Does Outsourcing Smooth Labor Demand?

Duoxi Li Michael B. Wong*

Boston University HKU

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Abstract

We develop and test a model of labor market dynamics with domestic outsourcing, productivity shocks, and endogenous separations. In the model, outsourcing may reduce worker rents, smooth labor demand, or both. Depending on the relative strengths of these two effects, outsourcing has different effects on worker hazard into non-employment. We use comprehensive administrative data on security guards and cleaners from Brazil to quantify the two effects. The estimates suggest that outsourcing significantly smoothed labor demand among security guards but did not significantly reduce their rents. By contrast, outsourcing had both demand-smoothing and large rent-stripping effects on the lower-wage occupation of cleaners.

Keywords: outsourcing, job security, labor market volatility

JEL: J31, J62, L24

^{*}Emails: duoxili@bu.edu, mbwong@hku.hk. Access to Brazil's RAIS database is governed by the Data Use Agreement between MIT and Brazil's former Ministry of Labor. We thank David Atkin and Mayara Felix for procuring MIT's access to the database, and especially Mayara Felix for de-identifying, harmonizing, and translating the RAIS datasets, as well as discussions on related projects. We thank David Autor, Brigham Frandsen, Bob Gibbons, Simon Jäger, Kevin Lang, Johannes Schmieder, John Van Reenen, Birger Wernerfelt, Sammy Young, and seminar participants at MIT for helpful comments and suggestions. We acknowledge funding from the National Science Foundation, the Kuok Foundation, and the George and Obie Shultz Fund at MIT.

1 Introduction

The rise of domestic outsourcing for professional services such as cleaning, security, IT and HR is widely perceived to have fundamentally altered the labor market. Because outsourced workers are more easily replaced and reassigned across firms, outsourcing may reduce both the wage bargaining power of workers (Abraham 1990; Dube and Kaplan 2010; Goldschmidt and Schmieder 2017; Drenik et al. 2020) and the level of frictions in the labor market (Abraham and Taylor 1996; Houseman 2001). The goal of this article is to analyze these two effects of domestic outsourcing by developing a model of labor market dynamics with domestic outsourcing. We then use both semi-parametric and non-parametric methods to measure the effects of domestic outsourcing using employment records from Brazil.

To model domestic outsourcing, we use a search-and-matching framework with productivity shocks, wage bargaining, and endogenous separations. In the model, matched workers and firms can enter direct employment or an outsourcing arrangement. The key difference between the two is that outsourcing involves an intermediary who can flexibly reallocate workers across firms. After a worker-firm pair is matched under either arrangement, a one-time productivity shock arrives stochastically, as in Blanchard and Landier (2002). This shock may be an aggregate shock or a firm-specific shock. When a firm-specific shock hits, a direct-hire worker may exit to non-employment, but an outsourced worker can be reassigned to another firm. Firms that directly employ also incur vacancy costs, while firms that outsource do not, since the intermediaries can flexibly provide replacement workers.

Outsourcing has two effects in our model. First, outsourcing *smooths labor demand*. Because outsourced workers can be reassigned to other clients, they need not become unemployed in response to a negative productivity shock. Consequently, outsourcing reduces hazard into non-employment. The magnitude of this demand-smoothing effect depends on the correlation of labor demand volatility across firms. Second, outsourcing *reduces workers rents*. Since firms who outsource need not incur vacancy costs before finding a new match, outsourcing reduces worker hold-up power, lowers the bargained wage, and increases the hazard into non-employment. The magnitude of the rent-stripping effect depends on the size of the vacancy

costs. Both of these effects have been highlighted in the literature, but to date there is no known way to compare their importance from data.

These two effects can be separately identified from observational employment data because they have different implications for worker employment trajectories. If the rent-reduction effect dominates, then the outsourced worker has *increased* hazard into non-employment and reduced wages throughout their employment spells. If instead the demand-smoothing effect dominates, then the outsourced worker has *reduced* hazard into non-employment at the beginning of their spell. Outsourced workers would also accumulate less specific human capital, so their hazard into non-employment is flatter with respect to tenure.

We next use administrative data from Brazil to estimate the effect of outsourcing on worker hazard into non-employment. We focus on security guards and cleaners, since outsourced workers in these occupations are cleanly identifiable from Brazil's high-quality industry and occupation codes. We first estimate the non-employment hazards of outsourced and direct-hire workers using a non-parametric method. We then use a Cox proportional hazard model to control for observable worker selection.

We find strong evidence that outsourcing smoothed labor demand for both cleaners and security guards. For security guards, direct employees have non-employment hazard rates than outsourced workers for the first five years of their employment spells. This effect is large. During the first year of employment spells, the hazard of direct-hire guards is roughly double that of outsourced guards. It is only in the seventh year of employment that their hazard rates cross. Consistent with this, we estimate that outsourced security guards have only a small negative wage differential. Interpreted through our economic model, the estimated hazard profiles imply that outsourcing substantially smoothed demand among security guards and did not substantially reduce worker rents.

In addition, we find that outsourcing had a larger rent-reduction effect on cleaners than on security guards. For cleaners, the hazard rates of direct-hire workers fall below that of outsourced workers during their third year of employment, which is earlier than for security guards. Interpreted through our economic model, the hazard profiles for cleaners suggest that outsourcing had both a detectable demand-smoothing effect and large rent-reducing effects on

cleaners. Consistent with this, we estimate that cleaners have a more negative outsourcing wage differential. Since in Brazil the average wages for security guards are much higher than for cleaners, these results are consistent with a growing body of evidence showing that the effect of outsourcing on wages is more negative for lower-wage and less-skilled occupations (e.g. Spitze 2022).

It is unlikely that unobserved worker selection drives the differences between outsourced and direct-hire workers, since the non-parametric and semi-parametric estimates are very similar. It is also unlikely that firm selection into outsourcing drives these differences. In our model, we assume that the wage and hazard of outsourced workers do not depend on their client firm. Under this assumption, our estimates capture the average treatment effect of outsourcing on the hazard profile of the workers at the firms who directly employ. Since the remaining firms have higher vacancy costs and more volatile demand, and hence larger treatment effects in absolute terms, our estimated difference will tend to be attenuated relative to the average treatment effects of outsourcing in the occupation.

To our knowledge, we are the first to devise a search-theoretic model of domestic outsourcing that can explain the observed effects of outsourcing on both employment hazards and wages. Bilal and Lhuillier (2021) use a model with wage posting and on-the-job search to analyze domestic outsourcing. Spitze (2022) consider a search-and-matching model with constant match productivity and exogenous separations to analyze the effects of outsourcing. Neither of these models allows outsourcing to smooth labor demand. Both predict constant wages and separation rates within employment spells. Furthermore, the separation rates of outsourced workers are predicted to be either uniformly higher or identical to that of direct-hire workers. As shown below, the predictions of these models are rejected by Brazilian data.

Our empirical findings contribute to a growing body of evidence on outsourcing. Many papers have focused on the effect of outsourcing on wage levels (Dube and Kaplan 2010; Goldschmidt and Schmieder 2017; Drenik et al. 2020). More recently, Felix and Wong (2022) use cross-regional variation to study the effects of Brazil's 1993 outsourcing legalization on employment. Consistent with our findings, Felix and Wong (2022) find that outsourcing legalization increased total employment of security guard and had a limited effect on their wages. However,

there are very few papers that examine the effects of outsourcing on job hazard (Davis-Blake and Broschak 2009; Bernhardt et al. 2016). Notable exceptions are Batt, Doellgast and Kwon (2005) and Batt, Holman and Holtgrewe (2009), who use a comparatively small sample of survey data, rather than a comprehensive employment registry, to study the effects of outsourcing on job security among call center workers in the US.

Finally, this paper relates to the literature on labor market search inaugurated by Diamond (1982), Mortensen (1982), and Pissarides (1990). We build on insights from Blanchard and Landier (2002), who study the effects of fixed-term contracts using a similar model with a one-time productivity shock. Shimer (1999) and Prat (2006) provide similar 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. We extend this literature by incorporating the effects of domestic outsourcing into a search-theoretic framework and testing its empirical predictions with microdata.

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

2 A Model of Outsourcing with Endogenous Separations

To model domestic outsourcing, we now introduce a search-and-matching framework that features productivity shocks, continuous wage bargaining, and endogenous separations. Depending the size of vacancy costs and the correlation of productivity shocks in the market, outsourcing may either reduce worker rents, smooth labor demand, or both. We show that these two effects have different effects on the rate at which workers enter non-employment.

2.1 Economic Environment

The economy consists of a set of identical workers, a set of firms indexed by j, and a set of identical intermediaries. Time is continuous with discount rate r.

At t = 0, each firm chooses between either directly employing a worker or entering into an

outsourcing arrangement with a worker. Under an outsourcing arrangement, the intermediary employs the worker, but the worker is assigned to produce with the firm. Employment duration and wages are both endogenous.

Intermediaries have the scale to operate a liquid internal labor market, so they can reassign workers across firms without friction. For example, they may operate large human resource databases that track the performance and skills of the workers both under their employment as well as workers who may become available for future employment. Their internal databases also keep track of the the preferences and needs of their clients. Consequently, intermediaries can match workers with firms much more easily than if a firm had to directly search for workers themselves. Intermediaries also often keep a number of idle workers on staff, so that if clients face unexpected needs, such as unexpected departures or absences, then workers can be provided by the intermediary to the clients on demand.

To formalize the idea that intermediaries can reduce the search frictions that firms face, let c_{aj} denote firm j's vacancy cost under arrangement $a \in \{E, O\}$. Each firm j that directly employs faces a vacancy cost $c_{Ej} > 0$ in order to find another worker. We assume that, by contrast, firms that outsource can request a replacement worker without incurring any vacancy cost, so $c_{Oj} = 0.1$

For now, we focus on a single employment spell between a worker and their employer. Under either outsourcing or direct employment, a worker-firm match is formed at t=0 and has an initial productivity of y_0 . During the match, a single stochastic productivity shock arrives over time with Poisson rate λ . At this point, the match's productivity changes to a new level y_1 , where y_1 is a random variable with a continuous cumulative distribution function $G(y_1)$ on $[-\infty, \overline{y}]$, where $\overline{y} > y_0$.

The shock can be either a *firm-specific* shock or an *aggregate* shock. The firm-specific shock arrives at rate λ_F , while aggregate shocks arrive at rate λ_A , such that $\lambda_A + \lambda_F = \lambda$. If a firm-specific shock arrives, the outsourced worker can be costlessly reassigned to another firm and so they do not enter non-employment. At this new firm, match productivity re-starts at y_0 until another productivity shock arrives (with the same probabilities λ_A, λ_F). By contrast, a direct

¹We can consider alternative possibilities such as $c_{Oj} = \frac{1}{2}c_{Ej} > 0$ in future work.

employee cannot be reassigned and therefore enters non-employment with some probability. This assumption that outsourced workers can be reassigned without entering non-employment captures the idea that outsourcing may *smooth labor demand*. If instead an aggregate shock arrives, both the outsourced worker and the direct employee cannot be reassigned and so may enter non-employment.

Wage is determined by symmetric Nash bargaining with continuous renegotiation between the firm and the worker. Implicitly, we assume that the intermediary has zero bargaining power. This assumption is realistic since contract firms bid for service contracts competitively and the client often retains the ability to set wages for the outsourced workers. If the bargaining fails, the worker enters non-employment and receives an outside option \overline{W} . In future work, the outside option will be endogenized so that labor market flows are in steady state. Since wages are bargained, we say that match-specific rents are *shared* between the worker and firm.

The firm's outside option depends on the contractual arrangement. Under direct employment, the firm must incur a vacancy cost $c_{Ej} > 0$ before rematching with another worker with initial productivity y_0 . Under outsourcing, the firm incurs no vacancy cost, i.e. $c_{Oj} = 0$ before rematching.

2.2 Solving for Hazard into Non-Employment

We are interested in the worker's rate of hazard into non-employment, which we denote as $h_{aj}(t)$, when matched with firm j, separately for arrangements $a \in \{E, O\}$. The hazard rate is defined as the probability that a worker who has not yet separated from their employer at time t separates and enters non-employment. For now, we consider the employment dynamics for a given worker-firm match under the two arrangement without endogenizing the choice of contractual choice.

Let \hat{y}_{aj} denote the productivity cutoff above which firm j keeps the worker when the shock arrives and below which the firm fires or replaces the worker under arrangement a. The wage at firm j under arrangement a before and after productivity shock are denoted by w_{aj}^0 and $w_{aj}^1(y_1)$. The present value of a match for the worker before and after productivity shock are W_{aj}^0 and

 $W_{aj}^1(y_1)$. The present value of a match for the firm is V_{aj}^0 and $V_{aj}^1(y_1)$.

Under direct employment, the worker's Bellman equation before the shock is:

$$rW_{Ej}^{0} = \underbrace{w_{Ej}^{0}}_{\text{flow wage}} + \lambda \underbrace{\int_{\hat{y}_{Ej}}^{\overline{y}} \left[W_{Ej}^{0}(y) - W_{Ej}^{0}\right] dG(y_{1})}_{\text{stay after shock}} + \underbrace{\lambda G(\hat{y}_{Ej})(\overline{W} - W_{Ej}^{0})}_{\text{separate after shock}}. \tag{1}$$

The firm's Bellman equations before the shock is:

$$rV_{Ej}^{0} = \underbrace{(y_0 - w_{Ej}^{0})}_{\text{flow profit}} + \lambda \underbrace{\int_{\hat{y}_{Ej}}^{\overline{y}} [V_{Ej}^{0}(y) - V_{Ej}^{0}] dG(y_1)}_{\text{stay after shock}} + \underbrace{\lambda G(\hat{y}_{Ej})(-c_{Ej})}_{\text{separate after shock}}. \tag{2}$$

The Bellman equations under outsourcing are highly similar but are different in two aspects. First, firm-specific shocks do not lead to separation:

$$rW_{Oj}^{0} = \underbrace{w_{Oj}^{0}}_{\text{flow wage}} + \lambda \underbrace{\int_{\hat{y}_{Oj}}^{\overline{y}} [W_{Oj}^{1}(y) - W_{Oj}^{0}] dG(y_{1})}_{\text{stay after shock}} + \underbrace{\lambda_{A}G(\hat{y}_{Oj})(\overline{W} - W_{Oj}^{0})}_{\text{separate after shock}}. \tag{3}$$

Second, the firm does not need to incur a vacancy cost before rematching with a new worker:

$$rV_{Oj}^{1} = \underbrace{(y_0 - w_{Oj}^{0})}_{\text{flow profit}} + \lambda \underbrace{\int_{\hat{y}_{Oj}}^{\overline{y}} [V_{Oj}^{1}(y) - V_{Oj}^{0}] dG(y_1)}_{\text{stay after shock}}. \tag{4}$$

After the shock, the worker and firm Bellman equations if the worker remains matched with the same firm under arrangement *a* are given by:

$$rW_{ai}^{1}(y_{1}) = W_{ai}^{1}(y_{1}) (5)$$

$$rV_{ai}^{1}(y_{1}) = y_{1} - w_{ai}^{1}(y_{1}). {6}$$

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

$$W_{aj}^{0} - \overline{W} = V_{aj}^{0} - (V_{aj}^{0} - c_{aj})$$
 (7)

$$W_{aj}^{1}(y_{1}) - \overline{W} = V_{aj}^{1}(y_{1}) - (V_{aj}^{0} - c_{aj}).$$
 (8)

Firm j is also indifferent between separation and continuation at the productivity cutoff \hat{y}_{aj} , so we have

$$V_{aj}^{1}(\hat{y}_{aj}) = V_{aj}^{0} - c_{aj}. \tag{9}$$

The employment hazard $h_{aj}(t)$ can be obtained by first combining the above equations to solve for the productivity cutoffs separately for the two contractual arrangements, and then deriving the non-employment failure function. Derivations are provided in Appendix A.

2.3 Identifying Demand-Smoothing from Non-employment Hazards

The effect of outsourcing on the non-employment hazard depends on the importance of the demand-smoothing effects of outsourcing.

When vacancy costs are high under direct employment and firm-specific shocks are rare, the primary effects of outsourcing is to reduce worker rents. In this case, the direct employee can bargain for a higher initial wage than the outsourced worker and will only separate from the firm if there is a more negative productivity shock. Formally, we can show that $w_{Oj}^1 < w_{Ej}^1$ and $\hat{y}_{Oj} > \hat{y}_{Ej}$ for any firm j. Therefore, outsourced worker's non-employment hazard is higher than that of the direct employee. This difference is increasing in c_{Ej} .

If instead firm-specific shocks are frequent, then outsourcing smooths labor demand across firms. In this case, separation from the client firm does not necessarily lead to non-employment for the outsourced worker, since the outsourced worker can be reassigned to other firms in response. If firm-specific shocks are common relative to aggregate shocks, then the demand-smoothing effect actually implies a lower non-employment hazard for outsourced workers at the beginning of spell. This effect is large if the arrival rate of firm-specific shocks λ_F is large. However, fewer outsourced workers survive the one-time shock over time, since the productivity

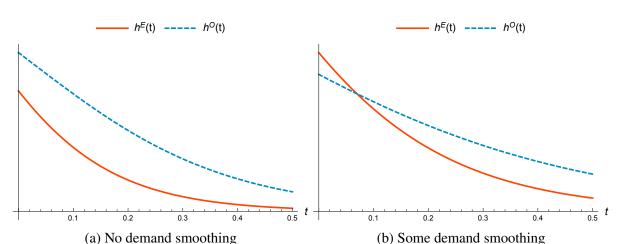


Figure 1: Model Predictions for Non-Employment Hazard, Outsourced Worker vs Employee

cutoff below which workers are dismissed is higher for outsourced worker, i.e. $\hat{y}_{Oj} > \hat{y}_{Ej}$. Separations under outsourcing thus falls more with time. After some time T, the hazard of the outsourced worker therefore falls below that of direct employee.

Figure 1 visualizes how the non-employment hazard profile depends on the underlying structural parameters. Panel (a) shows the case where there are no firm-specific shocks. In this case, the rent-sharing effect dominates and outsourcing does not smooth demand. Outsourced workers are more likely to separate into non-employment for all t. Panel (b) shows the case where firm-specific shocks are as frequent as aggregate shocks, so there is considerable demand smoothing. In this case, outsourced workers are less likely to separate into non-employment at the beginning of their employment spells. This is because when negative productivity shocks arrive, the outsourced workers can be reassigned to other firms. However, over time, more separation rates of outsourced workers falls less with time. There is therefore a cutoff time T where the hazard rate of outsourced workers "crosses" that of direct employees and becomes higher thereafter.

The following proposition formally states the above intuition.

Proposition 1. For any λ , there exists $\overline{c} > 0$ and $\overline{\lambda}_F > 0$ such that:

1. If $c_{Ej} \geq \overline{c}$ and $\lambda_F \leq \overline{\lambda}_F$, then non-employment hazard rate of outsourced workers is greater than that of direct employees at firm j for all t;

2. Otherwise, there exists T such that non-employment hazard rate of outsourced workers is less than that of direct employees at firm j for all t < T, but is greater than that of direct employees at firm j for all t > T.

Proof. See appendix A. \Box

3 Empirical Setting

The previous section showed how the effect of outsourcing on a worker's rate of hazard into non-employment depended on whether outsourcing primarily reduced worker rents or smoothed labor demand in a search-and-matching framework. In this section, we introduce the data and setting with which we will attempt to measure the magnitudes of the above two effects. We then provide descriptive statistics and estimates of the effect of outsourcing on wages.

3.1 Data and Sample Construction

To estimate the effects of outsourcing, 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 and end dates for employment spells. To identify direct-hire and outsourced workers, we use detailed industry and occupation codes. Appendix B provides data definitions.

Despite their richness and high quality, these data suffer from two weaknesses. First, we do not observe worker-firm-intermediary linkages, so we cannot control for the selection of firms

into outsourcing. As explained in the next section, our estimates of the effects of outsourcing on hazard into non-employment are likely to be attenuated. Second, there is a substantial informal sector in Brazil that is not covered by these data. Therefore, missing observations in our data could represent either non-employment or informal employment.

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.² We say that an employment spell ended in non-employment 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 non-employment 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. For comparison, we also present results wherein quits are not censored.

3.2 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 tasks requirements are relatively homogeneous. Second, there is a clean mapping from industry codes to contract firm status that does not exist in other occupations, so we confidently identify outsourced workers. For example, outsourced drivers work in the "road transport" industry, but this category also includes drivers who work for public transportation companies. It is therefore not possible to sharply identify the effects of domestic outsourcing in other occupations using industry codes.

In Brazil, security guards are highly professionalized, regulated, and well-paid. Because of 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. By contrast, cleaners are an unlicensed occupation with a larger share of workers in the informal sector.

²These 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.

Table 1: Employment spells, Brazil, 2003-2010

Age at spell start 32.8 33.4 35.8 32.7 Years of schooling at spell start 7.8 7.2 8.8 9.8 Male at spell start 0.49 0.43 0.95 0.94 Male at spell start 0.49 0.43 0.95 0.94 Non-white at spell start 0.46 0.52 0.52 0.50 Contract hours at spell start 43.7 43.7 43.4 43.7 Exit from formal employment 0.60 0.64 0.50 [0.50] Exit to other formal employment 0.05 0.14 0.07 0.17 Exit to other formal employment 0.05 0.14 0.07 0.17 Exit to other formal employment 0.05 0.14 0.07 0.17 Exit to other formal employment 0.05 0.14 0.07 0.17 Exit to other formal employment 0.05 0.14 0.07 0.17 Exit to other formal employment 0.05 0.14 0.07 0.07 Exit to other formal employment		Cleaners		Security guards	
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Non-white at spell start		[3.2]	[3.0]	[3.5]	[2.8]
Non-white at spell start 0.46 0.52 0.52 0.50 [0.50] [0.50] [0.50] [0.50] Contract hours at spell start 43.7 43.7 43.4 43.7 [1.4] [1.3] [2.0] [1.5] Exit from formal employment 0.60 0.64 0.50 0.47 [0.49] [0.48] [0.50] [0.50] Exit to other formal employment 0.05 0.14 0.07 0.17 [0.22] [0.35] [0.25] [0.38] Reason for exit from formal employment: Fired 0.47 0.48 0.42 0.38 Quit 0.13 0.16 0.07 0.09 Share of spells with duration of at least: one year 0.37 0.43 0.35 0.60 two years 0.21 0.21 0.19 0.35 three years 0.12 0.11 0.11 0.20 four years 0.07 0.06 0.07 0.12 five years<	Male at spell start	0.49	0.43	0.95	0.94
Contract hours at spell start		[0.50]	[0.50]	[0.22]	[0.23]
Contract hours at spell start 43.7 43.7 43.4 43.7 Exit from formal employment 0.60 0.64 0.50 0.47 [0.49] [0.48] [0.50] [0.50] Exit to other formal employment 0.05 0.14 0.07 0.17 [0.22] [0.35] [0.25] [0.38] Reason for exit from formal employment: Fired 0.47 0.48 0.42 0.38 Quit 0.13 0.16 0.07 0.09 Share of spells with duration of at least: one year 0.37 0.43 0.35 0.60 two years 0.21 0.21 0.19 0.35 three years 0.12 0.11 0.11 0.20 four years 0.07 0.06 0.07 0.12 five years 0.04 0.03 0.04 0.06 six years 0.02 0.01 0.01 0.01 seven years 0.01 0.01 0.01	Non-white at spell start	0.46	0.52	0.52	0.50
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Exit to other formal employment		[1.4]	[1.3]	[2.0]	[1.5]
Exit to other formal employment 0.05 0.14 0.07 0.17 Reason for exit from formal employment: [0.22] [0.35] [0.25] [0.38] Reason for exit from formal employment: Fired 0.47 0.48 0.42 0.38 Quit 0.13 0.16 0.07 0.09 Share of spells with duration of at least: 0.03 0.43 0.35 0.60 two years 0.21 0.21 0.19 0.35 three years 0.12 0.11 0.11 0.20 four years 0.07 0.06 0.07 0.12 five years 0.04 0.03 0.04 0.06 six years 0.02 0.01 0.02 0.03 seven years 0.01 0.01 0.01 0.01	Exit from formal employment	0.60	0.64	0.50	0.47
[0.22] [0.35] [0.25] [0.38] Reason for exit from formal employment: Fired 0.47 0.48 0.42 0.38 Quit 0.13 0.16 0.07 0.09 Share of spells with duration of at least: one year 0.37 0.43 0.35 0.60 two years 0.21 0.21 0.19 0.35 three years 0.12 0.11 0.11 0.20 four years 0.07 0.06 0.07 0.12 five years 0.04 0.03 0.04 0.06 six years 0.02 0.01 0.02 0.03 seven years 0.01 0.01 0.01		[0.49]	[0.48]	[0.50]	[0.50]
Reason for exit from formal employment: Fired 0.47 0.48 0.42 0.38 Quit 0.13 0.16 0.07 0.09 Share of spells with duration of at least: one year 0.37 0.43 0.35 0.60 two years 0.21 0.21 0.19 0.35 three years 0.12 0.11 0.11 0.20 four years 0.07 0.06 0.07 0.12 five years 0.04 0.03 0.04 0.06 six years 0.02 0.01 0.02 0.03 seven years 0.01 0.01 0.01 0.01	Exit to other formal employment	0.05	0.14	0.07	0.17
Fired Quit 0.47 0.48 0.42 0.38 0.16 0.07 0.09 Share of spells with duration of at least: one year 0.37 0.43 0.35 0.60 two years 0.21 0.21 0.19 0.35 three years 0.12 0.11 0.11 0.20 four years 0.07 0.06 0.07 0.12 five years 0.04 0.03 0.04 0.06 six years 0.02 0.01 0.02 0.03 seven years 0.01 0.01 0.01 0.01		[0.22]	[0.35]	[0.25]	[0.38]
Quit 0.13 0.16 0.07 0.09 Share of spells with duration of at least: one year 0.37 0.43 0.35 0.60 two years 0.21 0.21 0.19 0.35 three years 0.12 0.11 0.11 0.20 four years 0.07 0.06 0.07 0.12 five years 0.04 0.03 0.04 0.06 six years 0.02 0.01 0.02 0.03 seven years 0.01 0.01 0.01 0.01	Reason for exit from formal emplo	oyment:			
Share of spells with duration of at least: one year 0.37 0.43 0.35 0.60 two years 0.21 0.21 0.19 0.35 three years 0.12 0.11 0.11 0.20 four years 0.07 0.06 0.07 0.12 five years 0.04 0.03 0.04 0.06 six years 0.02 0.01 0.02 0.03 seven years 0.01 0.01 0.01 0.01	Fired	0.47	0.48	0.42	0.38
one year 0.37 0.43 0.35 0.60 two years 0.21 0.21 0.19 0.35 three years 0.12 0.11 0.11 0.20 four years 0.07 0.06 0.07 0.12 five years 0.04 0.03 0.04 0.06 six years 0.02 0.01 0.02 0.03 seven years 0.01 0.01 0.01 0.01	Quit	0.13	0.16	0.07	0.09
two years 0.21 0.21 0.19 0.35 three years 0.12 0.11 0.11 0.20 four years 0.07 0.06 0.07 0.12 five years 0.04 0.03 0.04 0.06 six years 0.02 0.01 0.02 0.03 seven years 0.01 0.01 0.01 0.01	Share of spells with duration of at	least:			
three years 0.12 0.11 0.11 0.20 four years 0.07 0.06 0.07 0.12 five years 0.04 0.03 0.04 0.06 six years 0.02 0.01 0.02 0.03 seven years 0.01 0.01 0.01 0.01	one year	0.37	0.43	0.35	0.60
four years 0.07 0.06 0.07 0.12 five years 0.04 0.03 0.04 0.06 six years 0.02 0.01 0.02 0.03 seven years 0.01 0.01 0.01 0.01	two years	0.21	0.21	0.19	0.35
five years 0.04 0.03 0.04 0.06 six years 0.02 0.01 0.02 0.03 seven years 0.01 0.01 0.01 0.01	three years	0.12	0.11	0.11	0.20
six years 0.02 0.01 0.02 0.03 seven years 0.01 0.01 0.01 0.01	four years	0.07	0.06	0.07	0.12
seven years 0.01 0.01 0.01 0.01	five years	0.04	0.03	0.04	0.06
J	six years	0.02	0.01	0.02	0.03
Number of spells 3,055,000 1,596,000 1,003,000 1,082,000	•	0.01	0.01	0.01	0.01
	Number of spells	3,055,000	1,596,000	1,003,000	1,082,000

Notes: Standard deviations are displayed in brackets.

Cleaners 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 are *more* likely to end in separation into non-employment than direct-hire cleaners. By contrast, the employment spells of outsourced

security guards are *less* likely to end in separation into non-employment than direct-hire security guards.

3.3 Effect of Outsourcing on Wages

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

$$\ln w_{it} = \gamma O_{it} + \theta_{omt} + X'_{it}\beta + \alpha_i + \epsilon_{imt}, \tag{10}$$

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.

The above estimates rely on the assumption that the job-to-job transitions are independent of the composite error. To assess the importance of endogenous transitions, we report estimates, inspired by Card, Heining and Kline (2013), from a specification with three indicator variables that are based on outsourcing status in period t - 1 and t: switchers from direct employment to outsourcing, stayers in outsourcing, and switchers from outsourcing to direct employment. The stayers in direct employment constitute the omitted group. The estimates reflect the wage differential relative to those who remain directly employed.³

Table 2 displays the estimated wage differentials. Panel A shows that outsourcing had significant negative effects on the wages of cleaners. Column (1) shows that, with occupation-microregion-year fixed effects, the wages of outsourced cleaners are roughly 18.6 log points lower

³Another 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 reason. First, Brazilian labor law prohibits nominal wage reductions through the firing and rehiring 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 (2022), 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 2: Outsourcing Wage Differential, Brazil, 2003-2010

Dep. var.: Log real wage	(1)	(2)	(3)	(4)
Panel A: Cleaners				
Outsourced	-0.186	-0.170	-0.115	
Outsourced	(0.000)	(0.000)	(0.000)	
E-to-O switcher	(0.000)	(0.000)	(0.000)	-0.125
				(0.002)
O-to-E switcher				-0.057
				(0.002)
O stayer				-0.130
				(0.001)
Observations	7355953	7355953	5785653	3019558
R^2	0.29	0.34	0.93	0.95
Panel B: Security guards				
Outsourced	-0.079	-0.072	-0.023	
	(0.000)	(0.000)	(0.001)	0.077
E-to-O switcher				-0.077 (0.004)
O-to-E switcher				-0.055
O-to-L switcher				(0.001)
O stayer				-0.055
				(0.001)
Observations	4474030	4474030	4006622	2434756
R^2	0.41	0.44	0.91	0.94
Occ X Year X Microregion FE	X	X	X	X
Demographic controls		X	X	X
Worker FE			X	X

Notes: Demographic controls include a full set of race X gender X education dummies interacted with age, age squared, and age cubed. Standard errors are displayed in parentheses.

than direct-hire cleaners. With additional demographic controls in Column (2), the estimate changes very slightly to 17.0 log points. With added individual fixed effects, as in Column (3), the wages of outsourced cleaners are smaller at 11.5 log points, suggesting that there is some unobserved selection into outsourcing. Column (4) shows that the wages of switchers from

employment to outsourced are 12.5 log point lower than those who stay direct employees, while the wage of switchers from outsourced to employment are -5.7 - (-13.0) = 7.3 log points higher than those who stay outsourced. These estimates confirm that outsourced cleaners tend to earn less regardless of the direction of mobility, but the asymmetry in these estimates also suggests that worker mobility is not independent of match effects.

Panel B shows that the outsourcing wage differential is smaller for security guards, a higher-wage occuaption. In Column (1), with occupation-microregion-year fixed effects, the wages of outsourced security guards are roughly 7.9 log points lower than direct-hire security guards. With additional demographic controls in Column (2), the estimate is very similar, at 7.2 log points. With the individual fixed effects, as in Column (3), the estimate is only 2.3 log points, suggesting a very small outsourcing wage differential after controlling for unobservable worker heterogeneity. Column (4) shows that the wages of switchers from employment to outsourced are 7.7 log point lower than those who stay direct employees, while the wage of switchers from outsourced to employment are no different than those who stay outsourced. Once again, the asymmetry suggests some degree of endogeneity in worker mobility.

Taken together, the estimated outsourcing wage differentials are consistent with growing evidence that outsourcing reduces wages more in lower-wage and less-skilled occupations (e.g. Spitze 2022). They anticipate our result below that outsourcing had larger rent-reducing effects on cleaners than on security guards. They also suggest a need to study the mobility patterns of outsourced workers, as done below.

4 Effect of Outsourcing on Hazard into Non-Employment

In this section, we distinguish between the demand-smoothing and rent-stripping effects of outsourcing by estimating the effect of outsourcing on the rate of hazard into non-employment. To our knowledge these hazards have not previously been estimated. We find that that outsourcing had large demand-smoothing effects for security guards in Brazil. Outsourcing also had large rent-stripping effects and some demand-smoothing effects on cleaners in Brazil.

4.1 Methods

We use both non-parametric and parametric methods to estimate the hazard of entering nonemployment. We use the first full-time spell for each worker at each employer. Because the model focuses on separation into non-employment, we censor spells ending in a job-to-job transition, in which case we do not know when the spell would have ended in non-employment.

First, we follow standard techniques to calculate the hazard. For each time interval $(t_{k-1}, t_k]$, where $k \in \{1, ..., K+1\}$, we denote the number of employment spells at the start as s_k , the number of spells ending in non-employment (failures) as f_k , and the number of spells ending but not in non-employment (censored) as c_k . We follow Klein and Moeschberger (2003) and assume that censoring and death times are uniformly distributed within each interval. The hazard at the midpoint \bar{t}_k for each interval k is:

$$\hat{h}\left(\overline{t}_{k}\right) = \frac{f_{k}}{\left(t_{k} - t_{k-1}\right)\left(s_{k} - \frac{c_{k} + f_{k}}{2}\right)}.$$

We calculate the hazard separately for outsourced and direct-hire workers and use intervals of 30 days. We compute confidence intervals based on the estimated standard deviation of the hazard function at the midpoint of interval j by assuming that the number of failures in the interval is a binomial random variable.

The key confounding factor in estimating the effect of outsourcing on hazard into non-employment is that the workers and firms who enter into outsourcing arrangements are not random. In the previous section, we derived the theoretical differences in hazard profiles for a given worker matched with a given firm j under outsourcing and direct employment arrangements. However, the workers and firms who choose to enter outsourcing arrangements may be systematically different from those who do not. This generates selection bias in our previous non-parametric hazard estimates.

To control for observable selection of workers into outsourcing, we next compute baseline hazard functions for outsourced and direct-hire workers using a stratified Cox proportional hazards model. This model allows for different baseline hazard functions for outsourced and

direct-hire workers, but constrains the coefficients on the covariates to be the same for outsourced and direct-hire workers. Specifically, we estimate

$$h(t \mid a, X) = h_a(t) \exp(X\beta)$$

where a is an indicator for whether the worker is outsourced and X are controls including observable worker demographic characteristics such as gender, age, race, and education at spell start, as well as the fixed effects for the first month of each employment spell.

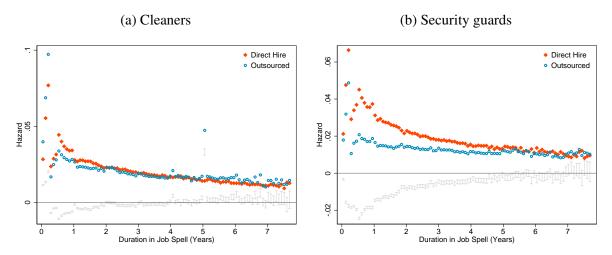
Even with controls, the differences in estimated baseline hazard rates may still differ from the causal effect of outsourcing due to unobserved worker and firm selection. First, there may remain unobserved heterogeneity in worker selection in outsourcing. As shown below, the hazard estimates are similar after adding controls, which leads us to believe that unobserved worker heterogeneity is unlikely to be a significant confound. Second, firms that choose to outsource may be systematically different from those who employ. The second confounding effect may be important since it is widely documented that the firms who outsource are systematically different from those who do not. However, we cannot control for firm selection into outsourcing since we do not observe the identity of the client firms in our data.

Because of firm selection in outsourcing, the estimated differences in hazard rates are likely to understate the magnitudes of the average effects of outsourcing. In our model, we assume that the hazard profile of outsourced workers does not depend on the features of their client firm. Under this plausible assumption, our estimates capture the average treatment effect of outsourcing on the hazard profile of the workers at the firms who do not outsource. Since firms with higher vacancy costs and more volatile demand choose to outsource, and these firms tend to have larger treatment effects in absolute terms, the observed differences in hazard profiles smaller in magnitude than the average treatment effect of outsourcing in the occupation.

4.2 Results

Figure 2 shows the non-parametric estimates of the hazard into non-employment. We plot the hazard function only at durations less than or equal to 7.75 years because of small sample sizes

Figure 2: Non-parametric Estimates of the Hazard into Non-employment



Notes: Sample includes all first full-time spells at each employer between 2003-2010. Confidence intervals are based on the estimated standard deviation of the hazard function at the midpoint of each 30-day interval, using that the number of failures in the interval is a binomial random variable.

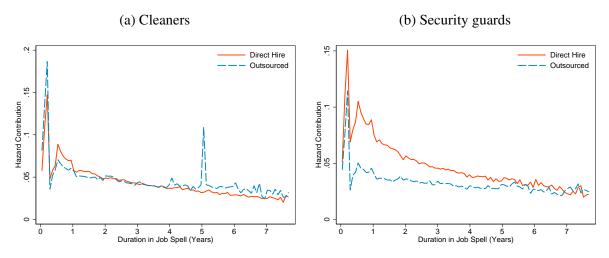
with longer durations.

For cleaners, the hazard into non-employment is initially higher for direct-hire workers than outsourced workers. However, hazard rates of outsourced and direct-hire workers become closer over the course of the employment spell, crossing at roughly three years of tenure. Thereafter, the hazard of outsourced workers is higher.

For security guards, the hazard into non-employment of direct-hire workers is nearly double that of outsourced workers during the first year of employment. However, the hazard rates of outsourced and direct-hire workers become closer over the course of the employment spell, eventually crossing at roughly seven years of tenure.

The "crossing" of the nonemployment hazard rate in both occupations suggest that that outsourcing meaningfully smoothed labor demand across firms. Recall from the previous section that outsourcing increases hazard into non-employment if it purely reduced worker rents. If instead outsourcing purely smoothed labor demand, then outsourcing should reduce hazard into non-employment at the beginning of employment spells but increase them later on. The fact that the effect of outsourcing on hazard is more positive for cleaners suggests that there is a larger rent-reduction effect for cleaners and is consistent with the wage differential previously documented.

Figure 3: Estimates of Hazard into Non-employment using Stratified Cox Model



Notes: Notes: Sample includes all first full-time spells at each employer between 2003-2010. Controls include gender, age, age squared, race, and years of schooling at spell start, as well as fixed effects for the first month of each employment spell.

In Figure 3, we present Cox proportional hazard estimates. As explained above, this specification include controls for the influence of observable worker demographic characteristics such as gender, age, race, and education at spell start, as well as fixed effects for the first month of each employment spell. The result is highly similar to that in Figure 2. Standard errors are not available from standard Stata packages and will be computed in the future.

4.3 Robustness

As shown in the appendix, results look similar when we identify employment spells for which the individual entered from non-employment and restrict to those spells. Results also look similar when restricting to workers who are no more than 30 at the start of the spell, as well as when restricting to male workers.

Smoothed hazards are presented in the appendix. We perform local linear smoothing using two sets of bandwidths. The hazard estimates from first three month are dropped, since employment protection legislation applies only after a three-month probationary period. The results confirm that the hazard rate of outsourced security guards "crosses" from above to below that of direct-hire security guards at around seven years of tenure. By contrast, the hazard rate

of outsourced cleaners "crosses" from above to below that of direct-hire cleaners at around three years of tenure.

Censoring transitions to non-employment due to quits leads to mildly more positive effects of outsourcing on the hazard into unemployment, in both occupations. This suggests that outsourced workers are generally more likely to quit into non-employment than direct-hire workers, because they are more likely to either encounter or take outside informal employment offers.

Outsourced workers are also more likely than direct employees to separate from their employers to take another formal job. We have ignored this possibility thus far, since employer-to-employer transitions are censored in our specifications above. Appendix Figure C.6 shows that in both occupations, outsourced workers are much more likely to separate into another formal-sector job within seven days after their employment spell ends. 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 work is needed to distinguish between these two possibilities.

5 Conclusion

This paper investigates whether domestic outsourcing smooths labor demand. We first develop a model of domestic outsourcing using a search-and-matching framework with productivity shocks, wage bargaining, and endogenous separations. We show that depending on whether outsourcing primarily reduced worker rents or smoothed labor demand, outsourcing has different effects on the rate at which workers separate into non-employment over an employment spell. We then use comprehensive administrative data on security guards and cleaners in Brazil to estimate the effect of outsourcing on non-employment hazard rates, controlling for observable worker-level heterogeneity.

The estimates strongly suggest that outsourcing smoothed labor demand among Brazilian security guards. The tell-tale sign of demand-smoothing is that outsourcing reduced the hazard

into non-employment at the beginning of an employment spell, but had less negative or even positive effects on the hazard into non-employment later in an employment spell. For cleaners, however, outsourcing both reduced wages and had less negative effects on the hazard into non-employment. This suggests that rent-stripping effects were larger in the lower-wage occupation.

To our knowledge, the search-theoretic model of domestic outsourcing devised in this paper is the first to enable the quantification of both the rent-stripping and demand-smoothing effects of outsourcing from observational employment data. The hazard patterns that we document using Brazilian data are consistent with our model and are not consistent with models of outsourcing with no role for demand smoothing. More work is needed to understand whether these demand-smoothing effects are important in other contexts. Our framework can also be extended and calibrated to measure the general equilibrium effects of outsourcing on both labor market frictions and wage inequality both in Brazil and beyond.

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A Derivations

By combining (1)-(9), we can show that

$$(r+\lambda)\left(\frac{\hat{y}_{aj}}{r}+2c_{aj}\right) = y_0 + \frac{\lambda}{r} \left[\int_{\hat{y}_{aj}}^{\overline{y}} y dG(y) + G(\hat{y}_{aj})\hat{y}_{aj}\right]. \tag{11}$$

By taking derivative with respect to c_{aj} on both sides of (11), $\frac{d\hat{y}_{aj}}{dc_{aj}} < 0$. Since $c_{Ej} > c_{Oj}$, it follows that $\hat{y}_{Oj} > \hat{y}_{Ej}$.

The same equations imply that

$$w_{aj}^{0} = (r+\lambda)c_{aj} + r\overline{W} - \frac{\lambda}{r} \int_{\hat{y}_{aj}}^{\overline{y}} \frac{y - \hat{y}_{aj}}{2} dG(y). \tag{12}$$

By taking derivative with respect to c_{aj} on both sides of (12), $\frac{d\hat{w}_{aj}^0}{dc_{aj}} > 0$. It follows that $w_{Oj}^0 < w_{Ej}^0$.

Symmetric Nash bargaining also implies that

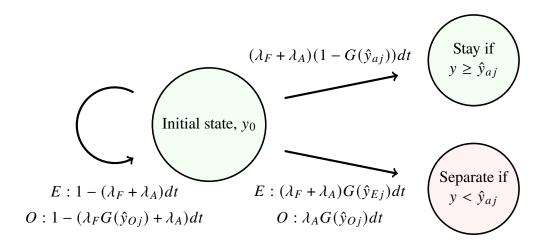
$$w_{aj}^{1}(y_{1}) = \frac{y_{1} - \hat{y}_{aj}}{2} + r\overline{W}.$$
 (13)

Since $\hat{y}_{Oj} > \hat{y}_{Ej}$, it follows that $w_{Oj}^1(y_1) < w_{Ej}^1(y_1)$ for all y_1 .

We now derive the probabilities of separation under direct employment and outsourcing. Note that employment and outsourcing differ both because the separation cutoffs are different, and also because when an outsourced worker separates from a firm, she does not necessarily separate into non-employment but instead can be reassigned to another firm. We say that a worker stays if a directly employed worker stays at the same firm or an outsourced worker stays at the same intermediary after the productivity shock is realized. We say that a worker separates if the worker separates into non-employment when the productivity shock arrives. The state transition probabilities are visualized in Figure A.1.

The probability of separation under direct employment at time t is given by the failure

Figure A.1: State Transition Probabilities



function:

$$F_{Ej}(t) = \int_0^t \Pr(\text{haven't stayed or separated before s}|E) \cdot \Pr(\text{sep at s}|E) ds$$

$$= \int_0^t e^{-\lambda s} \cdot \lambda G(\hat{y}_{Ej}) ds$$

$$= \left[1 - e^{-\lambda t}\right] G(\hat{y}_{Ej})$$

The probability of separation under outsourcing at time *t* is given by:

$$\begin{split} F_{Oj}(t) &= \int_0^t \Pr(\text{haven't stayed or separated before s}|O) \cdot \Pr(\text{sep at s}|O) ds \\ &= \int_0^t e^{-(\lambda_F (1-G_O) + \lambda_A)s} \cdot \lambda_A G(\hat{y}_{Oj}) ds \\ &= \left[1 - e^{-(\lambda_A + \lambda_F (1-G(\hat{y}_{Oj})))t}\right] \frac{\lambda_A}{\lambda_A + \lambda_F (1-G(\hat{y}_{Oj}))} G(\hat{y}_{Oj}) \end{split}$$

The survival function is defined as $S_{aj}(t) = 1 - F_{aj}(t)$. The non-employment hazard is defined as $h_{aj}(t) = \frac{dF_{aj}(t)/dt}{S_{aj}(t)}$. It follows that

$$h_{Ej}(t) = \frac{\lambda G(\hat{y}_{Ej}) \cdot e^{-\lambda t}}{S^{E}(t)},$$

$$h_{Oj}(t) = \frac{\lambda_A G(\hat{y}_{Oj}) \cdot e^{-(\lambda_A + \lambda_F (1 - G(\hat{y}_{Oj})))t}}{S^O(t)},$$

Note that $\frac{dh_{aj}(t)}{dt} < 0$.

Proof of Proposition 1

Let $L(t) \equiv \frac{h_{Oj}(t)}{h_{Ej}(t)}$ denote the ratio of the hazard rates, which is given by

$$L(t) = \frac{\lambda_A}{\lambda} \cdot \frac{G(\hat{y}_{Oj})}{G(\hat{y}_{Ej})} \cdot e^{\lambda_F G(\hat{y}_{Oj})t} \frac{S^E(t)}{S^O(t)}.$$

Letting $G_a = G(\hat{y}_{aj})$, note that

$$\begin{split} e^{\lambda_F G(\hat{y}_{Oj})t} \frac{S^E(t)}{S^O(t)} &= \frac{G_E}{G_O} \frac{\lambda_A + (1 - G_O)\lambda_F}{\lambda_A} \\ &\quad + \frac{(1 - G_E)e^{\lambda_F G_O t} - \frac{G_E}{G_O} \frac{\lambda_A + (1 - G_O)\lambda_F}{\lambda_A} (1 - \frac{\lambda_A}{\lambda_A + (1 - G_O)\lambda_F} G_O)}{(1 - \frac{\lambda_A}{\lambda_A + (1 - G_O)\lambda_F} G_O) + \frac{\lambda_A}{\lambda_A + (1 - G_O)\lambda_F} G_O e^{-(\lambda_A + \lambda_F (1 - G_O))t}} \end{split}$$

Note that the first term in the RHS of the equation above is a constant, and the second term in the RHS of the equation above is increasing in t. Therefore, $e^{\lambda_F G(\hat{y}_{Oj})t} \frac{S^E(t)}{S^O(t)}$ is increasing in t and so is L(t). Since $L(0) = \frac{\lambda_A}{\lambda} \frac{G(\hat{y}_{Oj})}{G(\hat{y}_{Ej})} > 0$, L(t) goes to infinity when t goes to infinity, and L(t) is continuous. Furthermore, if L(0) < 1, there exists a T such that L(T) = 1 by the intermediate value theorem. Meanwhile, since L(t) is increasing, L(t) < 1 if t < T and L(t) > 1 if t > T.

To guarantee the existence of T, we must have

$$L(0) = \frac{\lambda - \lambda_F}{\lambda} \frac{G(\hat{y}_{Oj})}{G(\hat{y}_{Ej})} < 1. \tag{14}$$

We first show the existence of \overline{c} . Note that \hat{y}_{aj} is pinned down by equation (11) and therefore are a continuous function of c_{aj} (holding y_0 , \overline{y} , r, and λ constant). Observe that if $c_{Ej} = 0$ and $\lambda_F > 0$, then $\hat{y}_{Ej} = \hat{y}_{Oj}$, so L(0) < 1. Meanwhile, in the limit as $c_{Ej} \to \infty$, $L(0) \to \infty$, since the firm would never fire the worker. Furthermore, \hat{y}_{Et} is decreasing in c_{Ej} , so L(0) is increasing in c_{Ej} . By the intermediate value theorem, given any λ , there exists \overline{c} such that L(0) < 1 if and

only if $c_{Ej} < \overline{c}$. Similarly, the existence of $\overline{\lambda}_F$ also comes from equation (14). Given any λ and c_{Ej} , and hence fixing \hat{y}_{Ej} and \hat{y}_{Oj} (since $c_{Oj} = 0$), there exists a cutoff $\overline{\lambda}_F$ such that L(0) < 1 whenever $\lambda_F > \overline{\lambda}_F$.

B Data Definitions

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

Table B.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 Brazilian Classification of Occupations established by the Ministry of Labor to identify occupations in the labor market.

Table B.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

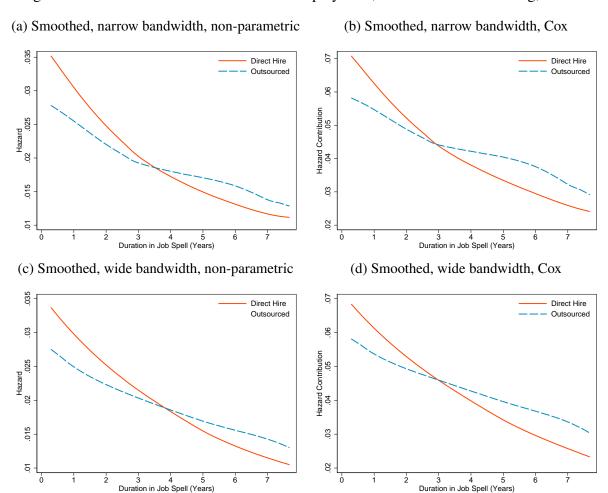
Notes: CNAE, National Classification of Economic Activities, is the official industry classification used by statistics and by federal, state and municipal bodies in Brazil.

Table B.3: Trend in 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%	

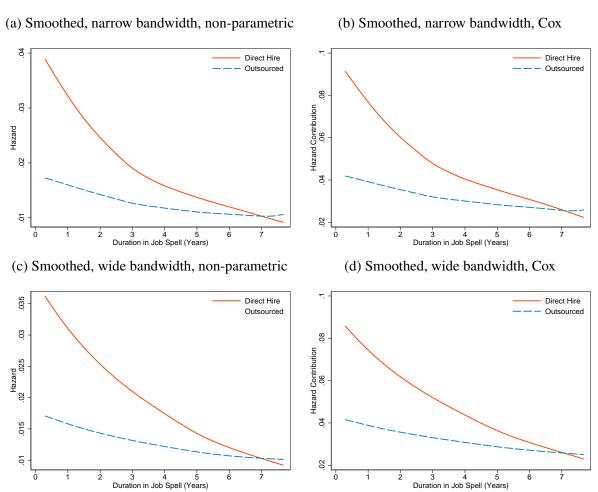
C Additional Figures and Tables

Figure C.1: Estimates of Hazard into Non-employment, Local Linear Smoothing, Cleaners



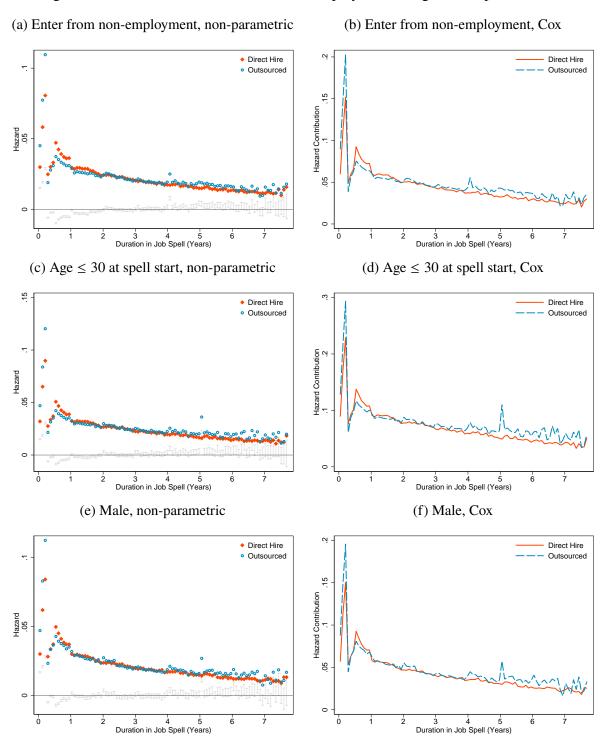
Notes: Panels (a) and (b) use local linear smoothing with a bandwidth of 1 year. The hazard estimates from first three month are dropped, since employment protection legislation applies only after a three-month probationary period. Panels (c) and (d) use a bandwidth of two years. For Cox model, controls include gender, age, age squared, race, and years of schooling at spell start, as well as fixed effects for the first month of each employment spell.

Figure C.2: Estimates of Hazard into Non-employment, Local Linear Smoothing, Guards



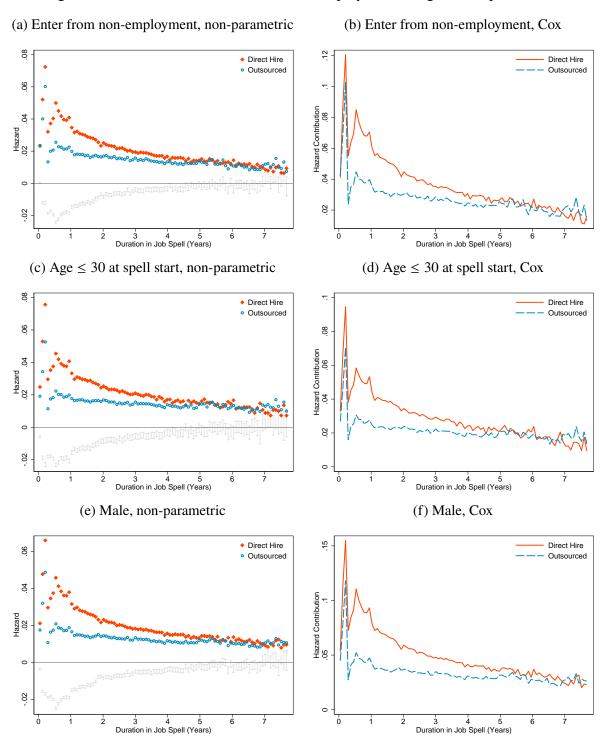
Notes: Panels (a) and (b) use local linear smoothing with a bandwidth of 1 year. Panels (c) and (d) use a bandwidth of two years. The hazard estimates from first three month are dropped, since employment protection legislation applies only after a three-month probationary period. For Cox model, controls include gender, age, age squared, race, and years of schooling at spell start, as well as fixed effects for the first month of each employment spell.

Figure C.3: Estimates of Hazard into Non-employment using Subsamples, Cleaners



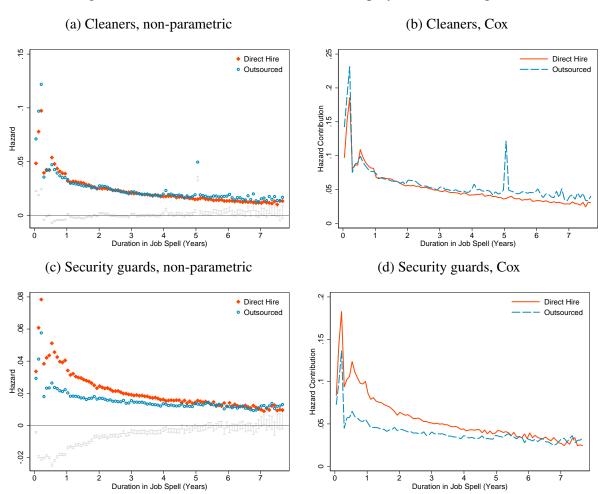
Notes: Panel (a) and (b) restrict to workers who were not employed in the formal sector for at least seven days prior to the beginning of the spell. Panels (c) and (d) restrict to workers who were age 30 or below. Panels (e) and (f) restrict to male workers. For Cox model, controls include gender, age, age squared, race, and years of schooling at spell start, as well as fixed effects for the first month of each employment spell.

Figure C.4: Estimates of Hazard into Non-employment using Subsamples, Guards



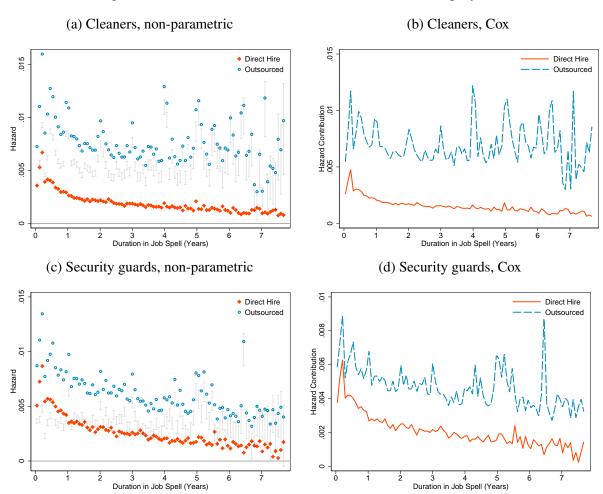
Notes: Panel (a) and (b) restrict to workers who were not employed in the formal sector for at least seven days prior to the beginning of the spell. Panels (c) and (d) restrict to workers who were age 30 or below. Panels (e) and (f) restrict to male workers. For Cox model, controls include gender, age, age squared, race, and years of schooling at spell start, as well as fixed effects for the first month of each employment spell.

Figure C.5: Estimates of Hazard into Non-employment Including Quits



Notes: Figure shows hazard estimates that do not censor quits. For Cox models, controls include gender, age, age squared, race, and years of schooling at spell start, as well as fixed effects for the first month of each employment spell.

Figure C.6: Estimates of Hazard into Other Formal Employment



Notes: Figure shows estimates of the rate at employment spells ends and the worker enters another formal employment spell within seven days. For Cox models, controls include gender, age, age squared, race, and years of schooling at spell start, as well as fixed effects for the first month of each employment spell.