Separations Revisited: Do Layoffs or Quits Drive Lower Separation Rates in High-Quality Firms? *

Cauê Dobbin[†] Daniel Fernandez[‡] Tom Zohar[§]

March 19, 2025

Abstract

We challenge the view that the negative correlation between firm quality and separation rates reflects efficient separations. Using Brazilian administrative data, we show that this correlation is driven by lower layoff rates at high-quality firms, not differences in quits. We develop a job search model where wage rigidity and productivity uncertainty generate inefficient layoffs. The model predicts that higher-quality firms have larger markdowns and, consequently, fewer layoffs. Empirically, we validate this by showing that firms facing stronger wage rigidity have higher layoffs and a steeper quality-layoff correlation, and that markdowns are higher in better firms and negatively correlated with layoffs.

*We thank Edoardo Acabbi, Nezih Guner, David Green, Simon Jäger, Kurt Mitman, Chris Moser, Pascuel Plotkin, Josep Pijoan-Mas, Jason Sockin, and Isaac Sorkin, along with seminar participants at George Mason University, CEMFI, the Econometric Society Winter 2024 meeting, and WALES 2025 for their helpful comments which greatly improved the paper. We thank Carles Pare Ogg, David Herskovits, and Moritz Osterhuber for their research assistantship. We gratefully acknowledge financial support from Georgetown University, Grant PRE2022-101381 funded by MCIN/AEI/10.13039/501100011033 and "ESF +", Fundación Carolina and CEMFI. All views and any errors are our own.

[†]Georgetown University. Email: caue.dobbin@georgetown.edu
[‡]CEMFI. Email: daniel.fernandez@cemfi.edu.es
[§]CEMFI. Email: tom.zohar@cemfi.es

Introduction

A well-established fact in labor economics is that high-quality firms tend to have lower separation rates (Topel and Ward, 1992; Davis et al., 2013; Haltiwanger et al., 2018a,b)—a pattern we refer to as the negative quality-separation correlation. Theoretical models often attribute this relationship to efficient separations, typically without distinguishing between quits and layoffs. However, recent empirical studies document widespread inefficient separations, highlighting the need to reassess the underlying drivers of the quality-separation correlation.[1]

In this paper, we address this gap in the literature. First, we provide empirical evidence that the negative correlation between firm quality and overall separation rates is primarily driven by a negative relationship between *firm quality and layoffs*, rather than quits. Second, we develop a parsimonious job search model in which wage rigidity and productivity uncertainty interact to generate inefficient separations. The model predicts that higher-quality firms have larger markdowns and, as a result, lower layoff rates, offering a theoretical foundation for our empirical findings. Third, we empirically validate the model's key mechanisms. We show that firms facing stronger wage rigidity experience higher layoff rates and a steeper quality-layoff correlation, and that markdowns are systematically higher in better firms and negatively correlated with layoffs.

Our empirical analysis draws on the Annual Manufacturing Survey (PIA), conducted by the Brazilian Institute of Geography and Statistics, and administrative records from the Brazilian Ministry of Labor (RAIS). RAIS covers the universe of formal labor contracts in Brazil and provides uniquely detailed information on separations, including precise separation dates and explicit distinctions between quits and layoffs. It also reports contract wages separately from variable pay, which we exploit to measure wage rigidity. PIA provides estimates of value added per worker—our baseline measure of firm quality—and markdowns.

We begin by highlighting key institutional features of the Brazilian labor market that enhance the accuracy of quit and layoff classifications in the RAIS data. Most importantly, firms are required to provide severance pay to workers and a fine to the govern-

[1] Examples of theoretical models attributing the quality-separation correlation to efficient separations include Burdett and Mortensen (1998); Postel-Vinay and Robin (2002); Postel-Vinay and Turon (2010). For empirical evidence on inefficient separations, see Davis and Krolikowski (2025); Jäger et al. (2023); Schmieder and von Wachter (2010).

ment in the case of layoffs, creating a financial incentive to classify separations as quits whenever possible. Conversely, workers benefit from layoff classification, as it grants access to severance payments and certain government benefits. These opposing incentives ensure that both parties have strong motivations to report separations accurately.[2] Moreover, we show that post-separation outcomes for laid-off workers are consistently worse than those for workers who quit. This empirical pattern further reinforces the reliability of the quit/layoff classification in the data.

Using this dataset, we document that layoff rates decline with firm quality across multiple quality measures—value added, firm size, and wage premium—all yielding similar results. While quits also decrease with firm quality, the slope is much flatter. Consequently, the negative correlation between firm quality and overall separation rates is primarily driven by lower layoff rates at high-quality firms. In fact, the slope of layoff rates with respect to firm quality closely matches that of overall separation rates, with the ratio between these slopes ranging from 0.81 to 0.93, depending on the quality measure used.

The negative correlation between separations and firm quality may, in part, reflect worker heterogeneity, as high-skill workers tend to sort into high-quality firms (Card et al., 2013; Gerard et al., 2021). If this were the primary mechanism, lower layoff rates at better firms would simply capture differences in workforce composition rather than firm characteristics. However, we show that this is not the case. Even after controlling for worker heterogeneity using a rich set of covariates, the majority of the quality-separation correlation remains driven by lower layoff rates at high-quality firms.[3]

To explain these empirical findings, we develop a partial-equilibrium wage-posting search model that features two central elements: worker-level productivity uncertainty and wage rigidity. In our framework, firms set wages by weighing the trade-off between average markdowns (the gap between average productivity and wages) and worker retention, which increases with wages. We introduce wage rigidity by assuming that firms must post wages *before* observing worker-specific productivity shocks and cannot adjust them ex post.

In the model, firm quality is defined as productivity, aligning with our baseline empir-

[2]Workers and firms could collude to misreport quits as layoffs for government benefit access, but this would require large upfront firm payments (severance and fines) with uncertain compensation, making enforcement difficult. Section 1.1 provides empirical evidence that such arrangements are rare.

[3]The worker covariates include age, tenure, education, gender, race, and occupation.

ical measure, value added. Additionally, we show that both wages and firm size increase with firm quality in equilibrium, providing theoretical validation for our two alternative empirical quality measures.

Our main theoretical result is that higher-quality firms have lower layoff rates. The mechanism operates as follows. Each firm's expected profit per worker equals the product of its retention rate and its expected markdown, making these factors complementary: an increase in markdowns strengthens the firm's incentive to retain workers, and vice versa. As a consequence, higher-quality firms optimally choose both larger expected markdowns and higher retention. Because of their larger markdowns, they can more easily absorb negative productivity realizations, resulting in fewer workers whose productivity falls short of the posted wage. Since layoffs occur when a worker's productivity is below the wage (i.e., when the markdown is negative), higher-quality firms end up with fewer layoffs overall.

We then turn to the data to empirically validate the mechanisms proposed by the model. First, we show that, consistent with the model's predictions, higher-quality firms exhibit larger markdowns and that these markdowns are associated with lower layoff rates.

Next, we investigate the model's prediction that layoffs are, in part, due to wage rigidity. We proxy wage rigidity using the share of total compensation determined by contract wages rather than variable pay. We validate this proxy by showing that a higher contract-wage share is associated with fewer wage reductions and more wage changes equal to zero. We then demonstrate that firms facing greater wage rigidity experience higher layoff rates. To assess the role of wage rigidity in the quality-layoff correlation, we define labor markets based on industry and location and estimate the correlation separately for each market. Our findings reveal that the quality-layoff correlation is stronger in markets where firms face greater wage rigidity.

Taken together, our empirical findings support the mechanisms proposed by our theoretical framework, where inefficient layoffs arise due to wage rigidity, and higher-quality firms experience lower layoff rates due to their larger markdowns.

Our work contributes to the empirical literature on wage rigidity and its role in generating layoffs (Schmieder and von Wachter, 2010; Jäger et al., 2023; Ehrlich and Montes, 2024; Davis and Krolikowski, 2025). We show that wage rigidity is associated not only with higher layoff rates but also with a stronger quality-layoff correlation. Our measure of wage rigidity builds on extensive evidence that variable pay is more flexible than contract pay (Altonji and Devereux, 1999; Messina et al., 2010; Anger, 2011; Grigsby et al., 2021).[4] Similar to our approach, Makridis and Gittleman (2022), Reizer (2022), and Sockin and Sockin (2025) analyze the relationship between employment volatility and wage rigidity, using the prevalence of variable pay as a measure of wage flexibility.

Our theoretical framework builds on the literature on wage dispersion and turnover, particularly the foundational work of Burdett and Mortensen (1998), which emphasizes the trade-off between wage markdowns and retention. A substantial body of research extends this framework, typically assuming separations are efficient and not differentiating between quits and layoffs (e.g., Postel-Vinay and Robin, 2002; Postel-Vinay and Turon, 2010). In contrast, we show empirically that lower layoff rates at high-quality firms primarily drive their lower separation rates and propose a model incorporating wage rigidity and inefficient separations to explain this pattern.

Our work also relates to previous work on the determinants of layoff rate variation. Prior research has shown that layoffs decline with tenure (Jovanovic, 1979; Topel and Ward, 1992; Ureta, 1993) and has examined the dynamics of layoff rates (Hopenhayn and Rogerson, 1993; Mortensen and Pissarides, 1994; Mueller, 2017; Carlsson and Westermark, 2022; Acabbi et al., 2024; Blanco et al., 2024). We offer a novel perspective by investigating firm-level heterogeneity in layoffs. This focus is motivated by evidence that firm-level differences in job stability play a crucial role in shaping unemployment persistence (Pinheiro and Visschers, 2015; Jarosch, 2023).

Finally, a large body of work estimates labor supply elasticities using the elasticity of separation rates to wages, following the methodology proposed by Manning (2003). See, for example, Hirsch et al. (2010), Ransom and Oaxaca (2010), Ransom and Sims (2010), Webber (2015), Bachmann et al. (2022), Bassier et al. (2022), and Webber (2022). Sokolova and Sorensen (2021) reviews this literature. However, as many of these studies acknowledge, the relevant elasticity for this exercise is the elasticity of *quits* to wages, not total separations. We show that the slope of quit rates with respect to firm wage premiums is much flatter than that of overall separation rates, suggesting

[4]Cardoso and Portugal (2005) and Card and Cardoso (2022) examine the "cushion" between wage floors and total wages. While they focus on wage floors determined by collective bargaining agreements, we consider worker-specific floors set by individual contracts.

that labor supply elasticities may be substantially smaller than previously estimated.[5]

The remainder of the paper is organized as follows. Section 1 provides an overview of the institutional setting and presents evidence supporting the reliability of the quit-layoff distinction in our data. Section 2 documents our main empirical finding: the negative correlation between firm quality and separation rates is primarily driven by layoffs. Section 3 develops a theoretical framework to explain this pattern. Section 4 empirically validates the mechanisms proposed by our theoretical framework. Finally, Section 5 concludes and discusses implications for future research.

1 Distinguishing quits and layoffs empirically

1.1 Data and sample

Employer-Employee Data from Brazil. We utilize the *Relação Anual de Informações Sociais* (RAIS), an extensive administrative record from Brazil that captures formal employment relationships. Annually, companies submit RAIS filings, documenting all employees from the preceding year, including personal data such as gender, birth date, and education level, alongside contract specifics like earnings, contracted hours, and detailed occupation according to the *Classificação Brasileira de Ocupações* (CBO 2002), which encompasses 2,638 different occupation codes. Crucially, RAIS mandates reporting the dates and reasons for employee separations, distinguishing between quits and layoffs. Additionally, RAIS reports contract wages separately from a variable pay component, which includes bonuses, performance pay, and overtime.

Firm Surveys. Our analysis utilizes data from the Annual Manufacturing Survey (Pesquisa Industrial Anual, PIA), run by the Brazilian Institute of Geography and Statistics, which provides detailed information on production, employment, and costs. Value added (VA) is defined as the value of industrial transformation per worker, calculated as the difference between the gross value of industrial production and the costs of industrial operations, divided by the number of workers. The PIA data is representative at the industry-state level.[6]

[5] Relatedly, other studies document a positive correlation between tenure and wages and interpret this as evidence that workers prefer high-wage jobs but do not estimate labor supply elasticities from this correlation (Krueger and Summers, 1988; Card et al., 2013; Drenik et al., 2023).

[6] "Labor Costs" includes salaries, benefits, and mandatory contributions to social security systems. PIA

Measuring Firm Quality. Our baseline measure of firm quality is value added, obtained from the PIA survey, as described earlier. Additionally, we consider two alternative proxies for firm quality commonly used in the literature: AKM pay premiums and firm size. AKM firm pay premiums are estimated following Abowd et al. (1999). To improve estimation precision, we classify firms into 100 clusters using a k-means clustering algorithm, as recommended by Bonhomme et al. (2019). Appendix C details the estimation procedures and validates the AKM model assumptions in our sample. Firm size is defined as the total number of employees in each firm. Since our focus is on cross-sectional heterogeneity rather than time variation, we measure value-added and firm size in the first year a firm appears in the sample and hold them fixed throughout the analysis.[7]

Sample: Urban, Private-Sector Jobs. Our sample spans the period from 2010 to 2017, starting after the Great Recession and ending before Brazil's 2018 labor market reforms. We focus on Brazilian men and women born between 1959 and 1987, with at least one year of potential labor market experience.[8] We restrict the sample to individuals employed on December 31 with at least one month of tenure, in open-ended contracts, and earning above the minimum wage in urban areas within Brazil's private sector. For individuals holding multiple jobs, we select the position with the highest contracted hours or, in case of a tie, the one with the highest hourly wage. We classify non-separated workers who remain with the same firm across consecutive years as *stayers* and use the reported cause of separation to distinguish between *layoffs* and *quits*.

Given the significant presence of informal employment in Brazil, which is not captured in our data, we follow Gerard et al. (2021) and restrict our sample to the Southeast region, comprising the states of Espírito Santo, Minas Gerais, Rio de Janeiro, and São Paulo. This region accounts for nearly half of the country's formal employment and has relatively lower informality rates. Additionally, its minimum-to-median wage ratio is comparable to those in other developing and developed economies.[9] Furthermore, to estimate firm and worker effects, we include only the largest connected set of firms and

uses 3-digit industry codes, corresponding to 285 industries, and Brazil is divided into 27 states, resulting in 7,695 unique industry-state combinations.

[7]AKM pay premiums are fixed by construction.

[8]"Potential labor market experience" is defined as age minus years of education minus 6. "Years of education" is inferred from the highest reported degree. For example, completing high school corresponds to 12 years, and completing college to 16 years.

[9]Using U.S. data, Davis and Krolikowski (2025) finds that the minimum wage is not a primary driver of wage rigidity.

workers, as proposed by Abowd et al. (1999).

Table I provides descriptive statistics comparing our final sample with the broader national and regional datasets. Workers in our sample have similar profiles in terms of education, age, and tenure with the broader Brazilian workforce. Hourly wages are slightly higher in the Southeast, reflecting its economic status. Our sample includes 74% of the firms in this region but captures 99% of worker-year observations. Notably, layoffs constitute 81% of all separations in our sample. This proportion is even higher across the broader national landscape, suggesting that the predominant role of layoffs in separation dynamics would be even more pronounced in a more expansive sample.

Finally, the PIA survey is restricted to the manufacturing sector and covers 8% of firms and 14% of workers in the RAIS dataset. Within this sample, firms in the Southeast region exhibit higher value-added levels compared to the national average. Moreover, our sample, being further restricted to larger firms, has value-added that is higher than the regional average.

1.2 Context: Quits and Layoffs in Brazil

The RAIS dataset distinguishes between quits and layoffs, a critical distinction given that the government uses this data for administrative purposes. In the case of a layoff, the firm must pay a fine to the government and provide severance pay to the worker. Additionally, the worker becomes eligible for unemployment benefits and gains access to their public pension fund, which is typically reserved for retirement. Given the low incidence of quits in the data, a natural concern is whether these policies create incentives to misclassify quits as layoffs. Appendix D provides more details on these policies, and below we discuss why such incentives are unlikely to result in systematic misreporting.

If a separation is reported as a quit, it benefits the firm; if reported as a layoff, it benefits the worker. Consequently, both parties have strong incentives to ensure that the separation is accurately reported. However, there is a potential issue: in the case of a layoff, the firm incurs a cost by paying a fine to the government, while the worker benefits from unemployment payments and gains early access to their pension funds. If a worker highly values immediate liquidity—such as accessing their pension funds early—the total benefits received from the government could outweigh the costs to the firm. This scenario might create an incentive for collusion between the worker and the

Table I – Descriptive statistics

	Brazil	Southeast region	Sample
Number of firms	4,307,522	2,105,805	1,523,100
Average firm size	7.9	8.5	9.8
Number of worker-year observations	146,878,704	78,877,496	74,910,200
Number of workers	35,403,116	19,023,076	14,868,221
Average age (years)	37.3	37.6	37.4
Average log-hourly wage	2.181	2.282	2.332
Average tenure (months)	46.5	48.0	46.4
Average schooling (years)	10.9	11.0	10.4
Average annual layoff rate (%)	20.17	20.18	17.03
Average annual quit rate (%)	3.34	3.34	4.03
Pesquisa Industrial Anual (PIA)			
Share of firms covered (%)	8.11	9.98	10.68
Share of workers covered (%)	13.85	17.24	17.43
Average log-value added	11.28	11.32	11.70

Notes: The first three panels of this table present summary statistics for the RAIS dataset. The first column covers the period from 2010 to 2017 and includes all urban manufacturing private-sector jobs in the Southeast Region. The second column further restricts the sample to firms located in the Southeast Region of Brazil, while the third column limits the sample to firms belonging to the largest connected component.The last panel provides summary statistics for the PIA dataset, which is restricted to manufacturing firms. "Share of workers covered" and "Share of firms covered" indicate the proportion of workers and firms in RAIS that are in the manufacturing sector and therefore also appear in the PIA dataset.

firm, where they agree to misclassify the separation as a layoff in exchange for side payments that leave both parties better off.

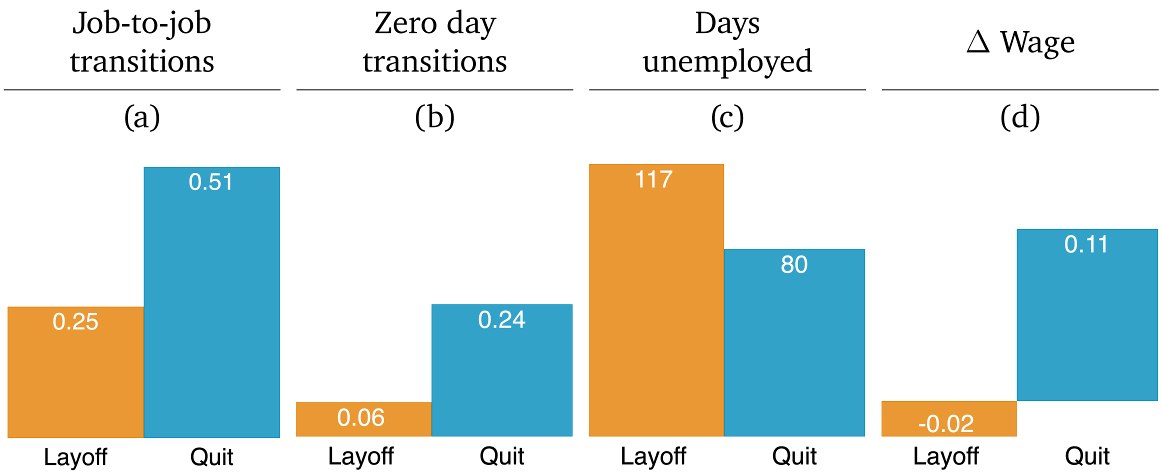
Nevertheless, such collusion is unlikely in practice. When a separation is classified as a layoff, the firm must make substantial payments to both the government and the worker. For collusion to succeed, the firm would need to trust that the worker will return a portion of these payments after accessing their pension funds, an arrangement that is difficult to enforce given its illegal nature.

Empirical evidence suggests that such collusion agreements are rare. Since 2018, firms and workers in Brazil have had the option to terminate contracts by mutual agreement. Under this arrangement, the worker receives severance pay and can access 80% of their pension funds, but the firm avoids the government fine. If early access to pension funds were a strong motivator for misreporting quits as layoffs, mutual agreement separations would be more common. However, they account for only 0.5% of all separations.

Another potential motive for misreporting is access to unemployment benefits. Using the same RAIS data, Van Doornik et al. (2023) find that workers eligible for unemployment insurance are 11% more likely to be laid off. However, their analysis shows that these excess layoffs are not merely misclassified quits, further suggesting that misreporting is uncommon.

Finally, we conducted further validation by comparing the post-separation outcomes of workers who quit versus those who were laid off. Figure I presents compelling evidence: workers who quit are significantly more likely to secure employment within a year compared to those who were laid off—51% versus 25%, respectively. Moreover, among those who found jobs, quitting workers tended to secure new positions more quickly (46% found immediate employment, compared to 25% of those laid off) and experienced more favorable wage growth, with an average increase of 11% in wages compared to a 2% decrease among those laid off. These patterns align with the hypothesis that separations categorized as quits are indeed voluntary and initiated by the workers, while those labeled as layoffs are not, further substantiating the accuracy of the reporting in our data.

Figure I – Quitting workers make better moves than laid-off ones



Notes: This figure compares labor outcomes and mobility patterns between laid-off and quitting workers. Panel (a) reports the share of separated workers who find a job in the same year (job-to-job transitions). Panel (b) reports the share of job-to-job transitions with no gap between the two jobs. Panel (c) reports the average number of days in non-employment for workers in a job-to-job transition. Panel (d) reports the difference in wage growth between workers who change jobs and those who do not. The data is from RAIS. The sample covers the period from 2010 to 2017, includes all urban manufacturing private-sector jobs in the Southeast Region, and is restricted to firms within the largest connected set, as detailed in Section 1.

2 The quality-separation correlation: Empirics

In this section, we empirically investigate the determinants of the quality-separation correlation. First, we demonstrate that the negative correlation between firm quality and separation rates is primarily driven by high-quality firms having lower layoff rates, the layoff-separation correlation. Second, we show that this result is not confounded by differential sorting of high-skill workers into high-quality firms.

Figure II presents our main finding: the *layoff*-separation correlation. The y-axis shows firm-level quit and layoff rates, while the x-axis represents different measures of firm quality. Panel (a) uses our preferred quality metric: value-added. However, value-added is available only for the manufacturing sector and is aggregated at the industry-state level, as detailed in Section 1.1. To extend the analysis to the full sample and explore firm-level variation, we complement our analysis with two additional proxies for firm quality: pay premiums (c) and firm size (b). Reassuringly, the same patterns emerge regardless of the measure used.

Our key finding is that layoff rates decline sharply with firm quality. The magnitude of this relationship is substantial. The layoff rate for firms in the top 5% of value-added is 8%, compared to 23% for firms in the bottom 5%. Quit rates also decline with firm quality: firms in the top 5% of value-added have a quit rate of 1.5%, whereas those in the bottom 5% have a quit rate of 3.3%. However, since quits are relatively rare, their contribution to overall separations is limited.[10]

To formally quantify the relative contributions of layoffs and quits to the overall quality-separation correlation, we estimate the following regression:

$$Y_{jt} = \beta_Y Q_{jt} + \epsilon_{jt}, \tag{1}$$

where t represents a year, j is a firm, and Q_{jt} is a measure of firm quality. The dependent variable Y_{jt} represents the firm's quit, layoff, or overall separation rate, and ϵ_{jt} captures residuals. The parameter of interest, β_Y, measures the relationship between firm quality and separations, layoffs, or quits. Since the overall separation rate is the sum of the layoff

[10]The relationship between quits and firm quality remains negative but is weaker when using pay premiums instead of value-added and is not significant when using firm size. However, these differences do not alter our main conclusion that layoffs primarily drive the quality-separation correlation, as confirmed by Table II.

and quit rates, it follows that:

$$\beta_{Separation} = \beta_{Layoff} + \beta_{Quit}. \tag{2}$$

Motivated by the decomposition in Equation (2), we assess the role of layoffs in the quality-separation relationship using the following ratio:

$$\text{Role of layoffs in quality-separation relationship} \equiv \frac{\beta_{Layoff}}{\beta_{Separation}}.$$

Estimates of this ratio, reported in the first column of Table II, reveal that the negative relationship between firm quality and overall separation rates is predominantly driven by layoffs. This conclusion is supported by the similarity in the slopes of layoff rates and separation rates with respect to firm quality. Specifically, the ratio of these slopes ranges from 0.81 to 0.93, depending on the firm quality measure used.

A possible explanation for the patterns observed in Figure II is sorting. There is substantial evidence showing that higher-skilled workers tend to sort into higher-quality firms (Card et al., 2013; Gerard et al., 2021). As a result, the lower layoff rates observed in high-quality firms could simply reflect the higher skill levels of their employees rather than firm quality itself.

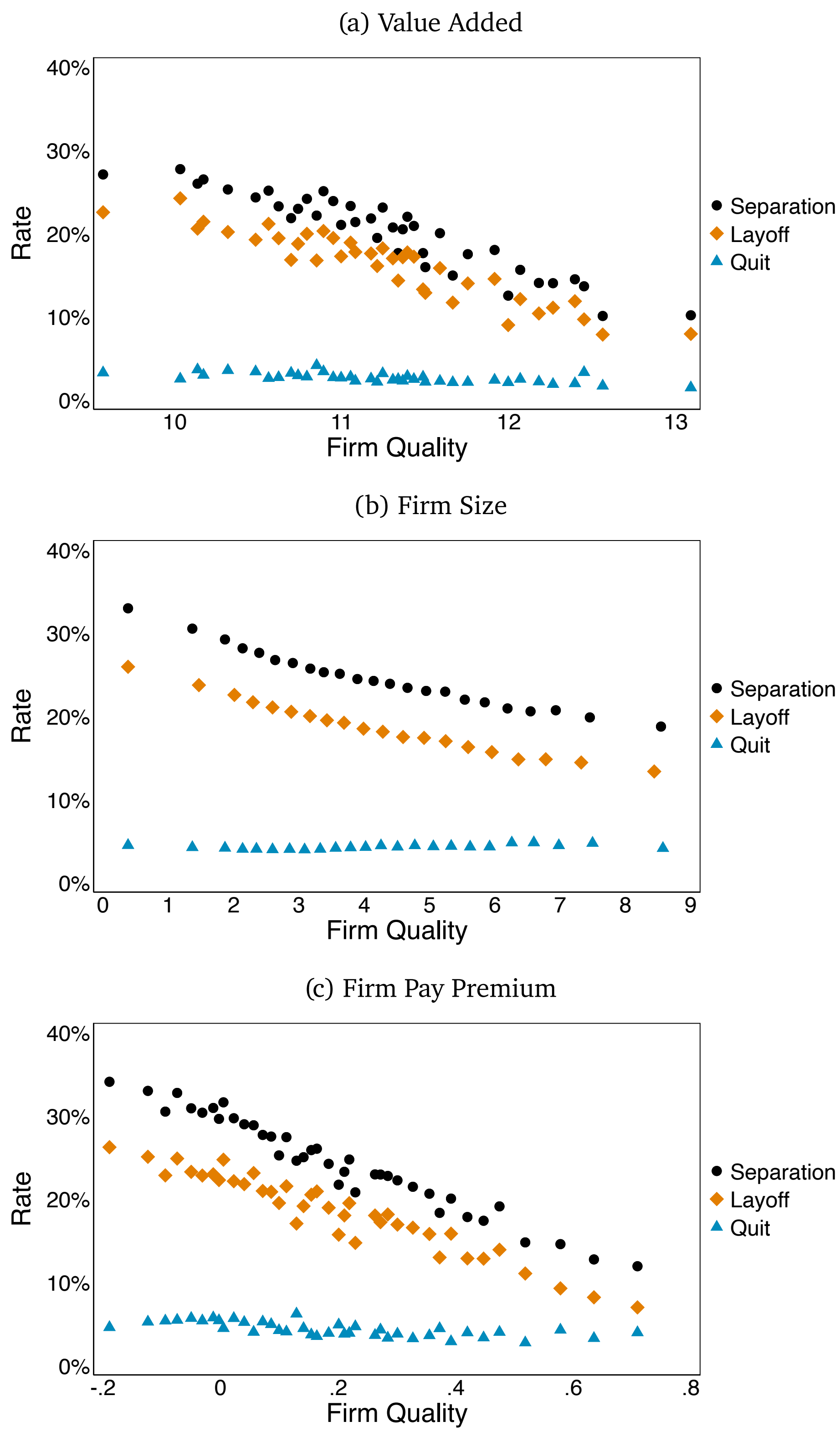
To assess the extent to which worker sorting influences our findings, we extend Equation (1) to account for worker heterogeneity by estimating the following regression:

$$Y_{it} = \beta_Y Q_{j(i,t)t} + \gamma X_{it} + \epsilon_{it}, \tag{3}$$

where t denotes a year, i represents an individual worker, and $j(i,t)$ is the firm employing worker i at time t. We estimate two separate regressions: one where the dependent variable, Y, is an indicator for whether the worker was laid off in that year, and another where Y indicates whether the worker separated for any reason. The key independent variable, Q, measures firm quality, while X includes a set of worker characteristics to control for heterogeneity. The residual term, ϵ, captures unobserved factors. The coefficient of interest, β_Y, estimates the relationship between firm quality and separations or layoffs, net of worker-specific differences.

We control for a comprehensive set of worker characteristics. First, since tenure

Figure II – Quality-layoff correlation drives the quality-separation correlation



Notes: This figure illustrates the relationship between yearly separation rates and firm quality, using three measures of firm quality: (1) "Value Added" (Panel a), as described in Section 1.1; (2) "Firm Size" (Panel b), defined as the total number of workers in the firm in the first year of the sample; and (3) "Firm Pay Premium" (Panel c), derived from AKM firm fixed effects (Appendix C). Total separation rates are shown in black, layoffs in orange, and quits in blue. The data is at the firm level, and all estimates are weighted by firm size. Value added is sourced from the PIA dataset, which is aggregated at the industry-state level. Pay premiums, firm size, and separation rates are calculated using the RAIS dataset. The sample covers the period from 2010 to 2017, includes all urban private-sector jobs in the Southeast Region, and is restricted to firms within the largest connected set, as detailed in Section 1. Panel (a) is further restricted to manufacturing firms.

is a key determinant of layoff rates (Jovanovic, 1979; Topel and Ward, 1992; Ureta, 1993), we include both tenure and tenure squared. Second, recognizing that career trajectories vary by gender and skill level, we control for age and age squared, interacted with gender and education fixed effects. Third, to account for potential discrimination, we include race fixed effects. Fourth, to capture differences across occupations—such as variations in unionization rates—we introduce occupation fixed effects. Finally, to adjust for unobserved heterogeneity in worker ability, we incorporate AKM worker effects.[11]

We examine the role of layoffs in driving the negative quality-separation correlation by estimating the ratio $\frac{\beta_{\text{Layoff}}}{\beta_{\text{Separation}}}$.[12] The results are reported in Table II. Panel A presents our baseline estimates, showing that even after controlling for worker heterogeneity, $\frac{\beta_{\text{Layoff}}}{\beta_{\text{Separation}}}$ declines only slightly, from 0.87 to 0.80, in the most flexible specification. This suggests that worker heterogeneity does not account for the observed patterns. Panels B and C, which use alternative measures of firm quality, yield similar results, further supporting the robustness of our findings.

3 The quality-separation correlation: Theory

This section introduces a simple labor search model to explain our empirical finding that high-quality firms have lower layoff rates. Previous theoretical work has established that both quits and layoffs can occur even within a framework of fully efficient separations (McLaughlin, 1991). However, recent empirical research has revealed that inefficient layoffs are pervasive (Schmieder and von Wachter, 2010; Davis and Krolikowski, 2025; Jäger et al., 2023).

Building on these empirical findings, we develop a model that generates endogenous inefficient layoffs through the interaction of two key features: wage rigidity and uncertainty about workers' productivity. Specifically, firms commit to a wage rate before the worker's productivity shock is realized. There is a productivity threshold below which it becomes unprofitable for the firm to retain the worker at the predetermined wage, resulting in a layoff. In some of these cases, the firm would prefer to reduce the wage and keep the worker, but cannot do so due to wage rigidity, which is the source of inn-

[11]Due to measurement error in the estimated AKM effects, results using this covariate should be interpreted with caution.

[12]Appendix Table B.1 presents separate estimates of β^{Layoff} and $\beta^{\text{Separation}}$.

Table II – Worker sorting does not drive the quality-layoff correlation

	(1)	(2)	(3)	(4)
Panel A - Value Added				
$\frac{\beta^{\text{Layoff}}}{\beta^{\text{Separation}}}$	0.871***	0.852***	0.776***	0.804***
	(0.0055)	(0.0090)	(0.0096)	(0.0116)
Observations	9,308,341	9,307,701	9,308,341	9,307,701
Panel B - Firm Size				
$\frac{\beta^{\text{Layoff}}}{\beta^{\text{Separation}}}$	0.928***	0.950***	0.946***	0.957***
	(0.0032)	(0.0048)	(0.0046)	(0.0062)
Observations	49,835,818	49,830,114	49,835,818	49,830,114
Panel C - Firm Pay Premium				
$\frac{\beta^{\text{Layoff}}}{\beta^{\text{Separation}}}$	0.811***	0.774***	0.698***	0.703***
	(0.0018)	(0.0025)	(0.0034)	(0.0033)
Observations	49,835,818	49,830,114	49,835,818	49,830,114
Worker covariates			✓	✓
Worker AKM Effect		✓		✓

Notes: This table reports OLS estimates of Equation (3), which describe the relationship between separation rates and firm quality. Firm quality is measured using three metrics: (1) "Value Added" (Panel A), as described in Section 1.1; (2) "Firm Pay Premium" (Panel B), derived from AKM firm fixed effects (Appendix C); and (3) "Firm Size" (Panel C), defined as the total number of workers in the firm during the first year of the sample. The table reports the ratio of the estimates from two separate regressions where the outcome changes from layoff rates total separations. Controls include worker-specific wage components from an AKM estimation (detailed in Appendix C) and the following covariates: race and occupation fixed effects, tenure and tenure squared, and interactions between age, age squared, gender, and education fixed effects. Estimates of β^{Layoff} and $\beta^{\text{Separation}}$ are presented separately in Table B.1 in the Appendix. The data is at the worker level. Value added is sourced from the PIA dataset, which is aggregated at the industry-state level. Pay premiums, firm size, and separation rates are calculated using the RAIS dataset. The sample covers the period from 2010 to 2017, includes all urban private-sector jobs in the Southeast Region, and is restricted to firms within the largest connected set, as detailed in Section 1. Panel A is further restricted to manufacturing firms.

eficiency in the model. Aside from these key features, we keep the model as simple as possible.

We consider a partial-equilibrium random-search model with homogeneous workers. The assumption of a homogeneous workforce is motivated by the results in Section 2, which demonstrate that worker heterogeneity does not explain the negative relationship between layoff rates and firm quality. This framework can be interpreted as representing the labor market for a specific worker type—for instance, defined by education level or occupation. In our model, random search implies that firms are matched with an exogenously determined type and number of workers. Furthermore, the partial-equilibrium framework assumes that the distribution of workers' outside options is exogenous. In other words, the firm is atomistic, and its decisions do not affect the factors determining workers' outside options, such as offers from other firms, government policies, or market-level conditions.

The rest of this section proceeds as follows. First, we present the economy in which our model operates and the timing of agents' decisions. Second, we delve into the quality-separation correlation and present our key theoretical result: more productive firms have both fewer quits and fewer layoffs.

3.1 Set up

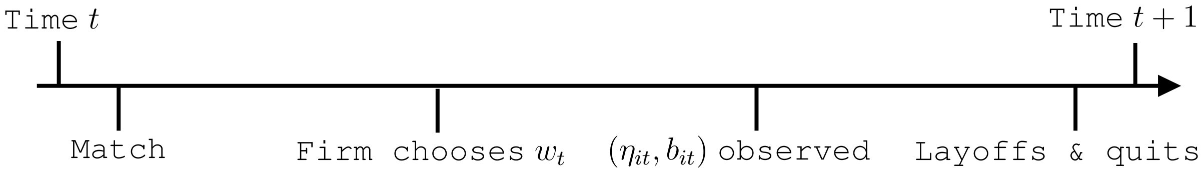
There is a single firm, characterized by quality ψ. In each period t, it chooses the wage rate w_t, common to all its workers, and whether to layoff each worker to maximize the present value of expected profits. There is a continuum of ex-ante homogeneous workers, with expected productivity α. In each period t, each worker i receives a productivity shock η_{it}. Hence, the total revenue the firm receives from worker i in period t is $\psi+\alpha+\eta_{it}$.

If employed, workers derive utility equal to the wage rate w_t, and if unemployed, they receive a stochastic, exogenously determined outside option b_{it}. For simplicity, we assume workers discount the future infinitely and hence quit if $w_t < b_{it}$. Both shocks, η_{it} and b_{it}, are idiosyncratic and follow known distributions, F_η and F_b, respectively. We normalize α such that $\mathbb{E}_\eta[\eta_{it}] = 0$.

The firm maximizes the present value of expected profits, discounted at rate β. For clarity, we define an equilibrium under $\beta = 0$ in the main text, while Appendix A shows that all results hold for any $\beta \in [0, 1)$. The firm's per-worker profit in each period is given by the wage markdown $\mu_{it}(w_t)$, which represents the difference between worker-specific productivity and wages:

$$\overbrace{\mu_{it}(w_t)}^{\text{markdown}} \equiv \overbrace{\psi}^{\text{firm productivity}} + \overbrace{\alpha + \eta_{it}}^{\text{worker productivity}} - \overbrace{w_t}^{\text{wage}}. \tag{4}$$

Figure III – Model timeline



Notes: This figure shows the timeline of one period in the model presented in Section 3.

The timing of the model in each period t is depicted in Figure III. The firm begins the period with s_t workers. It then meets an additional unit mass of potential hires, consisting of ex-ante homogeneous workers with expected productivity α. Next, the firm selects a wage w_t to offer both to existing employees and new hires. Subsequently, firms and workers observe productivity shocks (η_{it}) and outside option shocks (b_{it}). After shocks are observed, the firm decides which workers to lay off, and workers simultaneously decide whether to quit. These decisions are made conditional on the wage, which defines the layoff rate function $\delta_\psi(w_t)$ and the retention rate function $\rho(w_t)$, where retention is one minus the quit rate. Finally, payoffs are realized, and the firm enters the next period with $s_{t+1} = \rho(w_t) \cdot [1 - \delta_\psi(w_t)](1 + s_t)$ workers.

The key feature of this timing is that it generates wage rigidity by requiring firms to set wages before observing the productivity shock (η), while allowing them to decide on layoffs after the shock is realized. If a worker's markdown at the predetermined wage level is negative ($\mu_{it}(w_t) \leq 0$), the worker is laid off. Crucially, because firms cannot adjust wages after observing the shocks, layoffs occur even in cases where an alternative wage w'_t exists such that both the worker and the firm would prefer to continue the match—i.e., even if $w'_t \geq b_{it}$ and $\mu_{it}(w'_t) > 0$. This mechanism illustrates how wage rigidity can lead to inefficient layoffs.

Note that workers can quit the same period they meet with the firm. In this formulation, the retention rate represents both the share of current workers that stays in the firm and the share of new matches that accepts the offer. Since all shocks are independent across periods and workers are ex-ante homogeneous, these two shares are identical.

An equilibrium is defined by the optimality of three decisions: layoffs, quits, and wages. First, the firm lays off a worker if their markdown is negative. Second, workers quit if the outside option is higher than wages. Third, the firm chooses wages to maximize expected profits. Appendix A.1 defines an equilibrium formally.

3.2 Drivers of the quality-separation correlation

In Section 2, we showed empirically that the primary driver of the quality-separation correlation is the lower layoff rate observed among high-quality firms. We now use our theoretical model to explore *why* higher-quality firms lay off workers less frequently. To build intuition, we present a simplified version of the relevant theorem below; the full technical statement is in Appendix A.

Key Insights *Under mild assumptions about the distribution of productivity and outside option shocks—which hold for a wide range of common distributions such as uniform, normal, and Gumbel—we establish the following:*

(I) Firm size is increasing in firm quality;
(II) Wages are increasing in firm quality;
(III) The separation rate is decreasing in firm quality;
(IV) The quit rate is decreasing in firm quality;
(V) The layoff rate is decreasing in firm quality;
(VI) Th average markdown is increasing in firm quality.

Formal statement: *Theorem 1 in Appedix A.1.*
Proof: *Appendix A.2.*

Consistent with prior theoretical work (Postel-Vinay and Robin, 2002; Elsby and Gottfries, 2022), our model shows that wages and firm size are increasing in firm quality. These findings justify the use of wages and size as proxies for firm quality in our empirical analysis (Section 2). We also confirm that separation rates decline with firm quality, in line with earlier research.

We extend this literature by decomposing separations into quits and layoffs to investigate how each margin relates to firm quality. Our model predicts that *both* quits and layoffs decline as firm quality rises. The negative quality-quit relationship is straightforward: workers are less likely to quit higher-quality firms because these firms pay higher wages.

Our main theoretical contribution is to explain why higher-quality firms lay off workers less frequently. A layoff occurs when a worker's individual markdown is negative, which happens when their realized productivity shock is sufficiently low to offset the firm's average markdown.[13] Consequently, layoff rates decline as markdowns increase. The key question, then, is whether higher-quality firms systematically exhibit larger markdowns.

While it is intuitive that higher-quality firms would have larger markdowns, this result is not straightforward. Higher-quality firms pay higher wages to increase worker retention. If the incentives to retain workers were sufficiently strong, higher-quality firms could end up with *lower* markdowns. Indeed, the framework in Burdett and Mortensen (1998) predicts a negative relationship between wages and markdowns in equilibrium. However, this is not the case in our model, as established in the *Key Insights* above.

We can gain further insight into why markdowns increase with firm quality by reformulating the firm's decision problem as a choice over *retention* (ρ) and *average markdown* (μ), subject to the constraint that a supporting wage w exists for the chosen $\{\rho, \mu\}$. We refer to this constraint as the production possibility frontier (PPF).[14] Since higher wages increase retention but reduce markdowns, the PPF slopes downward. Given the PPF, the firm solves:

$$\max_{\rho,\mu} \overbrace{s_t \cdot \rho \cdot \big[1 - \delta(\mu)\big]}^{\text{firm size}} \cdot \overbrace{\pi(\mu)}^{\text{profit per worker}} \quad \text{subject to PPF,} \tag{5}$$

where s_t is the initial size of the firm, $\delta(\mu)$ is the layoff rate (decreasing in μ), and $\pi(\mu)$ is per-worker profit (increasing in μ). The objective is total profits, given by firm size times average profit per worker.

Equation (5) highlights the trade-offs firms face when choosing between retention and markdowns. Expected profits are determined by firm size and average profits per worker, both of which can be expressed as functions of retention and markdown. Firm size depends on its initial workforce—unaffected by the firm's choices at this stage—the retention rate, and the layoff rate. As discussed earlier, the layoff rate decreases with the average markdown. Meanwhile, profits per worker increase with the average markdown.[15]

[13] The firm's average markdown is given by $\psi + \alpha + E[\eta_{it}] - w_t = \psi + \alpha - w_t$.

[14] Formally, the PPF requires the existence of a wage w such that $\mu = \psi + \alpha - w$ and $\rho = P(b_{it} \leq w)$.

[15] Profits per worker and average markdown are distinct. The average markdown considers all workers employed at the beginning of the period, whereas profit per worker accounts only for those still employed at the end, when profits are realized. Formally, $\pi(\mu) = \mu + \mathbb{E}[\eta_{it} | \mu + \eta_{it} > 0]$. The function $\pi(\mu)$ is

To see why higher-quality firms choose larger markdowns, consider a simple calibration where $\eta_{it} \sim U[-\sigma_\eta, \sigma_\eta]$ and $b_{it} \sim U[0, \sigma_b]$. Under this parameterization, the firm's maximization in (5) becomes:[16]

$$\begin{aligned} &\max_{\rho,\mu} \rho \cdot (\mu+1)^2 \\ &\text{subject to: } \mu + \sigma_b \rho = \psi + \alpha. \end{aligned} \tag{6}$$

Next, we analyze how retention and markdowns respond to firm quality, as illustrated in Figure IV, which represents Equation (6). The solid lines depict the production possibility frontier (PPF), while the dashed lines correspond to isoprofit curves. The position of the PPF depends on firm quality (ψ): a higher-quality firm (orange line) can sustain a higher μ for any given ρ. The PPF also depends on the average productivity of workers (α), which is held constant across firms.

Crucially, the firm's objective function depends on the *product* of ρ and μ,[17] implying that these are *complementary inputs*: an increase in markdowns strengthens the firm's incentive to retain workers, and vice versa. As a result, when the PPF expands due to an increase in ψ, the firm optimally raises *both* ρ and μ. This implies that higher-quality firms exhibit higher markdowns, even though they pay higher wages, leading to lower layoff rates. Additionally, since the quit rate is defined as $1-\rho$, more productive firms also experience fewer quits.

This simple framework is also informative about the relative rates of quits to layoffs. This ratio depends on how the firm trades-off retention and markdowns, which is determined by the slope of the PPF. This slope is given by σ_b since it determines the labor-supply elasticity. The more elastic labor supply is (low σ_b), the "cheaper" it is for the firm to retain a worker and, hence, the firm will choose relatively higher retention and lower markdown, which results in fewer quits and more layoffs.

Why do our theoretical predictions diverge from Burdett and Mortensen (1998) and others, who predict a negative relationship between retention and markdowns? The key distinction lies in allowing for exogenous variation in firm quality (ψ). If all firms

strictly increasing for any μ provided that $\frac{\partial \mathbb{E}_\eta[\eta|\eta>x]}{\partial x} \leq 1$, a condition that holds for many commonly used distributions, including uniform, normal, and Gumbel (logit).

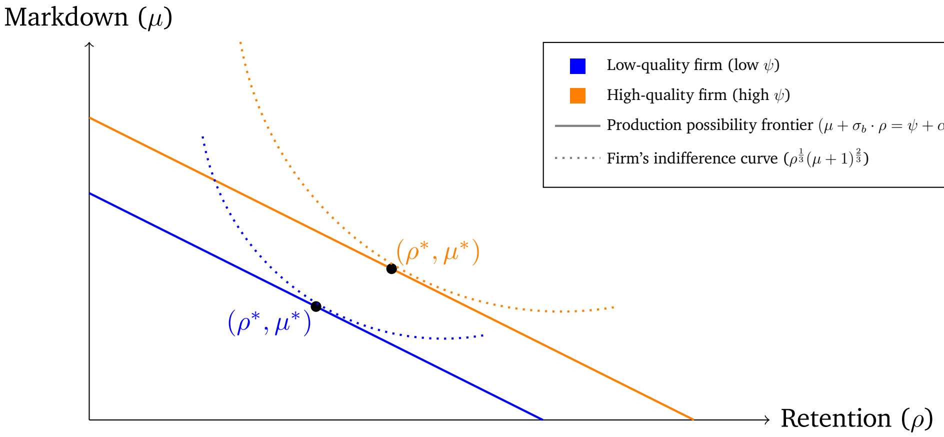
[16] Since layoff and quit rates depend only on the ratio σ_b/σ_η, we normalize $\sigma_\eta = 1$ without loss of generality. Additionally, since initial firm size s_t does not influence the firm's decisions, we set $s_t = 1$.

[17] The exponent on $(\mu+1)$ is twice that on ρ in Equation (6) because a higher markdown influences both per-worker profit *and* the layoff rate, as we can see in Equation (5).

have identical firm quality, they share the same PPF. This scenario leads to two possibilities: either all firms would have exactly the same markdown, as would occur under the parameterization we consider here, or firms would locate at different points along the PPF. In the latter case, this would induce a mechanical negative relationship between markdown and retention.

In summary, this section proposes an explanation for the negative quality-layoff correlation: higher-quality firms exhibit larger markdowns, and larger markdowns lead to lower layoff rates. Additionally, our framework emphasizes the interaction between wage rigidity and uncertainty in generating inefficient layoffs. Specifically, firms commit to a wage rate before the worker's productivity shock is realized. If the realized productivity falls below a certain threshold, retaining the worker at the predetermined wage becomes unprofitable, leading to a layoff. In some of these cases, the firm would prefer to lower the wage and retain the worker but is unable to do so due to wage rigidity. We investigate these patterns empirically in Section 4.

Figure IV – High-quality firm has *both* higher markdown and retention



Notes: This figure illustrates the model presented in Equation (6). Markdown and retention are defined in Definition (1). Solid lines represent the production possibility frontier and dashed lines represent firms' indifference curves. Stars denote equilibrium outcomes. Two firms are represented in the figure: high-quality (orange) and low-quality blue.

4 Empirical validation of the proposed mechanism

In this section, we empirically validate the mechanism proposed by the theoretical model in Section 3. First, in Section 4.1, we establish that higher-quality firms exhibit larger markdowns and that these markdowns are associated with lower layoff rates. Second, in Section 4.2, we show that the quality-layoff correlation is stronger among firms with tighter constraints on wage adjustments, providing evidence that this correlation is driven by wage rigidity. Together, these patterns align closely with the model's predictions.

4.1 Higher-quality firms have larger markdowns

In this subsection, we describe the empirical relationship between markdowns, firm quality, and layoffs, and show that it aligns with the predictions of our model. Markdowns are measured using the PIA dataset.[18] We measure markdowns empirically as the proportion of value added (VA) retained by firms after accounting for labor expenses: $\text{Markdown} = \frac{\text{VA}-\text{Labor Costs}}{\text{VA}}$.[19]

Figure V illustrates the relationship between markdowns and firm quality, using different measures of quality—value added, pay premium, and firm size. As predicted by our model, we find that higher-quality firms exhibit higher markdowns. The magnitudes are substantial. Using our preferred quality measure, value added, Panel (a) of Figure V shows that firms in the bottom 5% of quality have an average markdown of 32%, while those in the top 5% have 68%—more than double. Panels (b) and (c) show similar patterns using alternative quality measures.

Next, we test the model's prediction that markdowns and layoff rates are negatively correlated. The results, presented in Figure VI, indicate that higher-markdown firms exhibit lower layoff rates: each 10 percentage-point increase in markdown is associated with a 1 percentage-point reduction in layoffs. This effect is economically meaningful, as firms in the bottom 5% of markdowns have an average layoff rate of 18%, compared to just 11% for firms in the top 5%.

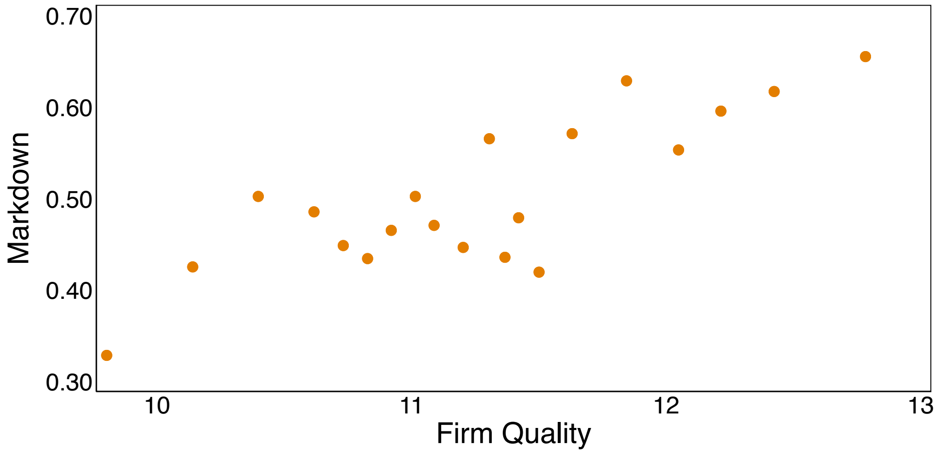
The findings in this section confirm key predictions of our model: higher-quality firms exhibit larger markdowns (Figure V), and these markdowns are associated with lower layoff rates (Figure VI). In the next section, we further validate the model's mechanisms by examining the role of wage rigidity.

[18]As described in Section 1, the PIA dataset is aggregated at the state-industry level and is available only for the manufacturing sector. Hence, all results in Section 4.1 are restricted to this sample.

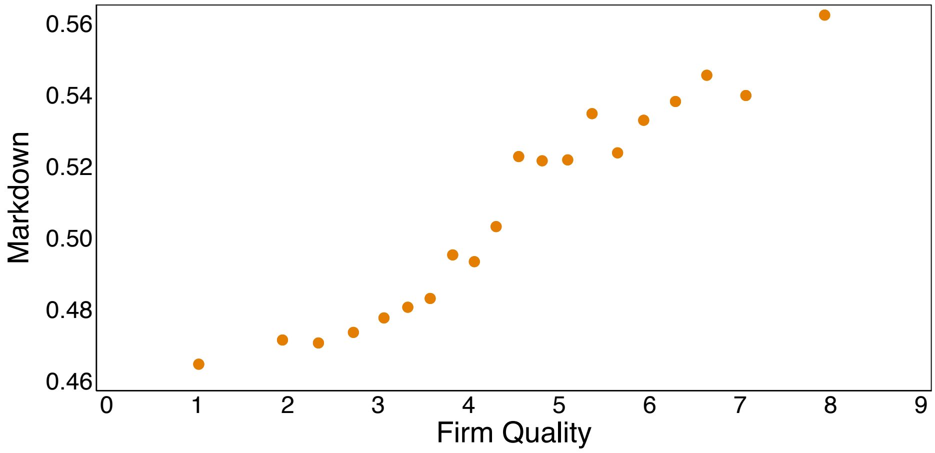
[19]Markdowns are often defined as the ratio of marginal product to wages (Estefan et al., 2024). However, marginal product estimates are not available in our setting.

Figure V – Higher-quality firms have larger markdowns

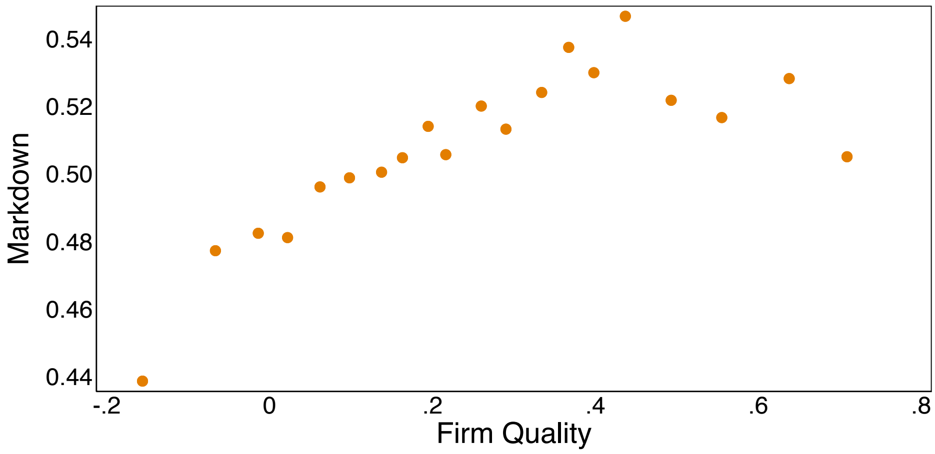
(a) Value Added



(b) Firm Size

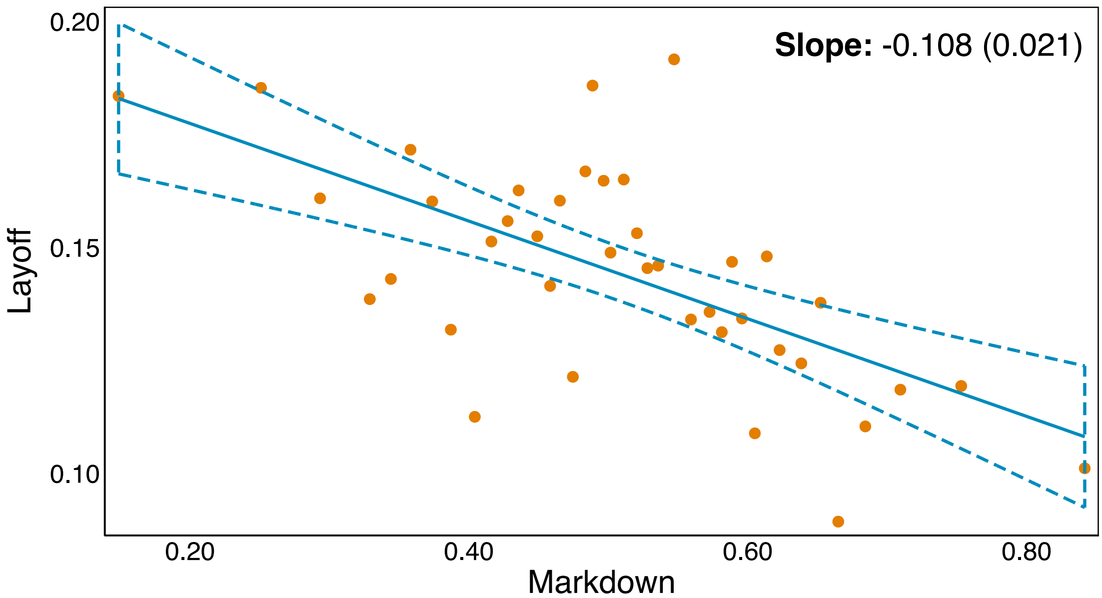


(c) Firm Pay Premium



Notes: This figure illustrates the relationship between markdowns and firm quality, using three measures of firm quality: (1) "Value Added" (Panel a), as detailed in Section 1.1; (2) "Firm Size" (Panel b), defined as the total number of workers in the firm in the first year of the sample; and (3) "Firm Pay Premium" (Panel c), derived from AKM firm fixed effects, with details in Appendix C. Markdowns are calculated as the proportion of value added retained by firms after accounting for labor expenses. Value added and markdowns are obtained from the PIA dataset, which is aggregated at the industry-state level. Pay premiums and firm size are computed using the RAIS dataset and are at the firm level. The sample covers the period from 2010 to 2017, includes all urban manufacturing private-sector jobs in the Southeast Region, and it is restricted to firms within the largest connected set, as detailed in Section 1. Estimates are weighted by firm size.

Figure VI – Firms with larger markdown have lower layoff rates



Notes: This figure illustrates the relationship between markdowns and layoff rates. Markdowns are calculated as the proportion of value added retained by firms after accounting for labor expenses and are derived from the PIA dataset, which is aggregated at the industry-state level. Layoff rates are computed at the firm level using the RAIS dataset. The blue line represents the best linear fit, with OLS estimates displayed in the upper-right corner, with robust standard errors in parentheses. The sample covers the period from 2010 to 2017, includes all urban manufacturing private-sector jobs in the Southeast Region, and it is restricted to firms within the largest connected set, as detailed in Section 1. Estimates are weighted by firm size.

4.2 Wage rigidity amplifies the quality-layoff correlation

In the model presented in Section 3, wage rigidity plays a central role in generating inefficient layoffs. When a worker experiences a negative productivity shock that reduces their markdown below zero—and the firm is unable to adjust wages downward due to wage rigidity—the worker is laid off. As a result, layoffs can occur even when a wage level exists that would make it mutually beneficial for both the firm and the worker to remain matched, rendering the layoff inefficient.

In this subsection, we empirically investigate the relationship between wage rigidity and layoffs. First, we document substantial wage rigidity in our context. Then, we construct a proxy for wage rigidity at the firm level, which we use to show that higher wage rigidity is associated with higher layoff rates and a stronger quality-layoff correlation.

4.2.1 Documenting wage rigidity

To study wage rigidity, we leverage the fact that the RAIS dataset reports contract wages separately from a variable wage component.[20] The variable component encompasses bonuses, performance pay, and overtime. Firms face substantial rigidity in adjusting contract wages, as the Brazilian Constitution prohibits wage reductions unless authorized by a collective bargaining agreement.[21] In contrast, the variable component is not constrained by these regulations. Figure VII presents the distribution of yearly wage changes for workers who remain in the same firm across two consecutive years. Consistent with these regulations, Panel (a) shows that only 1.34% of workers experience a reduction in their contract wage, whereas Panel (b) reveals that 9.28% see a reduction in their total wage. Additionally, contract wage changes cluster around zero, whereas total wages exhibit no such bunching. These patterns highlight the substantial rigidity of contract wages relative to the flexibility of variable pay, a phenomenon well-documented in other contexts (Altonji and Devereux, 1999; Messina et al., 2010; Anger, 2011; Grigsby et al., 2021).

Motivated by the patterns in Figure VII, we construct a firm-level measure of wage rigidity based on its reliance on contract wages versus variable pay, an approach similar to Makridis and Gittleman (2022), Reizer (2022), and Sockin and Sockin (2025). Specifically, we proxy wage rigidity using the average share of contract wages in total compensation:

$$\text{ContractShare}_j = \frac{1}{N_j} \sum_{i|j(i,t_{j0})=j} \frac{\text{ContractShare}_i}{\text{VariableWage}_i + \text{ContractWage}_i}, \tag{7}$$

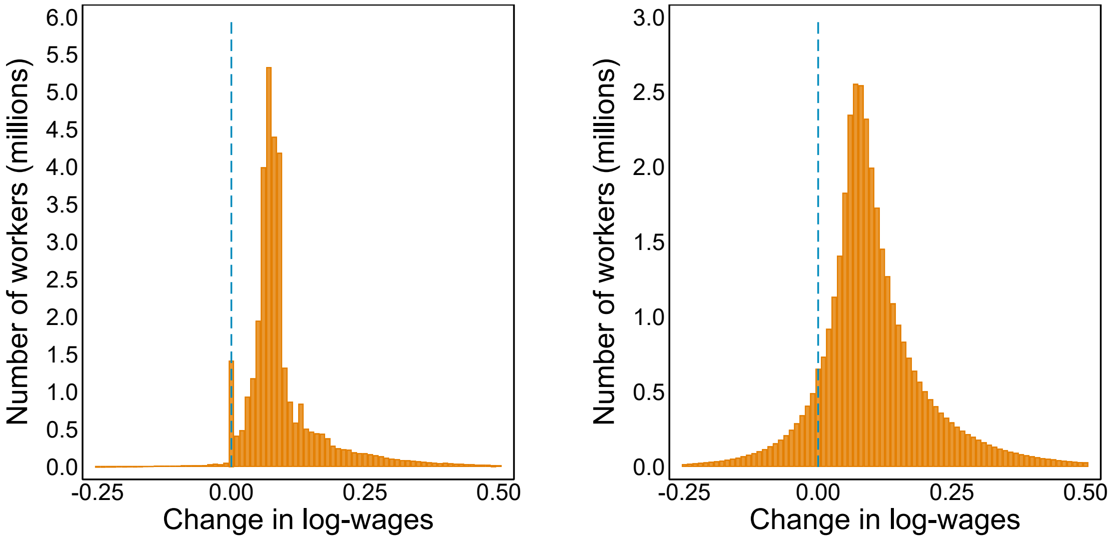
where $j(i, t_{j0})$ denotes the firm employing worker i in year t_{j0}, N_j is the size of firm j, and t_{j0} is the first year the firm appears in the sample. Since variable wages can be adjusted while contract wages cannot, higher ContractShare indicates stronger wage rigidity. To address concerns about endogeneity, such as ContractShare responding to productivity shocks, we compute ContractShare using the first year each firm appears in the sample and hold it fixed throughout the analysis. Furthermore, we exclude the year used to define ContractShare from subsequent analysis. Appendix Figure B.1, Panel (a),

[20]Throughout this paper, "wage" has referred to "total wage," which is the sum of the contract and variable components.

[21]Title II, Chapter I, Article 7, Paragraph VI of the 1988 Constitution.

Figure VII – Distribution of wage changes for stayers

(a) Contract Wages (b) Total Wages



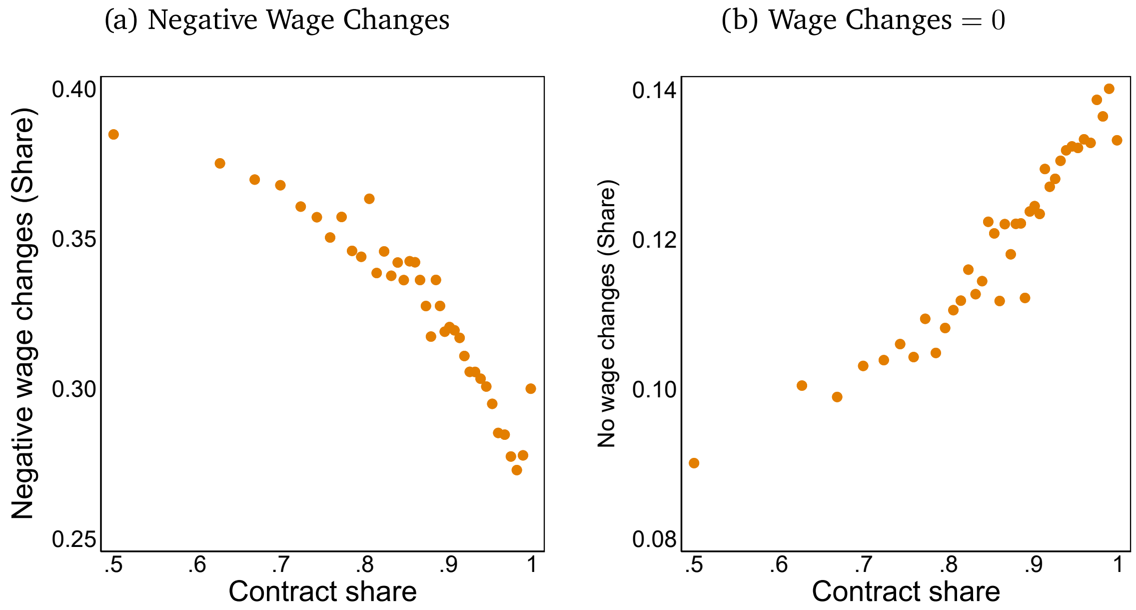
Notes: This figure depicts the distribution of wage changes between two consecutive years for workers who remain with the same firm. Panel (a) shows the distribution of changes in contractual wages, while Panel (b) illustrates the distribution of changes in total wages (the sum of contractual and variable wage components). Wages are not adjusted for inflation in either panel. The data is from the administrative records of the Brazilian Ministry of Labor (RAIS) and is at the worker level. The sample covers the period from 2010 to 2017, includes all urban private-sector jobs in the Southeast Region, and it is restricted to firms within the largest connected set, as detailed in Section 1.

presents the distribution of ContractShare across firms and reveals substation variation: the median share is 88%, the 5th percentile is 65%, and the 95th percentile is 99%.

To validate ContractShare as a proxy for wage rigidity, we examine its correlation with wage changes for workers who remain in the same firm for two consecutive years. The results are presented in Figure VIII. Consistent with the interpretation of higher ContractShare being associated with more rigid wages, we find that ContractShare is negatively correlated with the share of wage reductions in a firm and positively correlated with the share of wage changes equal to zero. The differences are economically significant. Firms in the top 5% of ContractShare have a share of unchanged wages that is 40% larger than that of firms in the bottom 5%.

The patterns observed in Figure VIII are not driven by worker sorting. Appendix Figure B.2 shows that these patterns remain robust after controlling for race, occupation, tenure, AKM worker effects, and flexible interactions of gender, age, and education.

Figure VIII – Higher ContractShare is associated with more wage rigidity



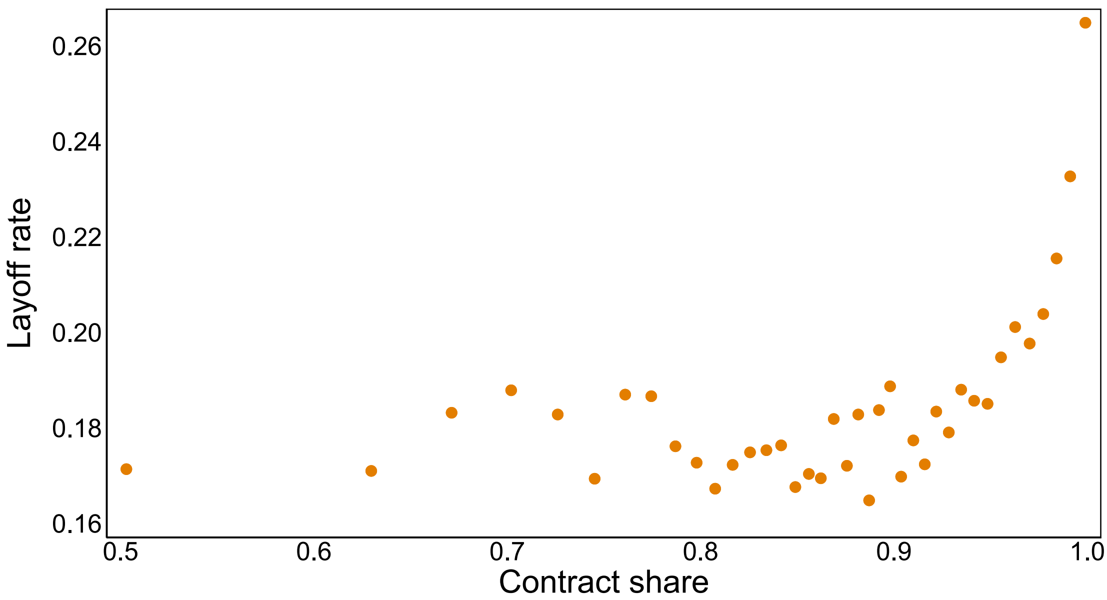
Notes: This figure illustrates the relationship between wage rigidity and ContractShare. ContractShare represents the average share of salaries disbursed as contract pay in each firm, as defined in Equation (7). The two panels depict correlations between ContractShare and different measures of wage changes for workers who remain in the same firm for two consecutive years: Panel (a) presents the share of workers experiencing negative wage changes; and Panel (b) presents the share of workers experiencing no wage changes. The data is from the RAIS dataset and is at the firm level. The sample covers the period from 2010 to 2017, includes all urban private-sector jobs in the Southeast Region, and is restricted to firms within the largest connected set, as detailed in Section 1. Estimates are weighted by firm size.

4.2.2 Greater wage rigidity is associated with higher layoff rates

After establishing that higher ContractShare is associated with more wage rigidity, we examine its relationship with layoff rates. Figure IX shows that firms with higher ContractShare exhibit higher layoff rates. Firms with a ContractShare of 100% have an average layoff rate of 28%, whereas those with a ContractShare around 90% have a rate of 17%. Notably, the relationship flattens for ContractShare below 90%, with layoff rates stabilizing at approximately 17% even for firms with ContractShare below 60%.

These patterns suggest two key conclusions. First, the strong positive correlation between ContractShare and layoff rates underscores the important role wage rigidity plays in contributing to layoffs. Second, the persistence of layoffs at low levels of ContractShare indicates that some observed layoffs are not driven by wage rigidity. Through the lens of our model, these layoffs correspond to productivity shocks so severe that no feasible wage adjustment could make retaining the match desirable for both the firm and the worker. Alternatively, such layoffs could be interpreted as the result of an exogenous job destruction shock (Sorkin, 2018; Jarosch, 2023).

Figure IX – Firms with higher ContractShare have more layoffs



Notes: This figure illustrates the relationship between layoff rates and ContractShare. The layoff rate is defined as the proportion of a firm's workers laid off per year, while ContractShare represents the average share of salaries disbursed as contract pay in each firm, as defined in Equation (7). The data is from the RAIS dataset and is at the firm level. The sample covers the period from 2010 to 2017, includes all urban private-sector jobs in the Southeast Region, and it is restricted to firms within the largest connected set, as detailed in Section 1. Estimates are weighted by firm size.

A potential concern with the results in Figure IX is the role of worker heterogeneity. High-skill workers are less likely to be laid off. If these workers tend to receive more bonuses, this could create a positive relationship between ContractShare and layoffs. To address this concern, Appendix Figure B.3 presents the relationship between ContractShare and layoff rates while controlling for a rich set of worker characteristics, and the results remain largely unchanged.

4.2.3 Greater wage rigidity is associated with stronger quality-layoff correlation

Next, we investigate whether wage rigidity contributes to the quality-layoff correlation. This presents a challenge, as this correlation is an equilibrium object observed at the market level rather than at the firm level. Ideally, we would observe a set of disconnected labor markets where firms exhibit varying degrees of wage rigidity, allowing for direct comparisons of the quality-layoff correlation across these markets.

As an approximation, we define markets based on the combination of industry and location. We use the firm's state as our definition of location and, since value-added (our preferred firm quality measure) is aggregated at the 3-digit industry level, we define industries using 2-digit CNAE codes to ensure variation in value-added within a market. This results in 341 distinct markets. We measure wage rigidity in each market by the average ContractShare of its firms, denoted as $\overline{\text{ContractShare}}$. Appendix Figure B.1, Panel (b), presents the distribution of $\overline{\text{ContractShare}}$, revealing substantial variation in wage rigidity at the market level: the 5th percentile of $\overline{\text{ContractShare}}$ is 72%, while the 95th percentile is 94%.

To assess whether $\overline{\text{ContractShare}}$ is a relevant proxy for wage rigidity, we replicate the analyses from Figures VIII and IX at the market level. Specifically, we estimate the following regression:

$$Y_m = \chi_Y \cdot \overline{\text{ContractShare}}_m + \epsilon_m^Y, \tag{8}$$

where $\overline{\text{ContractShare}}m$ is the average ContractShare of firms in market m, ϵ_m^Y represents residuals, and χ_Y is our parameter of interest. The outcome Y_m corresponds to either the share of negative wage changes in each market, the share of wage changes equal to zero, or the average layoff rate. Furthermore, the patterns in Figure IX suggests a highly nonlinear relationship between ContractShare and layoffs. To account for this, we also estimate Equation (8) using the average log layoff rate in each market as an outcome.[22]

OLS estimates of Equation (8) are reported in Columns (1) to (4) of Table III and confirm the patterns observed at the firm level. Specifically, in markets with higher $\overline{\text{ContractShare}}$, fewer workers experience wage reductions, more workers experience no wage changes, and layoff rates are higher. These results indicate that $\overline{\text{ContractShare}}$ serves as a reliable proxy for the wage rigidity faced by firms in different markets.

To quantify the strength of the quality-layoff correlation within each market, we estimate the following regression separately for each market:

$$\text{LayoffRate}_{jt} = \beta_{M(j)} \cdot Q_{jt} + \epsilon_{jt}^M, \tag{9}$$

where t denotes a year, j represents a firm, and $M(j)$ identifies firm j's market. The de-

[22] As in Figure VIII, the shares of negative and zero wage changes are calculated among workers who remain in the same firm for two consecutive periods.

pendent variable, LayoffRate_{jt}, captures the firm's yearly layoff rate, while Q_{jt} measures firm quality. The term ϵ_{jt}^{M} represents residuals. Following our approach in Equation (8), we estimate the model using both layoff rates and log layoff rates as the outcome variable to account for the nonlinearity observed in Figure IX. The parameter of interest, β_m, captures the market-specific relationship between firm quality and layoffs. Appendix Figure B.4 presents the distribution of estimated $\hat{\beta}_m$ across markets.[23]

We then examine whether the quality-layoff correlation is stronger in markets with greater wage rigidity by estimating the following regression:

$$\hat{\beta}_m = \chi_\beta \cdot \overline{CS}_m + \epsilon_m^\beta, \tag{10}$$

where χ_β is the parameter of interest and ϵ_m^β represents residuals.

OLS estimates of Equation (10), presented in Columns (5) to (10) of Table III, indicate that the quality-layoff correlation is stronger in markets with greater wage rigidity. Columns (5), (7), and (9) report results using $\hat{\beta}_m$ estimated with linear layoff rates, while Columns (6), (8), and (10) use $\hat{\beta}_m$ estimated with log layoff rates. The findings are consistent across these two specifications. Similarly, the results hold when using either value-added or firm size as the measure of firm quality. However, we do not find a significant relationship between $\hat{\beta}_m$ and $\overline{\text{ContractShare}}$ when using pay premiums as the quality metric. This may be due to pay premiums being estimated objects, and accumulated measurement error across multiple estimation steps reduces the reliability of the estimates of Equation (10) in this specification.

The magnitudes in Table III are substantial. Estimates in Column (5)—which use value-added as the firm quality measure and a linear specification for layoff rates—indicate that $\hat{\beta}_m$ is 34% larger (in absolute terms) than the median in markets in the top 5% of $\overline{\text{ContractShare}}$ and 81% smaller in markets in the bottom 5%. Similar patterns emerge when using firm size as the firm quality measure or when adopting the log specification for layoff rates.

In summary, this section links wage rigidity to differential layoff patterns across firms and markets. We show that firms facing stronger wage rigidity exhibit both higher layoff rates and a more pronounced quality-layoff correlation. These findings suggest

[23]Since $\hat{\beta}_m$ is an estimated parameter and thus subject to measurement error, its distribution should be interpreted with caution.

that layoffs partly stem from firms' inability to adjust wages, empirically validating the mechanisms proposed in our theoretical framework.

5 Final Remarks

In this paper, we investigate the determinants of the negative quality-separation correlation. We show empirically that high-quality firms have lower layoff rates and propose a parsimonious theoretical framework that explains this pattern.

Our findings indicate promising directions for future research on the literature that estimates job-search models from job flows. We have shown that layoffs are the majority of separations and that layoff rates depend on firm quality. While several previous papers allow for firm-specific involuntary separation rates, they do not directly observe layoffs. Some papers assume that involuntary separation are exogenous and treat them as residuals (Sorkin, 2018; Jarosch, 2023), others infer layoff rates indirectly from other moments (Acabbi et al., 2024; Blanco et al., 2024). Revisiting these models taking advantage of the Brazilian data, which explicitly flags layoffs, could bring valuable new insights.

Table III Quality-layoff correlation is stronger in markets with more wage rigidity

	$\Delta W < 0$	$\Delta W = 0$	Layoff		$\hat{\beta}_m$					
					VA		Size		ψ	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\overline{\text{ContractShare}}$	-0.437***	0.106***	0.178**	0.148**	-0.211**	-0.175**	-0.032**	-0.027**	0.057	0.045
	(0.0393)	(0.0208)	(0.0774)	(0.0634)	(0.0883)	(0.0724)	(0.0156)	(0.0130)	(0.0987)	(0.0841)
Observations	341	341	341	341	71	71	336	336	336	336
Avg. Outcome	0.276	0.092	0.191	0.191	-0.036	-0.036	-0.013	-0.013	-0.194	-0.194
Specification			Linear	Log	Linear	Log	Linear	Log	Linear	Log

Notes: This table examines the relationship between $\overline{\text{ContractShare}}$ and various market-level outcomes. A market is defined as a region-industry pair. $\overline{\text{ContractShare}}$ represents the share of total wages in a market allocated to contracted wages rather than variable pay. Columns (1)–(4) present OLS estimates of Equation (8). The outcome in Column (1) is the share of negative wage changes, while Column (2) considers the share of wage changes equal to zero, both measured among workers who remain in the same firm for two consecutive years. Columns (3) and (4) examine the relationship between $\overline{\text{ContractShare}}$ and average layoff rates, using levels and logs, respectively. Columns (5)–(10) present OLS estimates of Equation (10). The outcome, β_m, captures the market-specific relationship between firm quality and layoffs, estimated via OLS in Equation (9). The "Specification" row indicates whether β_m was estimated in levels or logs. Each column uses a different measure of firm quality to estimate β_m: Columns (5) and (6) use Value Added (Section 1.1); Columns (7) and (8) use Firm Pay Premiums, derived from AKM firm fixed effects (Appendix C); and Columns (9) and (10) use Firm Size, defined as the total number of workers in a firm in the first year of the sample. The sample covers the period from 2010 to 2017, includes all urban private-sector jobs in the Southeast Region, and is restricted to firms within the largest connected set, as described in Section 1.

References

Abowd, John, Francis Kramarz, and David Margolis, "High Wage Workers and High Wage Firms," *Econometrica*, 1999, *67* (2), 251–333.

Acabbi, Edoardo Maria, Andrea Alati, and Luca Mazzone, "Human Capital Ladders, Cyclical Sorting, and Hysteresis," 2024.

Altonji, Joseph G and Paul J Devereux, "The Extent and Consequences of Downward Nominal Wage Rigidity," *NBER Working Paper Series*, 1999.

Anger, Silke, "The Cyclicality of Effective Wages within Employer–Employee Matches in a Rigid Labor Market," *Labour Economics*, December 2011, *18* (6), 786–797.

Bachmann, Ronald, Gökay Demir, and Hanna Frings, "Labor Market Polarization, Job Tasks, and Monopsony Power," *Journal of Human Resources*, April 2022, *57* (S), S11–S49.

Bassier, Ihsaan, Arindrajit Dube, and Suresh Naidu, "Monopsony in Movers: The Elasticity of Labor Supply to Firm Wage Policies," *Journal of Human Resources*, April 2022, *57* (S), S50–s86.

Blanco, Andrés, Andrés Drenik, Christian Moser, and Emilio Zaratiegui, "A Theory of Labor Markets with Inefficient Turnover," 2024.

Bonhomme, Stephane, Thibaut Lamadon, and Elena Manresa, "A Distributional Framework for Matched Employer Employee Data," *Econometrica*, 2019, *87* (3), 699–739.

Burdett, Kenneth and Dale T. Mortensen, "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, May 1998, *39* (2), 257.

Card, David and Ana Rute Cardoso, "Wage Flexibility Under Sectoral Bargaining," *Journal of the European Economic Association*, 2022.

_ , Jörg Heining, and Patrick Kline, "Workplace Heterogeneity and the Rise of West German Wage Inequality," *The Quarterly Journal of Economics*, 2013, *128* (3), 967–1015.

Cardoso, Ana Rute and Pedro Portugal, "Contractual Wages and the Wage Cushion under Different Bargaining Settings," *Journal of Labor Economics*, October 2005, *23* (4), 875–902.

Carlsson, Mikael and Andreas Westermark, "Endogenous Separations, Wage Rigidities, and Unemployment Volatility," *American Economic Journal: Macroeconomics*, January 2022, *14* (1), 332–354.

Davis, Steven J. and Pawel M. Krolikowski, "Sticky Wages on the Layoff Margin," *American Economic Review*, February 2025, *115* (2), 491–524.

_ , R. Jason Faberman, and John C. Haltiwanger, "The Establishment-Level Behavior of Vacancies and Hiring*," *The Quarterly Journal of Economics*, May 2013, *128* (2), 581–622.

Doornik, Bernardus Van, David Schoenherr, and Janis Skrastins, "Strategic Formal Layoffs: Unemployment Insurance and Informal Labor Markets," *American Economic Journal: Applied Economics*, January 2023, *15* (1), 292–318.

Drenik, Andres, Simon Jäger, Pascuel Plotkin, and Benjamin Schoefer, "Paying Outsourced Labor: Direct Evidence from Linked Temp Agency-Worker-Client Data," *The Review of Economics and Statistics*, January 2023, *105* (1), 206–216.

Ehrlich, Gabriel and Joshua Montes, "Wage Rigidity and Employment Outcomes: Evidence from Administrative Data," *American Economic Journal: Macroeconomics*, January 2024, *16* (1), 147–206.

Elsby, Michael W L and Axel Gottfries, "Firm Dynamics, On-the-Job Search, and Labor Market Fluctuations," *The Review of Economic Studies*, May 2022, *89* (3), 1370–1419.

Estefan, Alejandro, Roberto Gerhard, Joseph P. Kaboski, Illenin O. Kondo, and Wei Qian, "Outsourcing Policy and Worker Outcomes: Causal Evidence from a Mexican Ban," January 2024.

Gerard, François, Lorenzo Lagos, Edson Severnini, and David Card, "Assortative Matching or Exclusionary Hiring? The Impact of Employment and Pay Policies on Racial Wage Differences in Brazil," *American Economic Review*, 2021, *111* (10), 40.

Grigsby, John, Erik Hurst, and Ahu Yildirmaz, "Aggregate Nominal Wage Adjustments: New Evidence from Administrative Payroll Data," *American Economic Review*, February 2021, *111* (2), 428–471.

Haltiwanger, John C., Henry R. Hyatt, Lisa B. Kahn, and Erika McEntarfer, "Cyclical Job Ladders by Firm Size and Firm Wage," *American Economic Journal: Macroeconomics*, April 2018, *10* (2), 52–85.

Haltiwanger, John, Henry Hyatt, and Erika McEntarfer, "Who Moves Up the Job Ladder?," *Journal of Labor Economics*, 2018, *36.*

Hirsch, Boris, Thorsten Schank, and Claus Schnabel, "Differences in Labor Supply to Monopsonistic Firms and the Gender Pay Gap: An Empirical Analysis Using Linked Employer-Employee Data from Germany," *Journal of Labor Economics*, April 2010, *28* (2), 291–330.

Hopenhayn, Hugo and Richard Rogerson, "Job Turnover and Policy Evaluation: A General Equilibrium Analysis," *Journal of Political Economy*, October 1993, *101* (5), 915–938.

Jäger, Simon, Benjamin Schoefer, and Josef Zweimüller, "Marginal Jobs and Job Surplus: A Test of the Efficiency of Separations," *The Review of Economic Studies*, May 2023, *90* (3), 1265–1303.

Jarosch, Gregor, "Searching for Job Security and the Consequences of Job Loss," *Econometrica*, 2023, *91* (3), 903–942.

Jovanovic, Boyan, "Job Matching and the Theory of Turnover," *Journal of Political Economy*, 1979, *87* (5), 972–990.

Krueger, Alan B. and Lawrence H. Summers, "Efficiency Wages and the Inter-Industry Wage Structure," *Econometrica*, March 1988, *56* (2), 259.

Makridis, Christos A and Maury Gittleman, "On the Cyclicality of Real Wages and Employment: New Evidence and Stylized Facts from Performance Pay and Fixed Wage Jobs," *The Journal of Law, Economics, and Organization*, October 2022, *38* (3), 889–920.

Manning, Alan, *Monopsony in Motion: Imperfect Competition in Labor Markets*, Princeton University Press, 2003.

McLaughlin, Kenneth J., "A Theory of Quits and Layoffs with Efficient Turnover," *Journal of Political Economy*, February 1991, *99* (1), 1–29.

Messina, Julián, Cláudia Filipa Duarte, and Mario Izquierdo, "The Incidence of Nominal and Real Wage Rigidity: An Individual-Based Sectoral Approach," *Journal of the*

European Economic Association, 2010.

Mortensen, D. T. and C. A. Pissarides, "Job Creation and Job Destruction in the Theory of Unemployment," *The Review of Economic Studies*, July 1994, *61* (3), 397–415.

Mueller, Andreas I., "Separations, Sorting, and Cyclical Unemployment," *American Economic Review*, July 2017, *107* (7), 2081–2107.

Pinheiro, Roberto and Ludo Visschers, "Unemployment Risk and Wage Differentials," *Journal of Economic Theory*, 2015, *157* (C), 397–424.

Postel-Vinay, Fabien and Hélène Turon, "ON-THE-JOB SEARCH, PRODUCTIVITY SHOCKS, AND THE INDIVIDUAL EARNINGS PROCESS*," *International Economic Review*, August 2010, *51* (3), 599–629.

Postel-Vinay, Fabien and Jean-Marc Robin, "Equilibrium Wage Dispersion with Worker and Employer Heterogeneity," *Econometrica*, 2002, *70* (6), 2295–2350.

Ransom, Michael R and David P. Sims, "Estimating the Firm's Labor Supply Curve in a "New Monopsony" Framework: Schoolteachers in Missouri," *Journal of Labor Economics*, April 2010, *28* (2), 331–355.

_ **and Ronald L. Oaxaca**, "New Market Power Models and Sex Differences in Pay," *Journal of Labor Economics*, April 2010, *28* (2), 267–289.

Reizer, Balázs, "Employment and Wage Consequences of Flexible Wage Components," *Labour Economics*, October 2022, *78*, 102256.

Schmieder, Johannes F. and Till von Wachter, "Does Wage Persistence Matter for Employment Fluctuations? Evidence from Displaced Workers," *American Economic Journal: Applied Economics*, July 2010, *2* (3), 1–21.

Sockin, Jason and Michael Sockin, "Variable Pay and Risk Sharing between Firms and Workers," *SSRN Electronic Journal*, 2025.

Sokolova, Anna and Todd Sorensen, "Monopsony In Labor Markets," *ILR Review*, 2021.

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

Topel, Robert and Michael Ward, "Job Mobility and the Careers of Young Men," *The Quarterly Journal of Economics*, 1992, *107.*

Ureta, Manuelita, "The Importance of Lifetime Jobs in the U.S. Economy, Revisited," *The American Economic Review*, 1993, *82.*

Webber, Douglas A., "Firm Market Power and the Earnings Distribution," *Labour Economics*, August 2015, *35*, 123–134.

_ , "Labor Market Competition and Employment Adjustment over the Business Cycle," *Journal of Human Resources*, April 2022, *57* (S), S87–S110.

1

Appendices

A Model details

A.1 Definitions

An equilibrium is defined by the optimality of three decisions: layoffs, quits, and wages. The firm lays off a worker if their realized productivity plus the continuation value of keeping the worker is lower than wages, which defines the layoff rate as a function of wages. Workers quit if the outside option is higher than wages, which defines the quit rate as a function of wages. The firm does not control workers' quit decisions and cannot commit to a layoff policy, hence it takes both the layoff and quit rate functions as given when it chooses wages to maximize profits. Below we define an equilibrium formally.

Definition 1 *An equilibrium is defined by wages w^*_ψ, retention function $\rho(w)$, and layof function $\delta_\psi(w)$, such that conditions (I), (II), and (III) below hold:*

(I) Workers quit if $w < b$. Hence, retention function is:

$$\rho(w) = P_b\big(b \leq w\big) = F_b(w).$$

(II) Firm lays off worker if realized markdown is negative. Hence, layoff function is:

$$\delta_\psi(w) = P_\eta\big(\mu_\psi(w) + \eta \leq 0\big) = F_\eta\big[-\mu_\psi(w)\big].$$

(III) Firm chooses wages to maximize the expected present value of profits:

$$w^*_\psi = \arg\max_w V_\psi(w). \tag{A.1}$$

Where $\mu_\psi(w)$ and V_ψ are defined as follows.

Since $\mathbb{E}_\eta\big[\eta\big] = 0$, ex-ante expected markdown is:

$$\mu_\psi(w) \equiv \psi + \alpha - w + \beta V^*_\psi + \mathbb{E}_\eta\big[\eta\big] = \overbrace{\psi + \alpha - w}^{\text{instant markdown}} + \underbrace{\beta V^*_\psi}_{\text{continuation value}}.$$

The expected present value of profits is:

$$V_\psi(w) \equiv \overbrace{\rho(w)}^{\text{retention rate}} \cdot \big[1 - \overbrace{\delta_\psi(w)}^{\text{layoff rate}}\big] \cdot \left\{ \overbrace{\psi + \alpha - w}^{\text{instant markdown}} + \underbrace{\mathbb{E}_\eta\big[\eta \big| \mu_\psi(w) + \eta \geq 0\big]}_{\text{expected productivity shock for non-laid off workers}} + \overbrace{\beta V^*_\psi}^{\text{continuation value}} \right\}.$$

And $\mu^*_\psi \equiv \mu_\psi(w^*)$, $V^*_\psi \equiv V_\psi(w^*)$, $\rho^*_\psi \equiv \rho_\psi(w^*)$, $\delta^*_\psi \equiv \delta_\psi(w^*)$.

A few clarifications regarding Definition 1. The term $V_\psi(w)$ represents the value of each individual worker that the firm meets, rather than the total firm value. Nonetheless, optimizing these two objects is equivalent because the number of meetings is exogenously determined. Additionally, note that the continuation value in $\mu_\psi(w)$ and $V_\psi(w)$ is βV_ψ^*, not $\beta V_\psi(w)$, since the firm does not commit to offering the same wage in subsequent periods.

We now delve into the determinants of the quality-separation correlation. First, we present a theorem that establishes our main theoretical result: high-quality firms have *both* lower quit and lower layoff rates. The theorem's assumptions impose only weak restrictions on the distributions of productivity and outside options shocks, which are necessary to guarantee a unique equilibrium. Second, we discuss the intuition behind this result.

Theorem 1 *Assume F_b is a log-concave distribution and F_η is such that $\frac{\partial \mathbb{E}_\eta\left[\eta \middle| \eta > x\right]}{\delta x} \leq 1$. Then, there is an unique equilibrium and:*

(I) Wages are increasing in firm quality $\left(\frac{dw_\psi^*}{d\psi} \geq 0\right)$;

(II) Markdown is increasing in firm quality $\left(\frac{d\mu_\psi^*}{d\psi} \geq 0\right)$;

(III) Quit rate is decreasing in firm quality $\left(\frac{d(1-\rho(w_\psi^*))}{d\psi} \leq 0\right)$;

(IV) Layoff rate is decreasing in firm quality $\left(\frac{d\delta_\psi(w_\psi^*)}{d\psi} \leq 0\right)$;

(V) Steady-state firm size is increasing in firm quality.

Proof: *Appendix A.2.*

The assumptions in Theorem 1 mean that F_b and F_η do not have heavy tails. These assumptions hold for a wide range of common distributions, as formalized in the following remark.

Remark 1 *The assumptions of Theorem 1 hold if F_b and F_η are any of the following distributions, under any set of parameters: uniform, Normal, and Gumbell.*

A.2 Proofs

Theorem 1: Define the following functions: $H_\eta(x) \equiv \mathbb{E}_\eta\left[\eta \middle| \eta \geq x\right] - x$ and $H_b(x) \equiv \frac{1}{\frac{\partial ln F_b(x)}{\partial x}}$. Taking first order conditions of Equation (A.1) with respect to w, we have that:

$$H_\eta(-\mu^*_\psi(w)) = H_b(w^*). \tag{A.2}$$

(I) Wages are increasing in firm quality: Replacing $\mu^*_\psi(w)$ from Definition (1) in Equation (A.2), taking total derivative with respect to ψ , and isolating $\frac{dw^*}{d\psi}$, we have:

$$\frac{dw^*}{d\psi} = \frac{H'_\eta \cdot (1+\beta V'^*)}{H'_\eta - H'_b}. \tag{A.3}$$

Under the assumptions of Theorem (1), $H'_b > 0$ [24], and $H'_\eta < 0$ [25]. Additionally, $V'^* > 0$ since the value of a match is always increasing in firm quality. Therefore, from Equation (A.3), $\frac{dw^*}{d\psi} > 0$.

(II) Expected markdown is increasing in firm quality: Replacing w from Definition (1) in Equation (A.2), taking derivatives with respect to ψ, and isolating $\frac{d\mu^*(w)}{d\psi}$, we have:

$$\frac{d\mu^*(w)}{d\psi} = \frac{\partial \mu}{\partial \psi} + \frac{\partial \mu}{\partial w} \cdot \frac{dw}{d\psi} = \frac{H'_b(1+\beta V'^*)}{H'_b - H'_\eta}. \tag{A.4}$$

Since $H'_b > 0$ and $H'_\eta < 0$ under the assumptions of Theorem (1), and $V'^* > 0$, from Equation (A.4), $\frac{d\mu^*(w)}{d\psi} > 0$.

(III) Quit rate is decreasing in firm quality: Since wages are increasing in firm quality, and quit rate is decreasing in wages, it is also decreasing in firm quality.

(IV) Layoff rate is decreasing in firm quality: Since expected markdown is increasing in firm quality, and layoff rate is decreasing in expected markdown, it is also decreasing in firm quality.

(V) Steady-state firm size is increasing in firm quality: Firm size dynamics can be described as $s_{t+1} = \rho(w_t) \cdot [1 - \delta_\psi(w_t)](1 + s_t)$. In steady-state, $s_t = s_{t+1} = s$. Isolating s, steady-state firm size is:

$$s = \frac{\rho(w) \cdot [1-\delta_\psi(w)]}{1 - \big[\rho(w) \cdot [1-\delta_\psi(w)]\big]}.$$

Therefore, since retention ($\rho(w)$) is increasing in firm quality and layoffs ($\delta_\psi(w)$) are decreasing, firm size is increasing in firm quality.

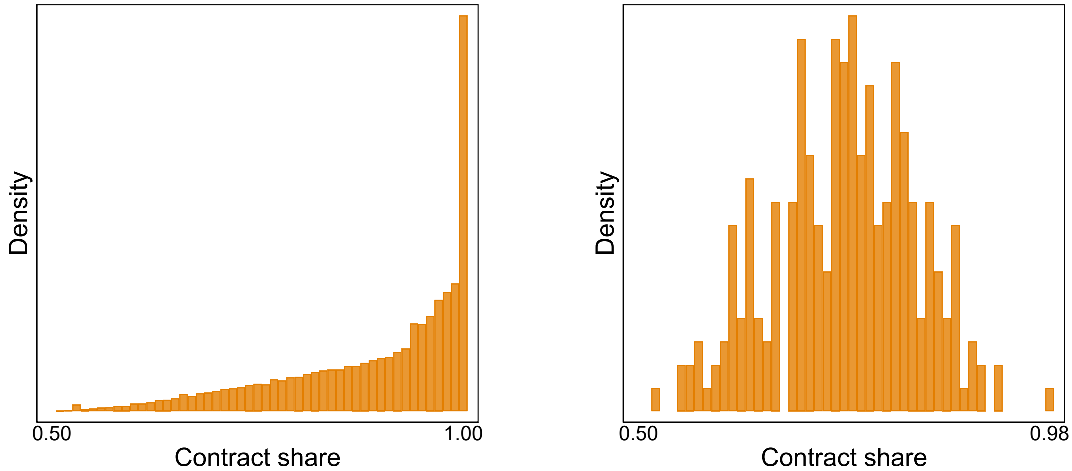
[24] Since $F_b(w)$ is log concave, $\frac{\partial \log F_b(w)}{\partial w}$ is decreasing, hence $\frac{1}{\frac{\partial \log F_b(w)}{\partial w}}$ is increasing. That is, $H'_b(x) > 0$.

[25] $H'_\eta = \frac{\partial \mathbb{E}_\eta\left[\eta \middle| \eta \geq x\right]}{\partial x} - 1$, so $H'_\eta < 0$ since $\frac{\partial \mathbb{E}_\eta\left[\eta \middle| \eta \geq x\right]}{\partial x} < 1$.

B Appendix figures and tables

Figure B.1 – Distribution of wage rigidity proxy (ContractShare) across firms & markets

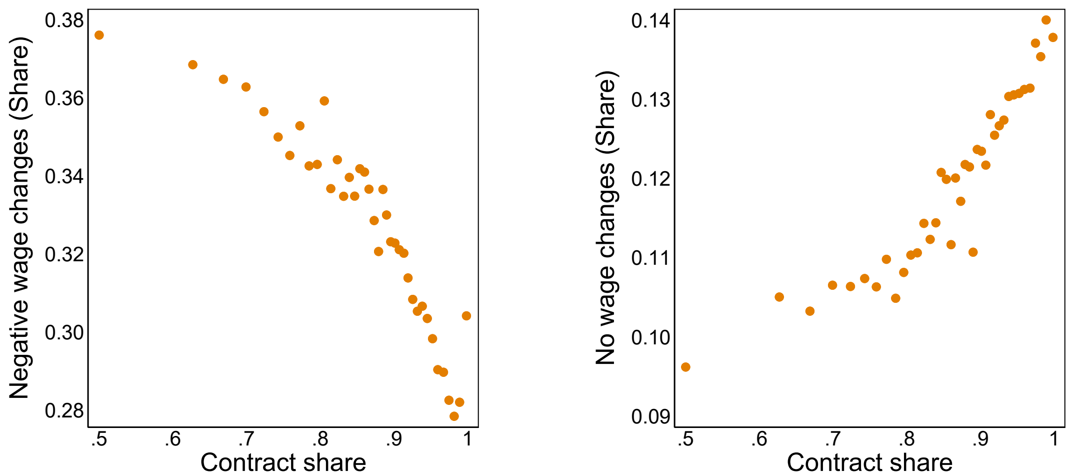
(a) Firms (b) Markets



Notes: This figure presents the distribution of ContractShare, the average share of contracted wages in total compensation, as opposed to variable pay, as defined in Equation 7. We compute ContractShare using the first year each firm appears in the sample and hold it fixed throughout the analysis. Panel (a) displays the distribution of ContractShare across firms, while Panel (b) shows its distribution at the market level, where a market is defined as a region-industry pair. The data comes from the administrative records of the Brazilian Ministry of Labor (RAIS). The sample spans 2010–2017, includes all urban private-sector jobs in the Southeast Region, and is restricted to firms within the largest connected set, as described in Section 1.

Figure B.2 – Higher ContractShare is associated with more rigidity wages (robustness)

(a) Negative Wage Changes (b) Wage Changes $= 0$



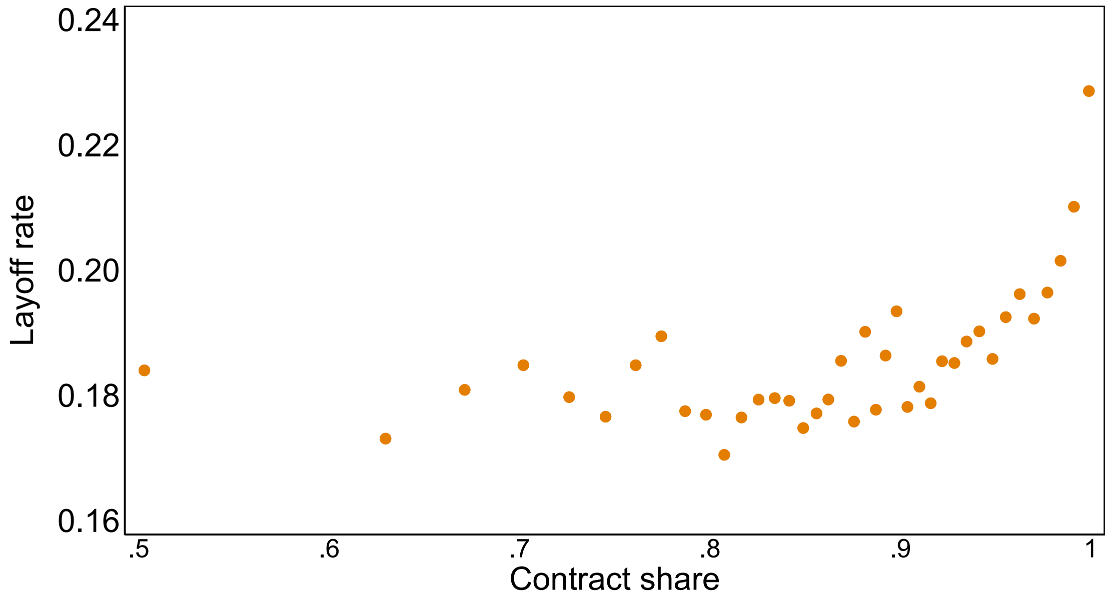
Notes: This figure shows that the relationship between wage rigidity and ContractShare is not driven by worker sorting. ContractShare represents the average share of salaries disbursed as contract pay in each firm, as defined in Equation (7). The two panels illustrate correlations between ContractShare and different measures of wage changes for workers who remain in the same firm for two consecutive years. Panel (a) plots the relationship with an indicator for negative wage changes, while Panel (b) considers an indicator for no wage changes. Both panels control for race, occupation, tenure, AKM worker effects, and flexible interactions of gender, age, and education. The data comes from the RAIS dataset and is at the worker level. The sample spans 2010–2017, includes all urban private-sector jobs in the Southeast Region, and is restricted to firms within the largest connected set, as described in Section 1. Estimates are weighted by firm size.

Table B.1 – Quality-layoff corr. drives quality-separation corr.: Robustness

	(1)	(2)	(3)	(4)
Panel A - Value Added				
β^{Layoff}	-0.048***	-0.034***	-0.025***	-0.024***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\beta^{\text{Separation}}$	-0.055***	-0.039***	-0.032***	-0.030***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\frac{\beta^{\text{Layoff}}}{\beta^{\text{Separation}}}$	0.871***	0.852***	0.776***	0.804***
	(0.0055)	(0.0090)	(0.0096)	(0.0116)
Observations	9,308,341	9,307,701	9,308,341	9,307,701
Panel B - Firm Size				
β^{Layoff}	-0.016***	-0.011***	-0.012***	-0.009***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\beta^{\text{Separation}}$	-0.017***	-0.012***	-0.012***	-0.010***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\frac{\beta^{\text{Layoff}}}{\beta^{\text{Separation}}}$	0.928***	0.950***	0.946***	0.957***
	(0.0032)	(0.0048)	(0.0046)	(0.0062)
Observations	49,835,818	49,830,114	49,835,818	49,830,114
Panel C - Firm Pay Premium				
β^{Layoff}	-0.213***	-0.183***	-0.114***	-0.131***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)
$\beta^{\text{Separation}}$	-0.263***	-0.236***	-0.163***	-0.186***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
$\frac{\beta^{\text{Layoff}}}{\beta^{\text{Separation}}}$	0.811***	0.774***	0.698***	0.703***
	(0.0018)	(0.0025)	(0.0034)	(0.0033)
Observations	49,835,818	49,830,114	49,835,818	49,830,114
Worker covariates			✓	✓
Worker AKM Effect		✓		✓

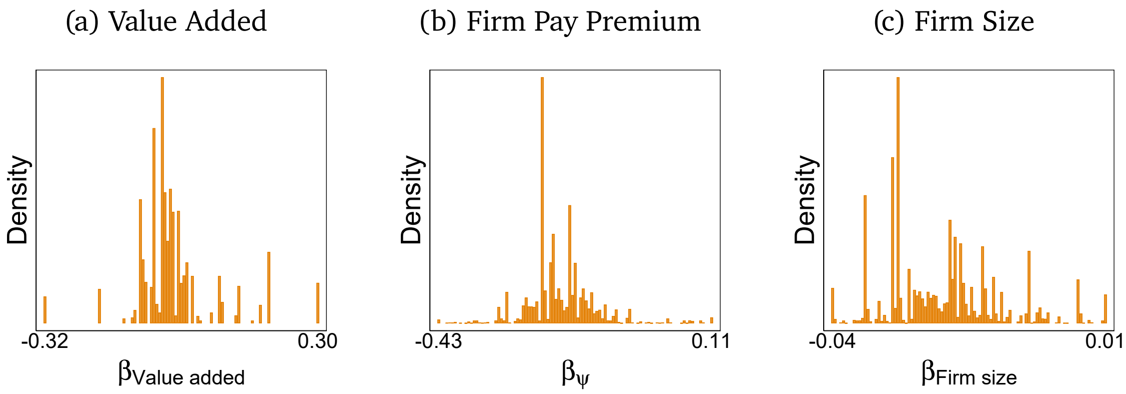
Notes: This table reports OLS estimates of Equation (3), which describe the relationship between separation rates and firm quality. Firm quality is measured using three metrics: (1) "Value Added" (Panel A), as described in Section 1.1; (2) "Firm Pay Premium" (Panel B), derived from AKM firm fixed effects (Appendix C); and (3) "Firm Size" (Panel C), defined as the total number of workers in the firm during the first year of the sample. Estimates for layoff rates and total separation rates are labeled β^{Layoff} and $\beta^{\text{Separation}}$, respectively. Controls include worker-specific wage components from an AKM estimation (detailed in Appendix C) and the following covariates: race and occupation fixed effects, tenure and tenure squared, and interactions between age, age squared, gender, and education fixed effects. The data is at the worker level. Value added is sourced from the PIA dataset, which is aggregated at the industry-state level. Pay premiums, firm size, and separation rates are calculated using the RAIS dataset. The sample covers the period from 2010 to 2017, includes all urban private-sector jobs in the Southeast Region, and is restricted to firms within the largest connected set, as detailed in Section 1. Panel A is further restricted to manufacturing firms.

Figure B.3 – Firms with higher ContractShare have more layoffs (robustness)



Notes: This figure shows that the relationship between layoff rates and ContractShare is not driven by worker sorting. The outcome variable is an indicator for whether a worker was laid off in a given year, while ContractShare represents the average share of salaries disbursed as contract pay in their firm, as defined in Equation (7). The analysis controls for race, occupation, tenure, AKM worker effects, and flexible interactions of gender, age, and education. The data comes from the RAIS dataset and is at the worker level. The sample spans 2010–2017, includes all urban private-sector jobs in the Southeast Region, and is restricted to firms within the largest connected set, as described in Section 1.

Figure B.4 – Distribution of Market-Level Quality-Separation Correlation ($\hat{\beta}_m$) Using Different Firm Quality Measures



Notes: This figure presents the distribution of the market-level quality-separation slope ($\hat{\beta}_m$), estimated by OLS in Equation (9). Each panel reports $\hat{\beta}_m$ estimated using a different measure of firm quality: Panel (a) uses Value Added, as described in Section 1.1; Panel (b) uses Firm Pay Premium, derived from AKM firm fixed effects (Appendix C); and Panel (c) uses Firm Size, defined as the total number of workers in the firm in the first year of the sample.

C AKM estimation

C.1 Estimation

In this appendix, we detail the estimation procedure for firm wage premiums.

To improve estimation precision, we first classify firms into 100 clusters using the method proposed by Bonhomme et al. (2019), which groups firms with similar wage distributions. Formally, we partition firms by solving the following weighted k-means problem:

$$\min_{k(1),...,k(J),H_1,...,H_K} \sum_{j=1}^{J} n_j \int \left(\hat{F}_j(y) - H_{k(j)}(y)\right)^2 d\mu(y), \tag{C.1}$$

where $\hat{F}_j(y)$ is the empirical cumulative distribution function (CDF) of log-wage in firm j, n_j is the number of workers in firm j, μ is a measure supported on a finite grid, $k(1), ..., k(J)$ denotes a partition of J firms into K clusters, and $H_1, ..., H_K$ are cluster-specific wage CDFs.

We then estimate firm wage premiums using the methodology of Abowd et al. (1999), but with cluster effects instead of firm effects. Specifically, we assume that the log of hourly wages for worker i of gender g in year t follows:

$$\log Y_{it} = \alpha_i + \psi_{gK(i,t)} + x'_{it}\beta^x_g + r_{it}, \tag{C.2}$$

where α_i is a worker fixed effect capturing the portable component of individual wages, x_{it} is a set of time-varying controls (including year fixed effects and a polynomial of age interacted with and education), ψ_k is a wage premium paid at cluster k, $K(i,t)$ is an index function indicating the cluster of worker i's workplace in year t, and r_{it} is an error component capturing all other factors. We allow all parameters to vary by gender, including wage premiums.

We estimate Equation (C.2) by OLS. Table C.1 presents the resulting variance decomposition. The results are broadly consistent with Gerard et al. (2021), who analyze the same setting. However, our estimates of cluster effects are lower than the firm effects reported in their study. This highlights the trade-off between firm effects—which may overestimate pay premiums due to small-sample bias—and cluster effects, which may underestimate them by ignoring within-cluster variation.

Table C.1 AKM Variance decomposition

	All	Female	Male
Mean of log-wages	2.332	2.209	2.420
Standard deviation of log-wages	0.664	0.654	0.658
AKM decomposition			
SD of worker effects	0.504	0.510	0.489
SD of cluster effects	0.213	0.200	0.220
SD of covariates	0.098	0.095	0.100
Corr. of worker and cluster effects	0.598	0.607	0.585
Percentage of variance of log wages due to:			
Worker effect	57.5	60.8	55.4
Custer effect	10.2	9.3	11.2
Cov. of worker and cluster effects	29.0	28.9	29.1
Cluster effects + covariance	39.3	38.3	40.2
Number of movers	12,013,818	4,913,018	7,100,800
Number of worker-year observations	74,910,201	31,473,978	43,436,223

Notes: This table presents an AKM variance decomposition of wages. Firm clusters are constructed using a k-means algorithm, as described in Appendix C, along with additional estimation details. The sample is restricted to full-time urban jobs in the Southeast region of Brazil, as detailed in Section 1.1.

C.2 Model Fit

We now test the restrictions imposed by the AKM framework. In particular, the restriction that wage follow a log-linear structure and that the job moving probability is uncorrelated with the error term. We test this restrictions with the approach proposed by Sorkin (2018).

From Equation (C.2), we have:

$$\log Y_{i,t} = \alpha_i + \psi_{gK(i,t)} + x'_{i,t}\beta^x_g + r_{i,t} \ ,$$

$$\log Y_{i,t+1} = \alpha_i + \psi_{gK(i,t+1)} + x'_{i,t+1}\beta^x_g + r_{i,t+1} \ , \ .$$

Taking first differences:

$$\Delta \log Y_{i,t} - \Delta x'_{i,t}\beta_g^x = \Delta\psi_{gK(i,t)} + \Delta r_{i,t}$$

We now take expectations, conditional on moving:

$$\mathbb{E}\big[\Delta \log Y_{i,t} - \Delta x'_{i,t}\beta_g^x | M_{i,t} = 1\big] = \Delta\mathbb{E}\big[\psi_{gK(i,t)} | M_{i,t} = 1\big] + \mathbb{E}\big[\Delta r_{i,t} | M_{i,t} = 1\big]$$

where $M_{i,t}$ indicates whether worker i moved between clusters in year t.

The key assumption to estimate Equation (C.2) by OLS is that the probability of moving is uncorrelated with the error term, that is $\mathbb{E}\big[\Delta r_{i,t} | M_{i,t} = 1\big] = 0$. Under this assumption:

$$\mathbb{E}\big[\Delta \log Y_{i,t} - \Delta x'_{i,t}\beta_g^x | M_{i,t} = 1\big] = \Delta\mathbb{E}\big[\psi_{gK(i,t)} | M_{i,t} = 1\big]$$

We take this restriction to the data by focusing on job switchers and comparing their residualized wages change against their firm-effect change. The results are in Figure C.1. The solid blue line plots the best-fitting line. The dashed line plots the 45 degree line. We find that wages change closely follow changes in firm premiums, showing that the AKM framework fits the data well.

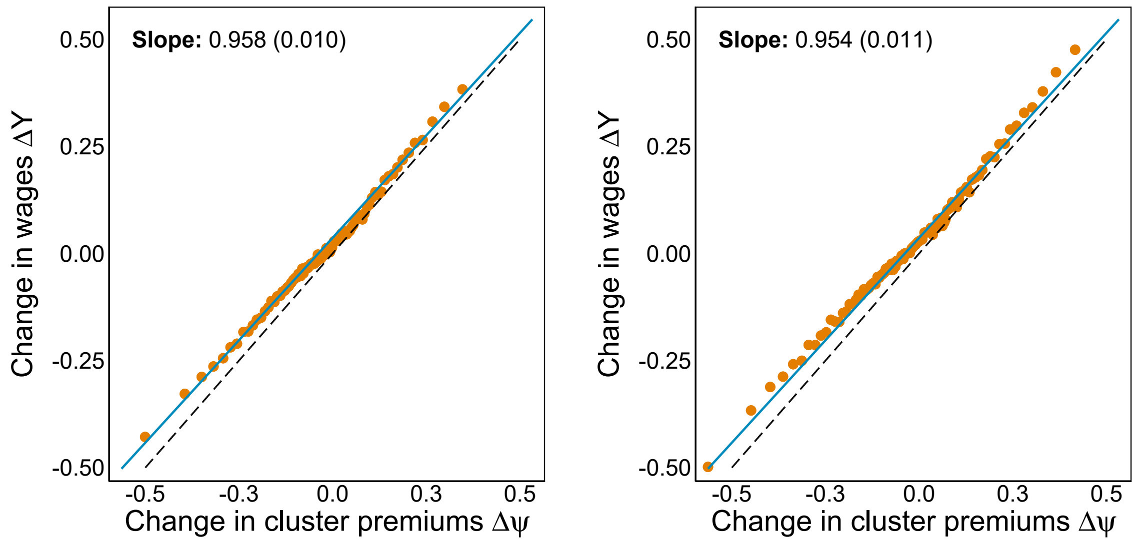
D Setting: Details

The Public Pension Fund: FGTS. All formally employed workers in the private sector are required to have an account at *Caixa*, a public bank. This account is known as FGTS (Fundo de Garantia do Tempo de Serviço). Employers must deposit 8% of each worker's gross monthly salary into this account. Furthermore, if a worker is laid off, they receive a severance payment amounting to 40% of the total balance accrued in their FGTS account. Workers can access these funds if they are laid off or upon reaching retirement age.

Layoff Fine. In the event of a layoff, firms are required to pay a government fine equivalent to 10% of the worker's total FGTS balance. This is in addition to the 40% severance payment made directly to the worker.

Figure C.1 Wage Change Corresponds to Firm Fixed Effect Change

(a) Female workers (b) Male workers



Notes: This figure illustrates the relationship between wage changes and changes in cluster pay premiums for workers who switch jobs across different clusters. The y-axis represents the change in residualized log hourly wages between the last year at the previous job and the first year at the new job. Job changes are grouped into equally sized bins based on the change in cluster effects. Dots represent bin means, the solid line shows the best-fit line estimated on the underlying micro-data, and the dashed line represents the 45-degree line.

Unemployment Benefits. Workers who are laid off are eligible for unemployment benefits, which are contingent upon the length of their formal employment. The benefits are structured as follows:

- Workers employed for 6 to 11 months within the last 36 months receive three months of benefits.
- Workers employed for 12 to 23 months within the last 36 months receive four months of benefits.
- Workers employed for 24 months or more within the last 36 months receive five months of benefits.

→ In 2015, the monthly unemployment payment ranged from one to 1.76 times the minimum wage, dependent on the worker's average salary prior to being laid off.