.019
5-6 years	0.007	0.007	0.008	0.010
6-7 years	0.003	0.002	0.003	0.004
Share with unobserved spell end	0.26	0.18	0.28	0.33
Reason for spell end:				
Enter unemployment	0.51	0.45	0.49	0.34
Quit and leave formal sector	0.13	0.15	0.08	0.08
Transition to other formal job	0.06	0.16	0.09	0.17
Other	0.05	0.06	0.06	0.07
Observations	2681874	1897053	797534	1201625

Notes: The sample is all employment spells of security guards and cleaners, respectively, between 2003 and 2010. Standard deviations are displayed in brackets.

Outsourcing wage differentials may be attributable to either compensating differentials or differences in labor market rents. To understand the source of wage differentials, we investigate the extent to which outsourcing wage differentials are explained by differences in firm-level wage premia. We measure firm-level wage premia using the two-way decomposition proposed by Abowd, Kramarz and Margolis (1999) — henceforth AKM — as described in Appendix A.

We first confirm that the AKM decomposition provides a useful measure of firm-level wage premia for cleaners and security guards. After correcting for measurement error, we find that the AKM firm effects estimated using only cleaners and security guards, respectively, are very highly correlated with the AKM effect estimated for all other workers. If a firm pays 10% higher wages to other workers, it pays 6.1% higher wages to cleaners and 9.7% higher wages to security guards (Appendix Figure B.2). We then investigate whether firm-level wage premia explains the observed outsourcing wage differential.

Cleaners. Table 2 Panel A displays the estimated outsourcing wage differentials for cleaners, which is -11.0 log points in our preferred specification of Column (3). Column (1) shows that, with occupation-microregion-year fixed effects, the wages of outsourced cleaners are roughly 19.4 log points lower than direct-hire cleaners. With additional demographic controls in Column (2), the estimate changes very slightly to 17.8 log points. With added individual fixed effects, as in Column (3), the wages of outsourced cleaners are smaller at 11.0 log points, suggesting that there is some unobserved selection into outsourcing.

Column (4) shows that the outsourcing wage differential is much smaller after controlling the AKM firm effect, at 4.9 log points. Column (5) uses a split sample IV approach, to remove the influence of measurement error, with AKM firm effects estimated from two equally sized samples of workers that include neither cleaners nor security guards, to remove mechanical correlation arising from using the same data on both sides of the equation (following Goldschmidt and Schmieder 2017). The correlation between cleaner wages and AKM firm effects is only somewhat attenuated in this specification. These estimates suggest that differences in firm-level wage premia substantially explain the outsourcing wage differential.

The event studies in Appendix Figure B.1 shows that that cleaners who switch from direct-hire to outsourced jobs experience relative wage declines, while cleaners who switch from outsourced to direct-hire jobs experience relative wage increases. There are no significant pre-event trends during the two years prior, which implies that the estimated outsourcing wage differential is likely to capture the causal effect of outsourcing.

Table 2: Outsourcing Wage Differential, Brazil, 2003-2010

Dep. var.: Log real wage	(1)	(2)	(3)	(4)	(5)
Panel A: Cleaners					
Outsourced	-0.194	-0.178	-0.110	-0.049	-0.072
	(0.006)	(0.006)	(0.003)	(0.002)	(0.003)
AKM firm effect				0.413	0.332
				(0.007)	(0.007)
Observations	7834355	7834355	6150003	6131898	5904192
R^2	0.30	0.35	0.94	0.94	0.04
Panel B: Security guards					
Outsourced	-0.173	-0.137	-0.013	-0.014	-0.003
	(0.026)	(0.020)	(0.005)	(0.003)	(0.005)
AKM firm effect				0.690	0.397
				(0.011)	(0.012)
Observations	4768878	4768878	4253501	4251537	4176299
R^2	0.44	0.48	0.93	0.93	0.03
Occ X Year X Microregion FE	X	X	X	X	X
Demographic controls		X	X	X	X
Worker FE			X	X	X

Notes: Sample includes all cleaners and security guards, respective, observed at year-end in RAIS between 2003-2010. Demographic controls include a full set of race X gender X education dummies interacted with age, age squared, and age cubed. AKM firm effect is estimated from a wage regression using the full worker sample in column (4), and two non-overlapping random sets of workers in column (5). Standard errors are displayed in parentheses.

Security guards. For security guards, a higher-wage occupation, the outsourcing wage differential is very small. Our preferred estimate, which controls for unobservable worker heterogeneity, is -1.3 log points.

Table 2 Panel B Column (1) shows that the wages of outsourced security guards are roughly 17.3 log points lower than direct-hire security guards with occupation-microregion-year fixed effects. With additional demographic controls in Column (2), the estimate is similar, at 13.7 log points. With the individual fixed effects, as in Column (3), the estimate is only 1.3 log points. Columns (4) and (5) show that the estimated outsourcing wage differential remains small after accounting for differences in firm-level wage premia.

The event studies in Appendix Figure B.1 show that security guards who move from direct employment to outsourcing and from outsourcing to direct employment both experience a wage increase. The asymmetry in wage responses suggests some degree of endogeneity in worker mobility, but confirms that the outsourcing wage differential is likely to be small.

3 Effect of Outsourcing on Hazard into Unemployment

Having examined the wage effects of outsourcing, this section estimates the effect of outsourcing on the rate at which workers enter unemployment from employment. These estimates are important for understanding the welfare effects of domestic outsourcing on workers. If outsourcing facilitates their transitions across firms in response to demand fluctuations, then outsourcing should reduce hazards of unemployment and thereby benefit workers. To our knowledge, this paper is the first to investigate these effects.

3.1 Method

We construct the first full-time spell for each worker at each employer. We estimate the hazard function only at duration less than or equal to 7 years because of small sample sizes with longer duration. Because the model focuses on separation into unemployment, we censor spells ending in a job-to-job transition, in which case we do not know when the spell would have ended in unemployment.

Following Schmieder and Trenkle (2020), we estimate the hazard rate of entering unemployment at each month $\tau = 1, \ldots, 84$ using the following regression model:

$$y_{i\tau} = \alpha_\tau + \delta_\tau \mathbf{1}_{outsourced} + X_i' \beta_t + +\theta_{omt} + \epsilon_{i\tau} \mid \tau_i \geq \tau, \tag{2}$$

where τ_i is the month when individual i enters unemployment. In each regression, conditional on worker i has survived in an employment relationship for $\tau - 1$ months, the dependent variable $y_{i\tau}$ is a dummy indicating whether worker i enters into unemployment at month τ. X_i are worker-level controls. θ_{omt} are suboccupation-microregion-year fixed effects. Estimating Equation (2) at each τ provides a vector of α_τ which represents the average hazard rate into unemployment of direct-hire workers in month τ, while δ_τ represents the shift in the hazard rate of outsourced workers in that month, which measures the effect of outsourcing on entering into unemployment.

There are two main potential sources of bias in our hazard estimates. First, outsourced workers may be more prevalent in certain locations and therefore are differentially exposed to local macroeconomic fluctuations. To account for this confounding influence, we add flexible controls for microregion-suboccupation-year fixed effects.

Second, outsourced workers may be selected. To address this concern, we use a rich set of demographic controls, including gender, age, race, and education at the start of the employment spell, as well as AKM worker effects as a proxy for unobserved worker ability. We also assess the potential impact of unobserved worker selection by constructing bias-adjusted estimates using the method proposed by Oster (2019).[9]

3.2 Results

Figure 1 displays the raw rate of hazard into unemployment of outsourced and direct-hire cleaners. Figure 2 shows the differences in hazard rate between outsourced and direct-hire workers with controls successively added. We first add suboccupation fixed effects, then microregion-suboccupation-year fixed effects, then observable worker demographic characteristics such as gender, age, race, and education at spell start, and finally unobservable worker ability using AKM worker effects.[10] Figure 3 shows the bias-adjusted estimates using the method pioneered by Oster (2019), to account for potential unobservable selection that is proportional to the observable worker selection after partialling out microregion-suboccupation-year fixed effects.

In the appendix, we report estimates with more restrictive samples or a less stringent definition of transitions to unemployment. Appendix Figure B.4 reports results when we restrict to employment spells for which the individual initially entered from unemployment, to workers

[9]We focus on unobserved worker selection that is potentially proportional to worker-level observable selection (based on demographic variables and AKM worker effects) after partially out microregion-suboccupation-year fixed effects. Following Oster (2019), we assume $R_{\max} = 1.3\tilde{R}$ and plot bias-adjusted estimates β^* assuming that $\delta = 1$.

[10]See Appendix A for details.

who are no more than 30 at the start of the spell, and to male workers, respectively. Appendix Figure B.5 reports results where transitions to unemployment due to quits are included in the hazard definition.[11] Appendix Figure B.6 shows the implied survival rates.

Cleaners. As shown in Figure 1, the hazard into unemployment of direct-hire cleaners is significantly higher than that of outsourced cleaners in almost all months during the first 4 years of employment, except for some unusual patterns in the first six months. For example, at the one-year mark, the raw 30-day hazard rate for outsourced cleaners is 3.7 percent, while it is 4.2 percent for direct-hire cleaners. The unusual pattern in the first three months is likely attributable to tenure-dependent employment protection legislation, which caused hazards to be significantly higher prior to the three-month mark than thereafter (Arnold and Bernstein 2021).[12]

The hazard rates of outsourced and direct-hire workers become closer over the course of the employment spell. They eventually cross at around four years of tenure, with the hazard of direct-hire workers becoming lower than those of outsourced cleaners thereafter.[13] The difference in survival gradually attenuates thereafter, so outsourcing generally has a small but positive effect on employment survival probability (see Appendix Figure B.6).

Figure 2 shows that the estimates are broadly similar after successive addition of controls. This suggests that selection due to observable worker characteristics and labor market conditions do not drive these differences in hazard rates.

Figure 3 shows that worker selection based on unobservable characteristics is unlikely to drive these differences using the bias-adjustment method of Oster (2019). The estimates are also robust to alternative sample and outcome variable definitions (Appendix Figure B.4 and B.5).

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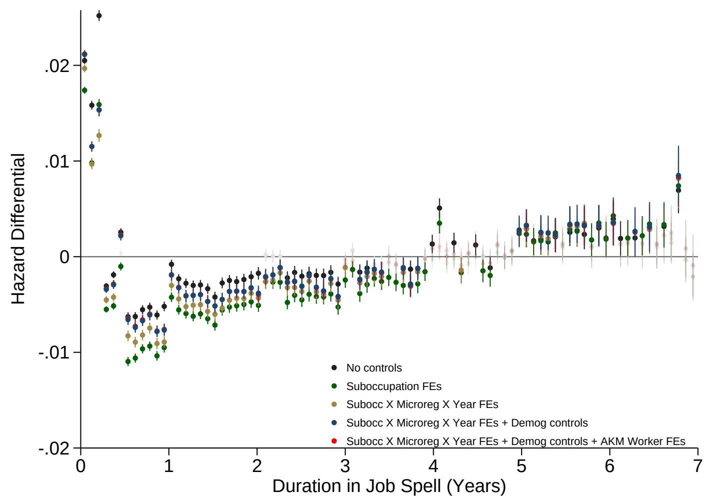
[11] Relately, we find that outsourced workers are more likely than direct employees to experience employer-to-employer transitions (see Appendix Figure B.7). This could be because either workers are more likely to encounter outside employment offers, or when a client firm decides to change their service provider, outsourced workers are more likely to stay in the same job even as the employment contract is moved to a different contract firm. Further exploration of the on-the-job search behavior of outsourced workers is left for future work.

[12] Specifically, the employer must pay a firing penalty in the event of an involuntary separation, which is equal to roughly one month of the worker's salary for every year the worker has been employed at the firm. The bulk of this penalty is paid to the worker as severance. This requirement is tenure-dependent and only applies after 3 months of employment.

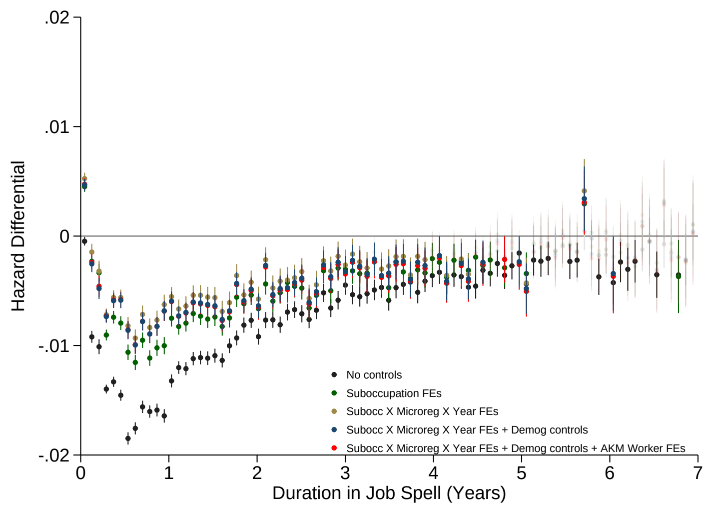
[13] As shown in Appendix Figure B.3, locally smoothed estimates of the outsourcing differential confirm that the hazard rate of outsourced cleaners "crosses" from above to below that of direct-hire security guards at around four years of tenure.

Figure 2: Effect of Outsourcing on Hazard into Unemployment, Alternative Controls

(a) Cleaners



(b) Security guards



Notes: Sample includes all first full-time spells at each employer between 2003-2010. We truncate the duration at 7 years. Each hazard differential is estimated at the midpoint of the 30-day interval. The black dots display the raw difference in hazards. The green dots show estimates with only suboccupation fixed effects. The mustard dots show estimates with suboccupation X microregion X year fixed effects. The red shows the estimates with the full set of controls in our main regression. The blue dots show the estimates with the full set of controls and AKM worker effects estimated from a wage regression with the full sample. 95% confidence intervals are shown. Statistically insignificant estimates are shown in light gray.

Security guards. The effect of outsourcing on hazard to unemployment is larger and more negative for security guards. Figure 1 shows that with the exception of the first few months, outsourced security guards have much lower probabilities of transitioning to unemployment than direct-hire workers. At the one-year mark, the raw 30-day hazard rate for outsourced workers is 3.7 percent, while it is 1.8 percent for direct-hire workers. The hazard rates of outsourced and direct-hire workers become closer over the course of the employment spell, eventually narrowing to a statistically indistinguishable difference in the sixth year of tenure. The hazard estimates imply that outsourcing significantly increased the survival of employment spells for security guards (Appendix Figure B.6).

Figure 2 shows that adding suboccupation fixed effects attenuates the estimates somewhat, suggesting that for security guards, it is important to account for suboccupation differences. However, the effects of outsourcing on hazard into unemployment among security guards remain large even after controlling for observable worker characteristics and labor market conditions.

Figure 3 shows that estimates are highly similar after accounting for unobservable worker selection using the method of Oster (2019). The estimates are also robust to alternative sample and outcome variable definitions (Appendix Figure B.4 and B.5).

4 Model of Outsourcing with Endogenous Separations

To explain the observed effect of outsourcing on hazard into unemployment, we consider a stylized partial equilibrium search-and-matching model. The model features endogenous job separation following Mortensen and Pissarides (1994). In the model, matched worker-firm pairs receive a stochastic productivity shock over time. Outsourcing alters the search and bargaining process in the labor market and thereby changes workers' wages and separation rates.

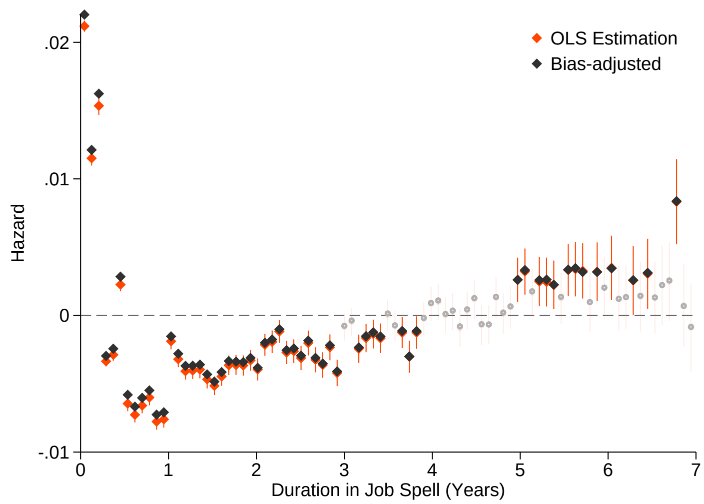
4.1 Setup

The model assumes that a worker is matched with firms under either an employment or outsourcing arrangement. Under employment, the firm directly employs the worker. Under outsourcing, an intermediary employs the worker, but the worker is assigned to the firm. Time is continuous with a discount rate r.

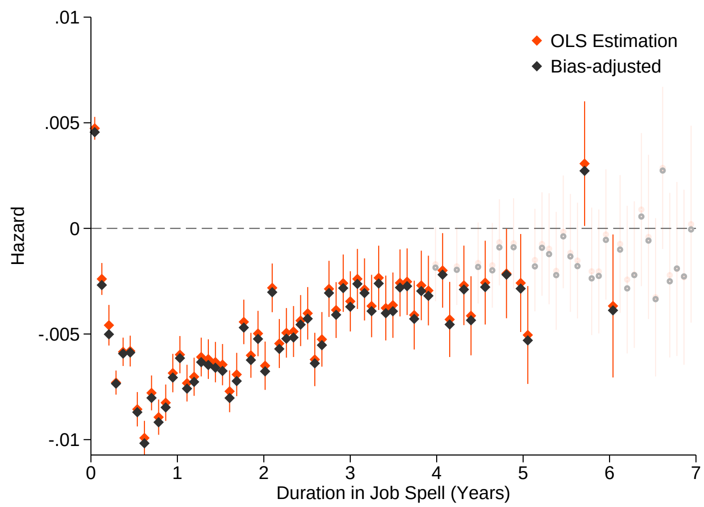
Under each arrangement $a \in \{E, O\}$, match productivity is initially y_a at $t = 0$. During the

Figure 3: Bias-adjusted Effect of Outsourcing on Hazard into Unemployment

(a) Cleaners



(b) Security guards



Notes: Following Oster (2019), we plot bias-adjusted estimates assuming that $\delta = 1$ and $R_{\max} = 1.3\tilde{R}$, after partially out microregion-suboccupation-year fixed effects. The black dots display the bias-adjusted estimates. The orange dots show estimates with the full set of controls in our main regression and AKM worker effects estimated from a wage regression with full sample. 95% confidence intervals are shown for the OLS estimates. Statistically insignificant estimates are shown in light gray.

match, a single stochastic productivity shock z arrives at Poisson rate λ. The match productivity then changes to $y_a + z$, where z is a random variable with a continuous cumulative distribution $G(z)$. Although we do not model it explicitly as such, the change in productivity can be interpreted as symmetric learning about match productivity, as in Jovanovic (1979).

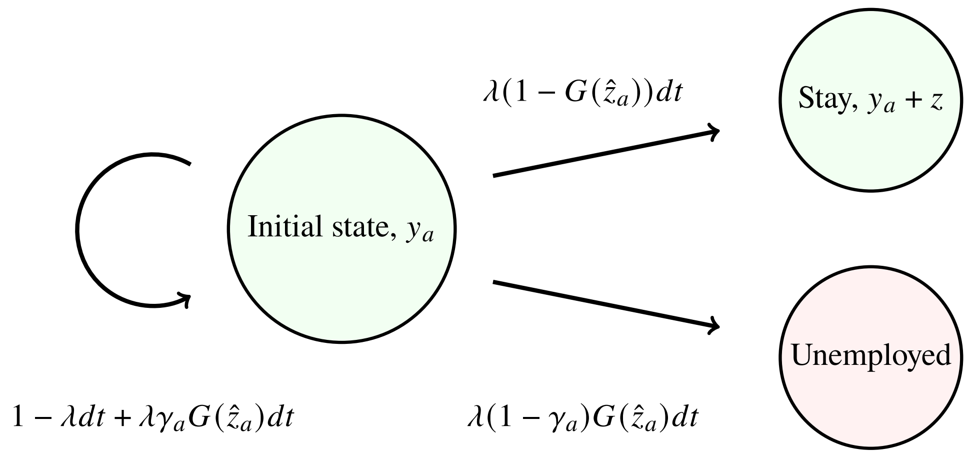
Wage is determined by Nash bargaining with worker bargaining parameter β_a through continuous renegotiation between the firm and the worker. Since wages are bargained, we say that match-specific rents are *shared* between the worker and firm. If bargaining fails, the worker enters unemployment and receives an outside option $\overline{W}$. Implicitly, we assume that the intermediary has zero bargaining power. This assumption is plausible since contract firms bid for service contracts competitively and the client often retains the ability to set wages for the outsourced workers.

Outsourcing has three potential effects in our model. First, outsourcing may alter the match productivity level y_a. This could be because the firms that select into outsourcing are systematically different. For example, Dube and Kaplan (2010) and Goldschmidt and Schmieder (2017) document that high-wage firms are more likely to outsource. It could also be that outsourced workers are positively selected due to the hiring and matching expertise of the intermediary. Yet another potential reason is that intermediaries may charge a fee for outsourced workers, which lowers the net productivity of outsourced workers.

Second, outsourcing may alter worker bargaining power β_a. By allowing bargaining power to differ, we incorporate the prevailing notion in extant literature (e.g., Dube and Kaplan 2010 and Goldschmidt and Schmieder 2017) that outsourcing lowers the rents that workers receive by circumventing within-firm fairness norms, avoiding collective bargaining agreements, or reducing efficiency wages.

Third, outsourcing allows workers to be reassigned across firms, while directly employed workers cannot. Specifically, we assume that if a worker-firm pair under outsourcing separates, then with some probability γ_O, the intermediary immediately matches the firm with a new worker and reassigns the worker to another firm. The productivity of the new match is y_O and another productivity shock z may arrive at rate λ. However, if worker-firm pairs under direct employment separate, then the worker must enter unemployment and the firm must open a vacancy. In other words, the probability of reassignment under outsourcing is $\gamma_O \in [0, 1]$, while under employment $\gamma_E = 0$. For simplicity, we define $\gamma \equiv \gamma_O$.

Figure 4: Worker State Transitions



4.2 Equilibrium under Employment and Outsourcing

Figure 4 visualizes the state transitions under arrangement a. At the initial state, workers' match productivity is y_a. Productivity shock z arrives at rate λ. There is a cutoff $\hat{z}_a$ such that separation will occur when z is below the cutoff. If $z \geq \hat{z}_a$, the match continues and no further productivity shock arrives. If $z < \hat{z}_a$, then with probability γ_a, the worker is reassigned to another firm with initial match productivity y_a, and another productivity shock z arrives at rate λ. Otherwise, the worker becomes unemployed.

Let $\bar{V}^a$ denote the value of the firm that opens a vacancy under arrangement a. Let V_0^a denote the value of the firm that is matched with a new worker under arrangement a. Let $V_1^a(z)$ denote the value of a firm that remains matched with the worker after the productivity shock z arrives under arrangement a.

Once matched with a worker, the firm's Bellman equations before the shock is:

$$\begin{aligned} rV_0^a = & \underbrace{(y_a - w_0^a)}_{\text{flow profit}} + \underbrace{\lambda \int_{\hat{z}_a}^{\infty} [V_1^a(z) - V_0^a] dG(z)}_{\text{stay after shock}} \\ & + \underbrace{(1 - \gamma_a)\lambda G(\hat{z}_a)(\bar{V}^a - V_0^a)}_{\text{separate after shock}} + \underbrace{\gamma_a \lambda G(\hat{z}_a)(V_0^a - V_0^a)}_{\text{re-assign after shock}} . \end{aligned} \tag{3}$$

The flow profit for firms is productivity subtracted by wages ($y_a - w_0^a$). With probability λ, the productivity shock arrives. When $z > \hat{z}_a$, workers will stay after the shock, and firms' utility gain is $V_1^a(z) - V_0^a$. When $z < \hat{z}_a$, with probability $1 - \gamma_a$, firms and workers are separated and firms do not get reassigned a new worker. In this case, the utility loss is $\bar{V}^a - V_0^a$. With probability γ_a, firms get a new worker and the utility change is $V_0^a - V_0^a = 0$.

If the productivity shock arrives and there is no separation, the firm's Bellman equation after the shock is

$$rV_1^a(z) = y_a + z - w_1^a(z) \tag{4}$$

The firm's flow profit is the post-shock productivity ($y_a + z$) subtracted by the post-shock wage ($w_1^a(z)$).

The worker's Bellman equation before the shock is:

$$\begin{aligned} rW_0^a = & \underbrace{w_0^a}_{\text{flow wage}} + \underbrace{\lambda \int_{\hat{z}_a}^{\infty} [W_1^a(z) - W_0^a] dG(z)}_{\text{stay after shock}} \\ & + \underbrace{(1-\gamma_a)\lambda G(\hat{z}_a)(\bar{W} - W_0^a)}_{\text{separate after shock}} + \underbrace{\gamma_a \lambda G(\hat{z}_a)(W_0^a - W_0^a)}_{\text{re-assign after shock}} \end{aligned} \tag{5}$$

The flow payoff for workers is their wages. With probability λ, the productivity shock arrives. When $z > \hat{z}_a$, workers stay after the shock, and their utility gain is $W_1^a(z) - W_0^a$. When $z < \hat{z}_a$, with probability $1 - \gamma_a$, workers separate from the firm and become unemployed, and the utility loss is $\bar{W} - W_0^a$. With probability γ_a, workers are re-assigned to a new firm and their utility change is $W_0^a - W_0^a = 0$.

After the shock, if the worker remains matched with the same firm, the worker's Bellman equation is given by:

$$rW_1^a(z) = w_1^a(z). \tag{6}$$

Workers' flow utility is simply their wages. This is a self-absorbing state as no further productivity shocks will occur.

Wages are continuously negotiated through Nash bargaining, so we have that

$$(1-\beta_a)(W_0^a - \bar{W}) = \beta_a(V_0^a - \bar{V}^a) \tag{7}$$

$$(1-\beta_a)(W_1^a(z) - \bar{W}) = \beta_a(V_1^a(z) - \bar{V}^a) \tag{8}$$

The free-entry condition suggests that the value of firms opening a vacancy is always zero, i.e., $\bar{V}^a = 0$.

The matched worker-firm pair is indifferent between separation and continuation at the productivity cutoff $\hat{z}_a$, so the cutoff $\hat{z}_a$ is pinned down by $V_1^a(\hat{z}_a) = \bar{V}^a$. Hence, we have

$$\hat{z}_a = -y_a + r\bar{W} \tag{9}$$

The cumulative probability of endogenous separation is

$$F_a(t) = \left[1 - e^{-(1-\gamma_a)\lambda t}\right] G(\hat{z}_a) \tag{10}$$

The hazard rate (the probability of separation in the current period conditional on being with the firm in the last period) is:

$$h_a(t) = \frac{F_a'(t)}{1 - F_a(t)} = \frac{(1-\gamma_a)\lambda G(\hat{z}_a)}{G(\hat{z}_a) + (1 - G(\hat{z}_a))e^{(1-\gamma_a)\lambda t}} \tag{11}$$

Workers' wages before and after the match productivity shock arrives are, respectively

$$w_0^a = \beta_a y_a + (1-\beta_a)r\bar{W} \tag{12}$$

and

$$w_1^a(z) = \beta_a(y_a + z) + (1-\beta_a)r\bar{W} \tag{13}$$

4.3 Theoretical Predictions

In Section 3, we documented a striking "crossing" pattern in the hazard among cleaners in Brazil, wherein the unemployment hazard of outsourced cleaners is initially lower than similar direct-hire cleaners but becomes higher after the first few years of employment tenure. Proposition 1 shows that this "crossing" pattern can be rationalized in our model by the possibility of flexible reassignment of workers across firms.

Proposition 1. *If the probability of reassignment under outsourcing, γ, is sufficiently large, then there exists some T such that $h_E(t) \gtreqless h_O(t)$ if and only if $t \lesseqgtr T$. Otherwise, $h_E(t) \lesseqgtr h_O(t)$ for all t.*

Proof. See appendix. □

The intuition for Proposition 1 is as follows. Combining Equations (9) and (11), we can show that the initial hazard rate $h_a(0) = (1 - \gamma_a)\lambda G(-y_a + r\bar{W})$. It follows that $h_O(0) < h_E(0)$ if either γ is large or y_O is high relative to y_E. In other words, transitions to unemployment are less likely at the start of an employment spell under outsourcing either if the intermediary reassigns workers across clients or if the initial worker-firm match productivity is larger for outsourced workers than direct-hire workers.

If the probability of reassignment γ is large, however, the slope of unemployment hazard respective to time under outsourcing flattens. This is because reassignment exposes the worker to the possibility of another match-specific shock at the new firm. As a result, there is a form of dynamic selection, wherein conditional on survival, outsourced workers are more likely to face a match-specific shock. This causes their hazard rates to fall more slowly than those of directly employed workers.

The combination of these two effects explains why there exists a cutoff T such that $h_E(t) \gtreqless h_O(t)$ if and only if $t \lesseqgtr T$ only if γ is sufficiently large. If the cutoff T exists, it is possible to derive an explicit formula for it:

$$T = \frac{1}{\lambda} \log \left[\frac{\gamma}{e^{1-\gamma}(1 - 1/G(\hat{z}_O)) - (1 - \gamma)(1 - 1/G(\hat{z}_E))} \right] \tag{14}$$

An immediate implication is that T increases in y_O, but decreases in y_E and λ. The relationship between T and γ is more ambiguous. It can be shown that T increases in γ if and only if $e^{1-\gamma}(1+\gamma) > \frac{G(\hat{z}_O)}{1-G(\hat{z}_O)} \cdot \frac{1-G(\hat{z}_E)}{G(\hat{z}_E)}$. Therefore, T increases in γ if $y_O \leq y_E$. However, T may be decreasing in γ if y_O is much larger than y_E.

5 Structural Estimation

This section estimates an extended structural model using observed wage and hazard distributions from Brazilian data. The model enables us to assess the fit of the model, understand the structural differences between the two occupations, and quantify the welfare effects of outsourcing on workers.

5.1 Method

We use an extended model where the initial match productivities, for both employees and outsourced workers, are drawn from a distribution $\log(y_{aj}) \sim N(\mu_a, \sigma_a)$, where $a \in \{E, O\}$. We assume that when outsourced workers are reassigned to a new firm, they are matched with a random firm, and the new match productivity is drawn from the same distribution $\log(y_{Oj}) \sim N(\mu_O, \sigma_O)$. This assumption allows us to better replicate the wage distribution observed in the data. We introduce an exogenous separation rate δ to better match the hazard rate. We discretize time and consider one period to be equivalent to one month.

We calibrate a set of parameters that cannot be easily estimated from our data. The monthly interest rate, denoted as r, is set at 0.0025, targeting an annual risk-free interest rate of 3%. The value of unemployment, denoted as $r\bar{W}$, is set at 70% of the value of employment at the average wage.[14] The bargaining power of direct-hire workers is set at 0.5. This allows us to identify the distribution of initial match productivity of direct-hire firms from the wage distribution of newly hired direct-hire workers. The difference in average initial match productivity between

[14]We do not estimate the value of unemployment since we cannot observe informal employment in the data. Appendix Table B.1 shows that after spells end in unemployment, a large fraction of workers are remain outside of our data even after a year. It is therefore difficult to know the subsequent earnings of unemployed workers. We will evaluate how our welfare estimates vary with the chosen value for unemployment in a robustness check.

Table 3: Parameters and Targeted Moments

Parameter	Meaning	Targeted Moments
μ_E	average log initial match productivity of E workers	average initial wages of E workers
β	bargaining power of O workers	average initial wages of O workers
σ_E	std of log initial match productivity of E workers	std of initial wages of E workers
σ_O	std of log initial match productivity of O workers	std of initial wages of O workers
λ	arrival rate of match-specific shock	slope of the hazard rates for E workers
γ	reassignment rate	slope of the hazard rates for O workers
μ_z	average productivity shock	average hazard rates of E workers
σ_z	std of productivity shock	difference in hazard rates between E and O workers
δ	exogenous separation rate	long-run hazard rates of E and O workers

E: direct-hire, O: outsourced.

outsourced and direct-hire workers is 10 log points, or $\mu_O - \mu_E = 0.1$.[15] In Section 5.3, we show the robustness of our results using alternative values of unemployment and productivity gap.

Table 3 lists the parameters that we estimate using GMM and the corresponding targeted moments. The average wages of newly direct-hire workers identify their average initial match productivity. The average wages of newly hired outsourced workers determine the bargaining power of outsourced workers. The standard deviations of initial wages for direct-hire and outsourced workers reflect the standard deviations of initial match productivity for the respective groups of workers. The arrival rate of match-specific shocks, denoted as λ, is identified by the slope of the hazard rates for direct-hire workers.[16] The re-assignment rate for outsourced workers, denoted as γ, is identified by the slope of their hazard rates.[17] The average hazard rates of direct-hire workers identify the average level of productivity shock, denoted as μ_z.[18] The standard deviation of productivity shock denoted as σ_z, impacts the average difference in hazard rates between direct-hire and outsourced workers.[19] The exogenous separation rate, denoted as δ, is identified by examining the long-run hazard rates for both types of workers.[20]

[15]Since we cannot observe the initial match productivity of outsourced workers and their bargaining power at the same time, we opt to calibrate the initial match productivity of outsourced workers and estimate their bargaining power using the wage distribution of newly hired outsourced workers. We later conduct a sensitivity analysis to demonstrate that our results remain robust to the chosen productivity gap between the two types of firms.

[16]The hazard rate in month t represents the conditional probability of separating from the current employer in period t, given that the individual was employed in period $t-1$. A steeper hazard profile indicates a higher λ, as the match-specific shock leads to endogenous separation.

[17]A higher re-assignment rate results in a flatter hazard profile.

[18]A higher μ_z corresponds to smaller hazard rates.

[19]Our simulation indicates that an increase in σ_z results in a smaller gap in hazard rates between the two groups of workers.

[20]In the model, it is assumed that productivity shocks only occur once. In the long run, almost every worker

Table 4: Estimation Results

Parameter	Cleaners		Guards	
λ	0.0326	(0.0008)	0.0288	(0.0013)
γ	0.3665	(0.0241)	0.1960	(0.0229)
β	0.3058	(0.1986)	0.3985	(0.1364)
δ	0.0094	(0.0001)	0.0072	(0.0000)
μ_E	3.3244	(0.2743)	3.7197	(0.3311)
σ_E	0.1440	(0.0163)	0.2241	(0.0307)
σ_O	0.1858	(0.0762)	0.2558	(0.0979)
μ_z	-33.7140	(0.4958)	-28.5253	(0.0885)
σ_z	0.2718	(0.1136)	0.0001	(0.1855)

Standard errors are reported in the parentheses.

To estimate the model, we use predicted hazard rates holding constant worker characteristics and local labor market conditions. We drop the first three months to remove the potential effects arising from employment protection regulations, and perform local smoothing with a bandwidth of one year. We also use the counterfactual wage distribution if all observed security guards and cleaners were either outsourced or direct-hire.[21]

5.2 Results

Table 4 displays the estimation results obtained using GMM. The estimated arrival rate of productivity shocks (λ) is roughly similar for both cleaners and guards, at approximately 3.3% and 2.9% per month, respectively. However, we estimate that 37% of cleaners are immediately re-assigned to a new firm following separation from their current client, while only 20% of guards are re-assigned. This difference arises because a crossing pattern in the hazard rates is observed for cleaners, but not for security guards (see Figure 1). As shown in Proposition 1, our model predicts that there is a crossing pattern in hazard rates only if the reassignment rate (γ) is

has experienced the productivity shock, and separation can only be driven by the exogenous shock.

[21] We predict this counterfactual using a regression of the log real wage on the outsourced dummy, tenure dummies, and the interaction terms of outsourced and tenure dummies. The regression includes worker fixed effects, demographic controls for gender, age, age squared, race, years of schooling, and the suboccupation X year X microregion fixed effects at the spell level. We then use the regression residual (the residualized log wage) to compute the mean and standard deviation of residuals as our targeted moments. New hires are classified as workers whose duration of job spells is less than one year. The residual wage distributions are plotted in Appendix Figure B.8.

Table 5: Model Fit — Wages

	Mean	Std		Mean	Std
Direct-hire cleaners			Direct-hire guards		
Data	3.01	0.10	Data	3.46	0.15
Model	3.01	0.10	Model	3.46	0.15
Outsourced cleaners			Outsourced guards		
Data	2.91	0.10	Data	3.46	0.15
Model	2.91	0.10	Model	3.46	0.15

sufficiently high.

The estimated bargaining power (β) for outsourced cleaners is 0.31, while for outsourced guards it is 0.40. Recall that the bargaining power of direct-hire workers is set at 0.5. The estimated wage bargaining power of outsourced workers is therefore lower than that of direct-hire workers in both occupations. Outsourced cleaners also have less bargaining power than outsourced guards. This result is consistent with the fact that the outsourcing wage differential is more negative for cleaners than for guards.

The estimated model fits the wage distributions and hazard rates very well. Table 5 presents the model fit for wages. Figure 5 plots the model fit for hazard rates.

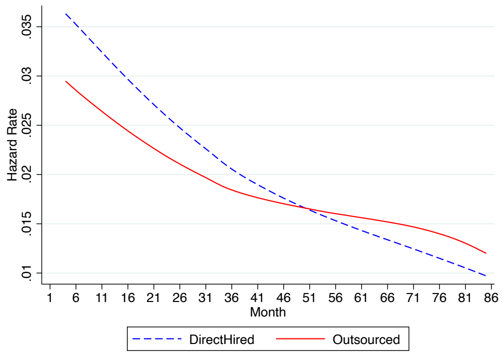
5.3 Robustness

We perform two robustness checks to assess the sensitivity of our estimation results to alternative calibration values. First, we re-estimate the model for various values for the difference in initial match productivity between outsourced and direct-hire workers ($\mu_O - \mu_E$). Table B.2 presents the estimation results.

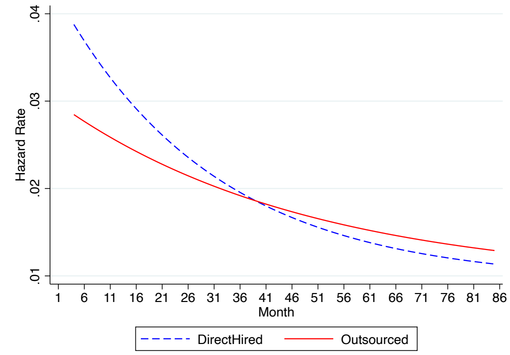
For cleaners, we find that key parameters such as re-assignment rates (γ) and productivity shock arrival rates (λ) are highly robust to values of the productivity gap ranging from 0 to 20 log points.[22] However, the estimated bargaining power of outsourced workers, β, falls with the productivity gap. This is intuitive, since a higher productivity gap implies that outsourced workers have higher initial match productivity on average, so to match the observed wages, the bargaining power of outsourced workers must be lower. Despite this, the estimated bargaining

[22] The estimated values of γ range from 0.372 to 0.366 as the productivity gap changes from 0 to 0.2.

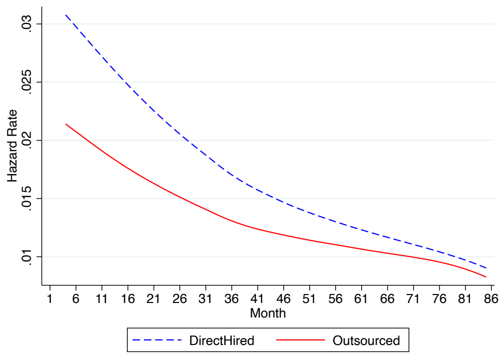
Figure 5: Model Fit — Hazard Rates



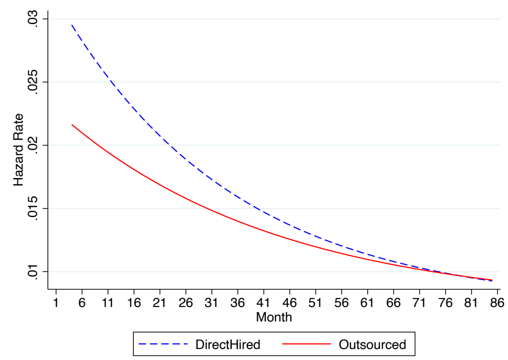
(A) Cleaners: Data



(B) Cleaners: Model



(C) Security guards: Data



(D) Security guards: Model

power of outsourced cleaners is still consistently lower than that of direct-hire cleaners in all specifications.

For guards, we find that the estimated re-assignment rates range from 7% to 20% when the productivity gap ranges from 10 to 20 log points, indicating a consistently low reassignment rate. However, the model fit substantially deteriorates as the productivity gap declines from 10 log points to 0. As shown in the last column of Table B.2, the average distance between the model's predicted hazard and the actual hazard in the data exceeds 1 percent when the productivity gap is smaller than 10 log points. The model also fails to predict the no-crossing pattern in the hazard rates when the productivity gap is below 10 log points. This suggests that the productivity gap needs to be at least 10 log points for the model to fit the observed hazard rate patterns.

Second, we re-estimate the model with different values of unemployment. In our baseline

Table 6: Effect of Outsourcing on Worker Welfare

	Cleaners	Guards
Wage	-11.0	-1.3
Welfare (in wage equivalence)	0.4	7.5

Note: The numbers are percentage changes relative to direct-hire workers.

specification, we calibrated the value of unemployment ($r\bar{W}$) to be 70% of the value of employment at the average wage. Here we use a range of values of unemployment, ranging from 50% to 90% of the value of employment at the average wage. The results are presented in Table B.3. The estimated average initial match productivity of direct-hire workers declines as the value of unemployment increases, as indicated by Equation 12. This will lead to a decrease in the average initial match productivity and a decline in the bargaining power of outsourced workers. However, the model fit and estimates of re-assignment rates for both cleaners and guards are broadly similar across different choices of unemployment values.

5.4 Welfare Analysis

We leverage our structural estimates to evaluate the impact of domestic outsourcing on worker welfare. The first row of Table 6 reproduces the reduced-form estimates of the effect of outsourcing on wages from Table 2. In the second row, we report the estimated effect of outsourcing on workers' utility, measured by wage equivalence, taking into account the effect on hazards in addition to the effect on wages.

When we consider only the wage differential between outsourced and direct-hire workers, the impact of outsourcing on workers' welfare is negative. Cleaners experience an 11.0 percent reduction in welfare, while guards face a 1.3 percent reduction. The negative effect is more pronounced for cleaners, as the wage gap between outsourced and direct-hire workers is larger in this occupation compared to guards. However, when we take into account the lower hazard rates for outsourced workers, the estimated effect of outsourcing on worker welfare becomes positive for both occupations. This positive effect translates to a 0.4 percent increase in wages for cleaners and a 7.5 percent increase for security guards. These findings diverge from the estimated wage differential caused by outsourcing, which is negative for both cleaners and guards. Outsourced cleaners have less bargaining power compared to outsourced guards, but they also have higher rates of re-assignment. We observe that the welfare effect of outsourcing is greater for guards than for cleaners, suggesting that the former channel dominates the latter.

In Table B.4, we present estimates from alternative models as robustness checks. We explore different calibration methods, such as setting the initial match productivity gap between outsourced and direct-hire workers to 0.05 or 0.15 instead of 0.1, and adjusting the value of unemployment to be 60 to 90 percent of the value of employment at the average wage. Our results demonstrate that the welfare implications for outsourced cleaners and guards remain consistent across different calibration assumptions of the productivity gap. As the value of unemployment increases, the welfare benefit of being an outsourced worker decreases for both cleaners and guards, as the advantage of re-assignment becomes smaller. Across various calibration methods, the welfare effect ranges from -6.6 percent to 4.1 percent for cleaners and from 4.5 percent to 11.6 percent for security guards.

6 Conclusion

This paper presents the first estimates of the effects of domestic outsourcing on worker employment security. Using comprehensive administrative data on security guards and cleaners in Brazil, we first confirm that outsourcing is associated with lower wages, especially for low-wage workers, as suggested by recent literature (Dube and Kaplan 2010; Goldschmidt and Schmieder 2017; Drenik et al. 2023). We then robustly find that outsourcing is associated with a much lower hazard of unemployment during the first few years of employment spells. This difference is not explained by observable worker characteristics or differential exposure to labor market conditions. Our findings therefore suggest that outsourcing has fewer negative consequences for workers than implied by prior literature.

To explain this novel fact, we develop a simple search-theoretic model wherein intermediary firms can both reassign outsourced workers across client firms in the event of negative productivity shocks and alter workers' wage bargaining power. The estimated model fits observed wage differentials and hazard profiles tightly. Under a wide range of calibrated parameters, we estimate that outsourced workers in Brazil have higher welfare than comparable direct-hire employees due to improved employment security. This finding is important since existing literature on the aggregate effects of outsourcing ignores the potential welfare gains to workers from increased employment security and flexible reassignment of workers across firms (e.g. Bilal and Lhuillier 2021; Spitze 2022). Future studies on the effects of domestic outsourcing should account for this potential benefit of domestic outsourcing.

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Appendix

A Data Definitions

Outsourcing definition. Appendix Table A.1 and A.2 shows our classification of occupation and industry codes. Appendix Table A.3 shows that the outsourced share of security guards steadily grew from 48 percent to 70 percent between 1998 and 2016. By comparison, there was only modest growth in outsourced employment of cleaners during the same period, which grew from 34 percent to 37 percent.

Estimating AKM effects. To construct worker and firm wage components, we use the two-way decomposition method of Abowd, Kramarz and Margolis (1999) (henceforth, "AKM effects"). Using data on all formal workers in RAIS spanning 1998-2016, we estimate:

$$\log w_{it} = \psi_{J(i,t)} + \alpha_i + \theta_t + X_{it}\beta + \epsilon_{ijt},$$

where w_{it} represents real monthly wage, α_i is an individual fixed effect (capturing the general productive characteristics of workers), $\psi_{J(i,t)}$ is a firm fixed effect (capturing the wage premia for all workers at the firm), θ_t is a year fixed effect, $X_{it}\beta$ are the effects of time-varying observable worker characteristics (such as education and age), and ϵ_{ijt} is a composite error that may include idiosyncratic worker-firm match effects.

The estimated "AKM firm effect" ($\hat{\psi}_j$) can be thought of as representing the time-invariant pay premium of a given firm. The estimated "AKM worker effect" ($\hat{\alpha}_i$) can be thought of as representing time-invariant unobserved worker ability. To ensure that firm and worker fixed effects are identified, we restrict our analysis to the largest connected set of firms that are linked by workers moving between them.[23] A further concern when estimating the AKM model is limited mobility bias, which may generate misleading variance decompositions, as discussed by

[23]Identification of the AKM model requires that workers do not move across firms in a manner that is systematically correlated with unmeasured productivity (Gibbons and Katz 1992). Alvarez et al. (2018) provide evidence that this assumption is justified in Brazilian RAIS data.

Andrews et al. (2008). We use a long panel so that limited mobility bias is more likely to be small (Bonhomme et al. 2023; Lachowska et al. 2023).

Table A.1: Occupation Classifications

Classification	CBO code	Description
Guard	517215	Municipal civil guard
Guard	517310	Security agents
Guard	517330	Guards
Guard	517420	Watchpersons
Cleaner	514210	Sweepers
Cleaner	514225	General services workers (preservation, maintenance and cleaning)
Cleaner	514225	Cleaning and public welfare services worker
Cleaner	514320	Janitor

Notes: CBO (*Classificação Brasileira de Ocupações*) is the Brazilian Classification of Occupations established by the Ministry of Labor to identify occupations in the labor market.

Table A.2: Contract Firm Classifications

Classification	CNAE Code	Description
Contract firm	74160	Business management advisory activities
Contract firm	74500	Selection, agency and hire of labor
Contract firm	74608	Investigation, surveillance and security activities
Contract firm	74705	Activ. of hygiene and cleaning in buildings
Contract firm	74993	Other activ. of serv. provided mainly to other companies

Notes: CNAE, National Classification of Economic Activities, is the official industry classification used by statistics and by federal, state, and municipal bodies in Brazil.

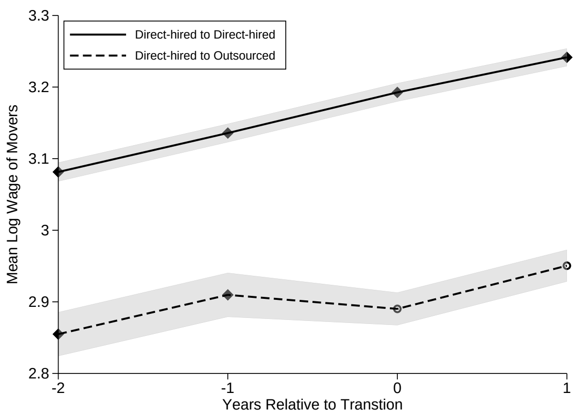
Table A.3: Trend in Outsourcing as Measured by Contract-firm Employment

Contract-firm share of employment		
Year	Cleaners	Guards
1998	33.5%	48.0%
1999	33.3%	52.1%
2000	36.7%	53.5%
2001	31.2%	55.1%
2002	31.4%	57.2%
2003	33.4%	57.9%
2004	34.2%	58.0%
2005	35.0%	58.6%
2006	34.8%	59.5%
2007	34.7%	60.0%
2008	37.9%	61.0%
2009	37.6%	62.3%
2010	37.2%	63.7%
2011	37.4%	64.6%
2012	37.2%	66.2%
2013	37.6%	67.5%
2014	37.0%	67.6%
2015	36.2%	68.6%
2016	36.5%	69.8%
Change	3.1%	21.9%

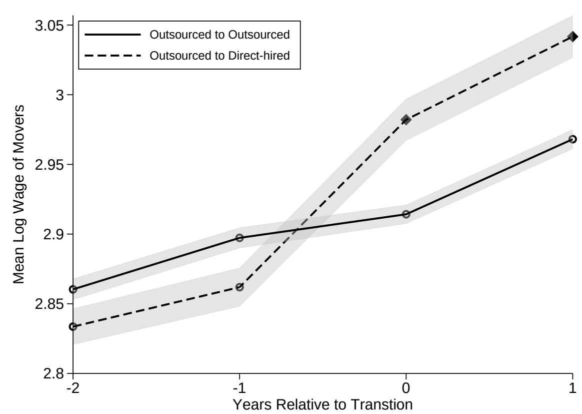
B Additional Figures and Tables

Figure B.1: Wage Evolution, Job Switchers

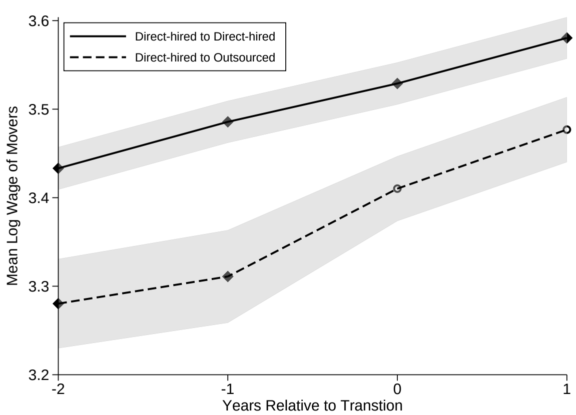
(a) Cleaners, Initially direct-hire



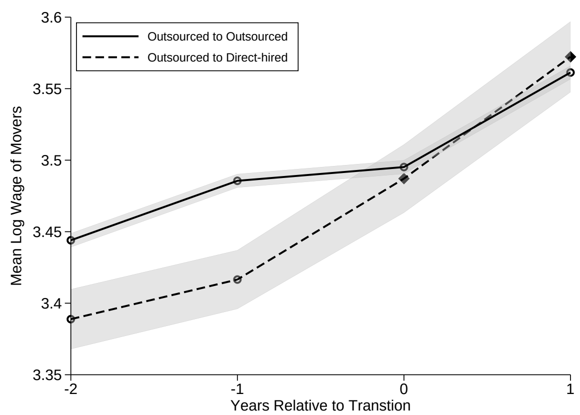
(b) Cleaners, Initially outsourced



(c) Security guards, Initially direct-hire



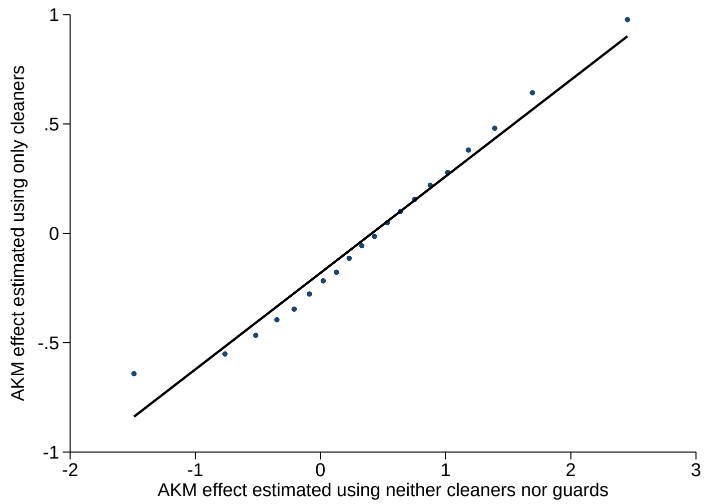
(d) Security guards, Initially outsourced



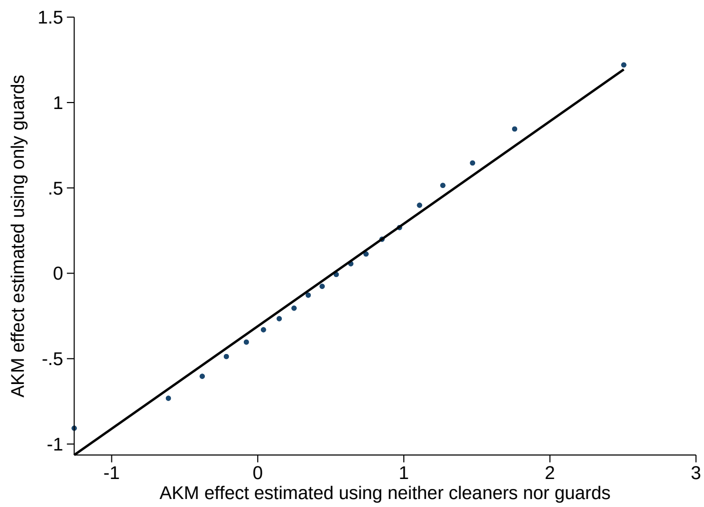
Notes: This figure shows the mean log wages of workers who transitioned between establishments in 2003-2010. We restrict the sample to job switchers who are observed not to change establishments during the two years before and during the two years after the transition. Panel (a) and (c) show cleaners and security guards, respectively, who were initially direct employees and switched to outsourcing. Panel (a) and (c) show cleaners and security guards, respectively, who were initially outsourced and switched to direct employment.

Figure B.2: Comparing Estimated Firm-level Wage Premia using Different Subsamples

(a) Cleaners vs. Other workers



(b) Security guards vs. Other workers

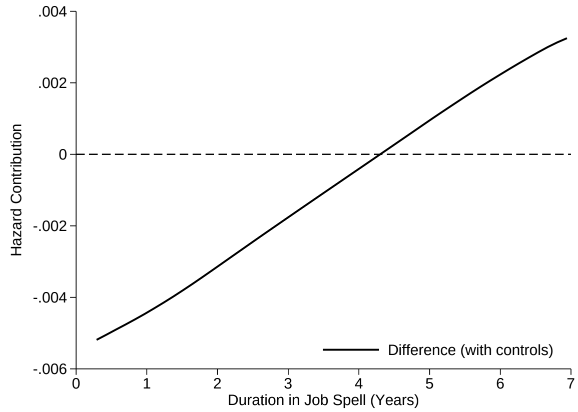


Notes: The figure shows a binned scatter plot of standardized AKM firm effects estimated using cleaners and other workers neither cleaners nor security guards, and another plot of standardized AKM firm effects estimated using security guards and other workers neither cleaners nor security guards. Each dot corresponds to 1/20 of the observations. We run a simple regression first and plot the fitting line in this figure.
Following Goldschmidt and Schmieder (2017), we use a split sample IV approach to correct measurement errors in the RHS. For cleaners, the regression coefficient of the simple regression is 0.441 (SE 0.0017). And the coefficient of IV regression is 0.606 (SE 0.0026). For security guards, the regression coefficient of the simple regression is 0.600 (SE 0.0033). And the coefficient of IV regression is 0.970 (SE 0.0050). All standard errors clustered on the firm level.

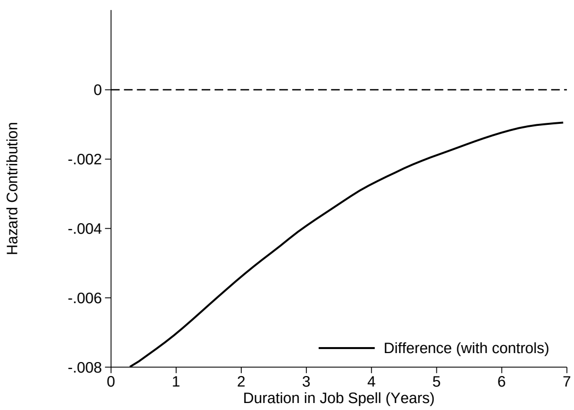
Figure B.3: Estimates of Hazard into Unemployment, Local Linear Smoothing

(a) Cleaners, narrow bandwidth

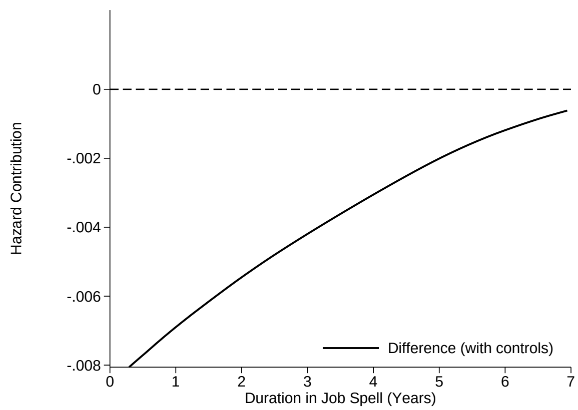
(b) Cleaners, wide bandwidth



(c) Security guards, narrow bandwidth



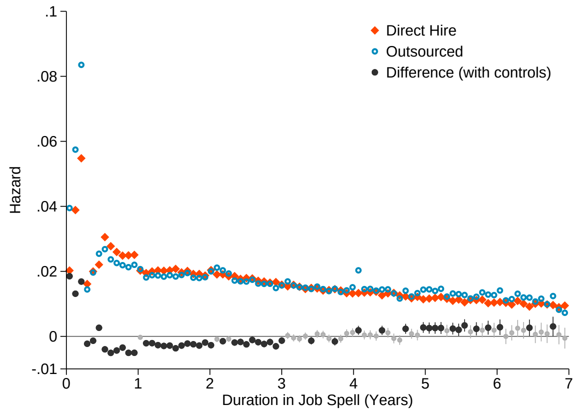
(d) Security guards, wide bandwidth



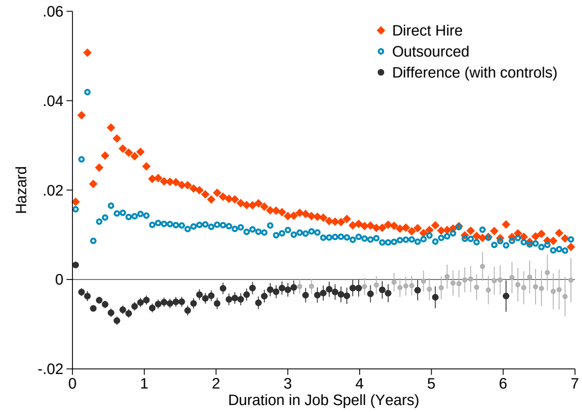
Notes: This figure plots the estimated hazard differential after linear smoothing using our main specification. The estimated hazard differential from the first three months are dropped, since employment protection legislation applies only after a three-month probationary period. Panels (a) and (c) use local linear smoothing with a bandwidth of 1 year. Panels (b) and (d) use a bandwidth of two years.

Figure B.4: Effect of Outsourcing on Hazard into Unemployment, Alternative Samples

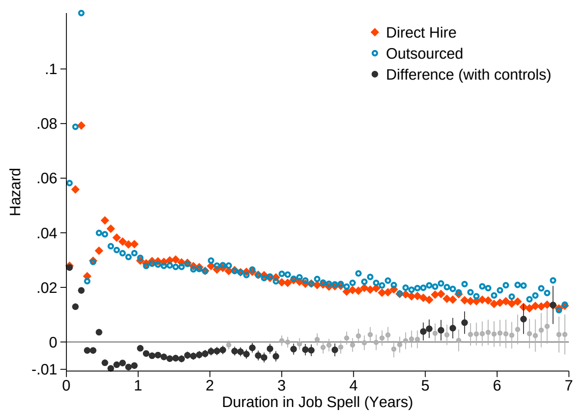
(a) Cleaners, Enter from unemployment



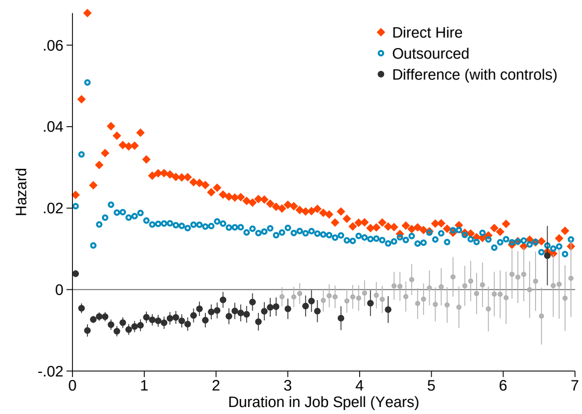
(b) Security guards, Enter from unemployment



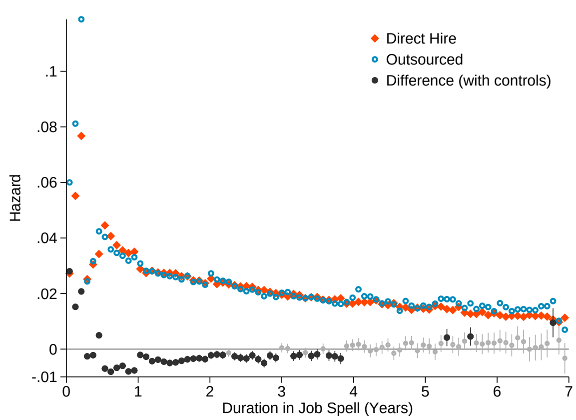
(c) Cleaners, Age $\leq$ 30 at spell start



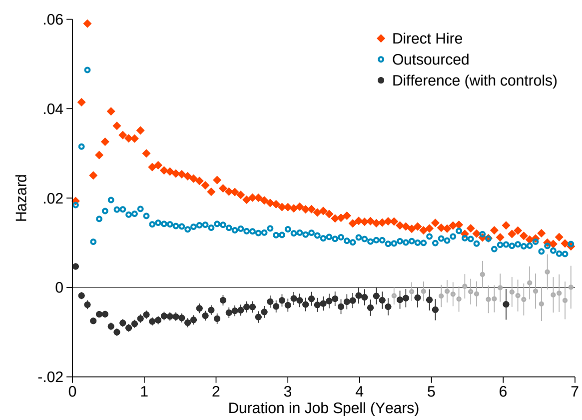
(d) Security guards, Age $\leq$ 30 at spell start



(e) Male, Cleaners



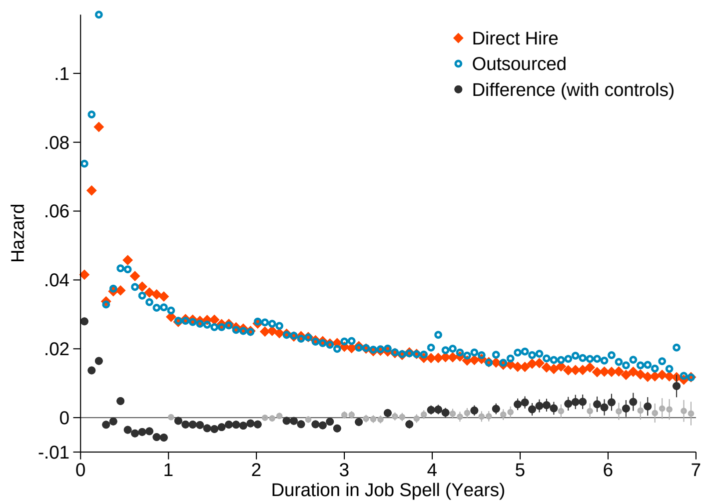
(f) Male, Security guards



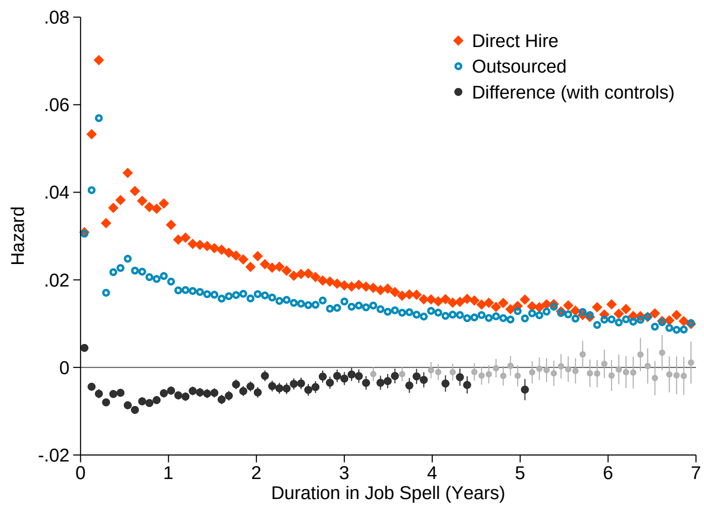
Notes: This figure replicates Figure 1 for subsamples. Panels (a) and (b) are restricted to workers who were not employed in the formal sector for at least seven days prior to the beginning of the spell. Panels (c) and (d) are restricted to workers who were age 30 or below. Panels (e) and (f) are restricted to male workers.

Figure B.5: Effect of Outsourcing on Hazard into Unemployment, Including Quits

(a) Cleaners



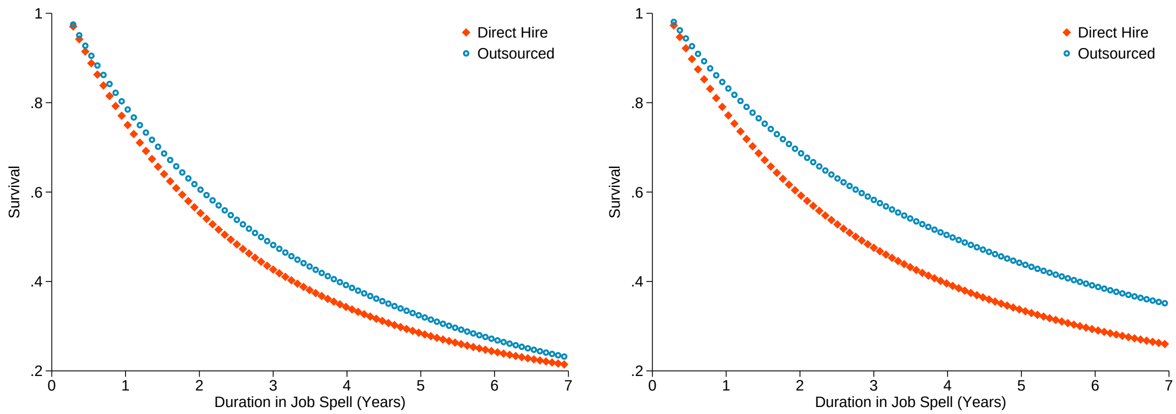
(b) Security guards



Notes: This figure replicates Figure 1 but does not censor quits.

Figure B.6: Survival Function Based on Estimated Hazard into Unemployment

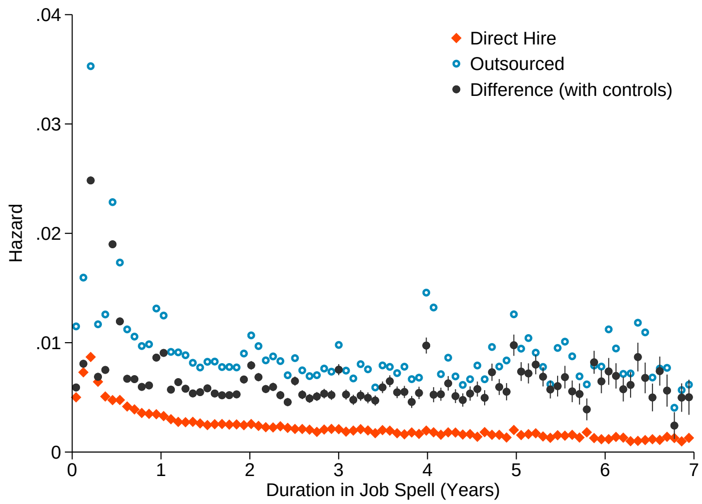
(a) Cleaners (b) Security guards



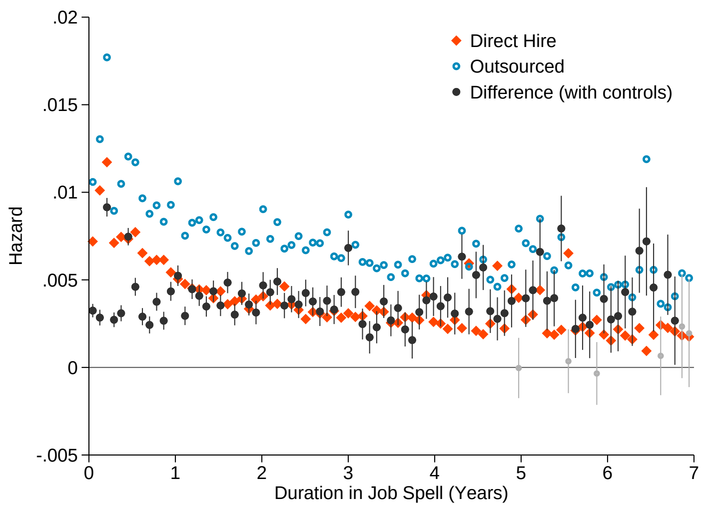
Notes: This figure shows the survival function implied by the hazard estimates from our main specification, after dropping the first three months and smoothing with a bandwidth of one year. The levels are calculated using the predicted mean hazard if observed workers were instead either all outsourced or directly employed.

Figure B.7: Effect of Outsourcing on Transitions to Other Jobs

(a) Cleaners



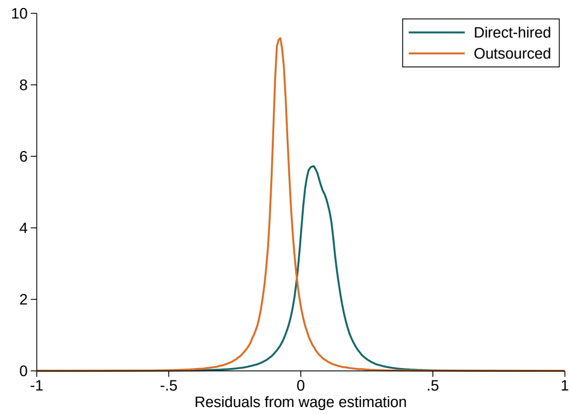
(b) Security guards



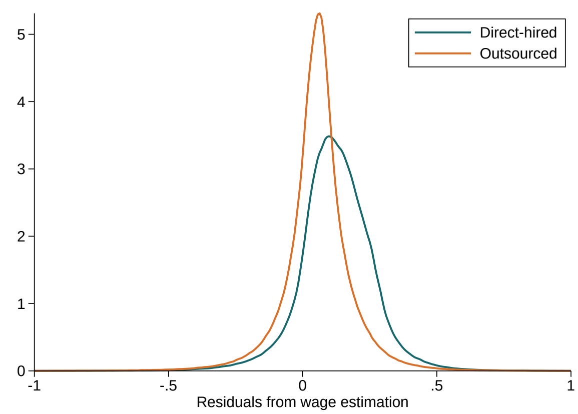
Notes: This figure replicates Figure 1 but instead shows transitions to other jobs as the hazard outcome.

Figure B.8: Residual Wage Distribution, Cleaners and Guards

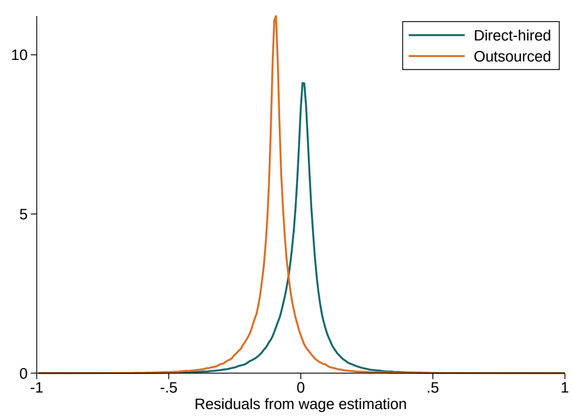
(a) All Cleaners



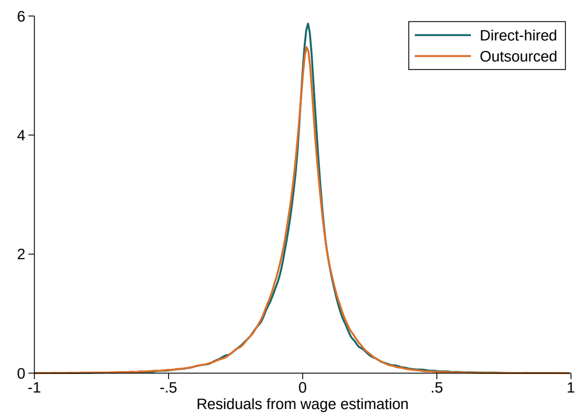
(b) All Guards



(c) Cleaners, Tenure Less than One Year



(d) Guards, Tenure Less than One Year



Notes: This figure shows the density of the residualized log wage for all and new-hire workers among cleaners and security guards, respectively. The residualized wages remove the influence of demographic variables and local labor market fluctuations. We compute the residualized wage as the sum of the residuals and the relevant estimated coefficients on the outsourced X tenure dummies from a regression of the log real wage on the outsourced dummy, tenure dummies, the interaction terms of outsourced and tenure dummies, worker fixed effects, demographic controls for gender, age, age squared, race, years of schooling, and the suboccupation X year X microregion fixed effects at the spell level.

Table B.1: Employment Status, One Month or Year after Unemployment

	Cleaners		Security guards	
	Direct-hire	Outsourced	Direct-hire	Outsourced
One month after				
Total formally employed	0.05	0.08	0.05	0.09
Same occupation, direct hire	0.01	0.01	0.01	0.01
Same occupation, outsourced	0.00	0.02	0.01	0.04
Different occupation	0.04	0.05	0.03	0.03
Observations	1341210	845388	386633	400652
One year after				
Total formally employed	0.36	0.38	0.32	0.39
Same occupation, direct hire	0.06	0.04	0.08	0.04
Same occupation, outsourced	0.02	0.08	0.04	0.19
Different occupation	0.29	0.26	0.20	0.16
Observations	1120331	718937	319257	332758

Table B.2: Robustness Checks — Productivity Gap

Productivity gap	λ	γ	β	δ	μ_E	σ_E	σ_O	μ_z	σ_z	Fit error
A. Cleaners										
0	0.032	0.372	0.367	0.0093	3.324	0.144	0.172	-52.90	0.514	0.377
0.05	0.033	0.369	0.334	0.0093	3.324	0.144	0.179	-32.63	0.041	0.376
0.1	0.033	0.366	0.306	0.0094	3.324	0.144	0.186	-33.71	0.272	0.375
0.15	0.033	0.366	0.281	0.0094	3.324	0.144	0.192	-36.58	0.738	0.375
0.2	0.033	0.366	0.258	0.0094	3.324	0.144	0.199	-40.00	1.299	0.375
B. Guards										
0	0.025	0.438	0.493	0.0056	3.720	0.224	0.229	-65.20	0.021	1.501
0.05	0.026	0.377	0.442	0.0060	3.720	0.224	0.243	-36.48	0.000	1.334
0.1	0.029	0.196	0.399	0.0072	3.720	0.224	0.256	-28.53	0.000	0.668
0.15	0.031	0.072	0.361	0.0080	3.720	0.224	0.268	-26.72	0.001	0.289
0.2	0.028	0.144	0.329	0.0071	3.720	0.224	0.280	-33.51	0.003	0.206

Fit error presents the average percentage difference between the model's predicted and the data's actual hazard rates.

Table B.3: Robustness Checks — Value of Unemployment

Value of unemployment (% of value of employment at average wage)	λ	γ	β	δ	μ_E	σ_E	σ_O	μ_z	σ_z	Fit error
A. Cleaners										
0.5	0.033	0.366	0.358	0.0094	3.450	0.127	0.140	-38.90	0.002	0.375
0.6	0.033	0.366	0.337	0.0094	3.389	0.135	0.159	-35.99	0.092	0.375
0.7	0.033	0.366	0.306	0.0094	3.324	0.144	0.186	-33.71	0.272	0.375
0.8	0.033	0.366	0.256	0.0094	3.255	0.154	0.236	-33.82	0.422	0.375
0.9	0.033	0.366	0.159	0.0094	3.180	0.166	0.390	-46.56	1.632	0.375
B. Guards										
0.5	0.029	0.179	0.428	0.0073	3.866	0.194	0.207	-41.01	0.000	0.601
0.6	0.029	0.193	0.417	0.0072	3.796	0.208	0.228	-34.99	0.000	0.644
0.7	0.029	0.196	0.399	0.0072	3.720	0.224	0.256	-28.53	0.000	0.668
0.8	0.029	0.193	0.363	0.0072	3.637	0.243	0.302	-22.14	0.000	0.651
0.9	0.028	0.204	0.260	0.0069	3.547	0.265	0.441	-18.94	0.001	0.518

The value of unemployment in the baseline model is 70% of the value of employment at the average wage. The fit error presents the average percentage difference between the model's predicted and the data's actual hazard rates.

Table B.4: Robustness Checks on Welfare

Value of	Productivity gap		
unemployment	0.05	0.1	0.15
Cleaners			
0.6	4.1	3.6	3.6
0.7	0.4	0.4	0.4
0.8	-2.8	-2.8	-2.8
0.9	-6.4	-6.4	-6.6
Guards			
0.6	11.6	9.0	10.1
0.7	10.6	7.5	9.2
0.8	7.5	6.3	8.5
0.9	4.5	5.5	5.5

Note: The numbers are percentage changes relative to direct-hired workers. We vary the value of unemployment from 60% to 90% of the value of employment at the average wage. We also vary the productivity gap from 5% to 15%.

C Proofs

Proof of Proposition 1

Let $G_a = G(\hat{z}_a)$ and $\eta = 1 - \gamma$. Let $L(t)$ be the ratio between two hazard rates:

$$L(t) \equiv \frac{h_O(t)}{h_E(t)} = \frac{\eta G_O}{G_E} \frac{G_E + (1 - G_E)e^{\lambda t}}{G_O + (1 - G_O)e^{\eta \lambda t}} \tag{15}$$

Let $\xi(t) \equiv \frac{G_E + (1-G_E)e^{\lambda t}}{G_O + (1-G_O)e^{\eta\lambda t}}$. We can then write $L(t) = \frac{\eta G_O}{G_E}\xi(t)$.

We first prove two useful lemmas.

Lemma C.1. *$L(T) = 1$ if and only if $T = \frac{1}{\lambda} \log\left[\frac{\gamma}{e^{1-\gamma}(1-1/G(\hat{z}_O)) - (1-\gamma)(1-1/G(\hat{z}_E))}\right]$.*

Proof. By equation (15), $L(T) = 1$ if and only if

$$e^{\lambda T} = \frac{1 - \eta}{(1 - 1/G_O)e^{\eta} - (1 - 1/G_E)\eta} \tag{16}$$

□

Lemma C.2. *$\xi'(t)$ is decreasing in η for all t.*

Proof. Note that $\xi(t) > 0$, so $\frac{d \log \xi(t)}{dt} = \frac{\xi'(t)}{\xi(t)}$ has the same sign as $\xi'(t)$. Taking logarithm, we have:

$$\log \xi(t) = \log[G_E + (1 - G_E)e^{\lambda t}] - \log[(G_O + (1 - G_O)e^{\eta\lambda t}] \tag{17}$$

It follows that

$$\frac{d \log \xi(t)}{dt} = \frac{(1 - G_E)\lambda e^{\lambda t}}{G_E + (1 - G_E)e^{\lambda t}} - \frac{(1 - G_O)\eta\lambda e^{\eta\lambda t}}{G_O + (1 - G_O)e^{\eta\lambda t}} \tag{18}$$

Notice that only the second term is related to η. Letting $c = \eta\lambda$, the second term can be rewritten as $-\frac{(1-G_O)ce^{ct}}{G_O+(1-G_O)e^{ct}}$. Taking derivative over c and noting that $G_O \in (0,1)$, we have:

$$-\frac{\partial \frac{(1-G_O)ce^{ct}}{G_O+(1-G_O)e^{ct}}}{\partial c} = -\frac{\overbrace{e^{ct}\overbrace{(G_O-1)}^{<0}[e^{ct}\overbrace{(G_O-1)}^{<0} - \overbrace{G_O(1+ct)}^{>0}]}^{>0}}{[-e^{ct}(G_O-1)+G_O]^2} < 0 \tag{19}$$

If η increases, then $c = \eta\lambda$ increases, and thus $\frac{d\log\xi(t)}{dt}$ decreases. $\square$

The desired proposition follows from combining the following lemmas.

Lemma C.3. *If $\eta = 1$, then $h_O(t) \lesseqgtr h_E(t)$ for all t if and only if $y_O \gtreqless y_E$.*

Proof. At $\eta = 1$, we have:

$$\begin{aligned}
\frac{d\log\xi(t)}{dt} &= \frac{(1-G_E)\lambda e^{\lambda t}}{G_E+(1-G_E)e^{\lambda t}} - \frac{(1-G_O)\lambda e^{\lambda t}}{G_O+(1-G_O)e^{\lambda t}} \\
&= \frac{(1-G_E)\lambda e^{\lambda t}[G_O+(1-G_O)e^{\lambda t}] - (1-G_O)\lambda e^{\lambda t}[G_E+(1-G_E)e^{\lambda t}]}{[G_E+(1-G_E)e^{\lambda t}][G_O+(1-G_O)e^{\lambda t}]} \\
&= \frac{[G_O(1-G_E) - G_E(1-G_O)]\lambda e^{\lambda t}}{[G_E+(1-G_E)e^{\lambda t}][G_O+(1-G_O)e^{\lambda t}]} \\
&= \frac{(G_O-G_E)\lambda e^{\lambda t}}{[G_E+(1-G_E)e^{\lambda t}][G_O+(1-G_O)e^{\lambda t}]}
\end{aligned} \tag{20}$$

The sign of $\frac{d\log\xi(t)}{dt}$ is the same as that of $G_O - G_E$. When $\eta = 1$, $L(0) = \frac{G_O}{G_E}$. If $y_O \gtreqless y_E$, then $G_O \lesseqgtr G_E$, so $\frac{d\log\xi(t)}{dt} \lesseqgtr 0$ and thus $\frac{dL(t)}{dt} \lesseqgtr 0$. Since $L(0) \lesseqgtr 1$, $h_O(t) \lesseqgtr h_E(t)$ for all t. $\square$

Lemma C.4. *If $\eta \in \left(\frac{G_E}{G_O}, 1\right)$ and $y_O < y_E$, then $h_O(t) > h_E(t)$ for all t.*

Proof. When $y_O < y_E$, $\hat{z}_O > \hat{z}_E$, $G_O > G_E > 0$, and $\frac{G_E}{G_O} \in (0,1)$. Notice that $\xi(0) = 1$, so $L(0) = \eta\frac{G_O}{G_E}$. Since $\eta \in \left(\frac{G_E}{G_O}, 1\right)$, $L(0) > 1$. At $\eta = 1$, since $G_O > G_E$, $\frac{d\log\xi(t)}{dt} > 0$ by Equation (20), which implies that $\xi'(t) > 0$. From Lemma C.2, $\xi'(t)$ is decreasing in η, so $\xi'(t) > 0$ for all $\eta \in (0,1)$. Therefore $L'(t) > 0$. We conclude that $L(t) > 1$, so $h_O(t) > h_E(t)$ for all t. $\square$

Lemma C.5. *If $\eta < \frac{G_E}{G_O}$ and $y_O < y_E$, then there exists T such that $h_O(t) < h_E(t)$ for all $t < T$ and $h_O(t) > h_E(t)$ for all $t > T$.*

Proof. Since $\eta < \frac{G_E}{G_O}$, $L(0) < 1$. Note that $L(t)$ increases in t for all t (by the same logic as the previous proof). By Equation (15), $L(t) \to \infty$ as $t \to \infty$. Since $L(t)$ is continuous and monotone, there exists T such that $L(t) < 1$ for all $t < T$ and $L(t) > 1$ for all $t > T$. □

Lemma C.6. *If $\eta < 1$ and $y_O \geq y_E$, then there exists T such that $h_O(t) < h_E(t)$ for all $t < T$ and $h_O(t) > h_E(t)$ for all $t > T$.*

Proof. Since $y_O \geq y_E$, $G_O \leq G_E$. Since $\eta < 1$, $L(0) = \eta \frac{G_O}{G_E} < 1$. By Equation (15), $L(t) \to \infty$ as $t \to \infty$. By the continuity of L, there exists some T_1 such that $L(t) < 1$ for all $t < T_1$, and T_2 such that $L(t) > 1$ for all $t > T_2$. By Lemma C.1, there is a unique T such that $L(T) = 1$, so $T_1 = T_2$. □

Proofs for additional results

Lemma C.7. *T increases in y_O, but decreases in λ and y_E.*

Proof. This follows from Equation (14) and noting that $G_a = G(-y_a + r\bar{W})$. □

Lemma C.8. *T increases in γ if and only if $e^{1-\gamma}(1+\gamma) > \frac{G(\hat{z}_O)}{1-G(\hat{z}_O)} \cdot \frac{1-G(\hat{z}_E)}{G(\hat{z}_E)}$.*

Proof. Equation (16) implies that

$$\frac{de^{\lambda T}}{d\eta} = \frac{(1-1/G_O)e^{\eta}(\eta-2) + (1-1/G_E)}{((1-1/G_O)e^{\eta} - (1-1/G_E)\eta)^2}. \tag{21}$$

Therefore, $\frac{dT}{d\gamma} \gtreqless 0$ if and only if

$$e^{1-\gamma}(1+\gamma) \lesseqgtr \frac{(1-1/G_E)}{(1-1/G_O)}. \tag{22}$$

□