Earnings Inequality and the Minimum Wage: Evidence from Brazil*

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Abstract

We show that a 128 percent real increase in the minimum wage accounts for a large decline in earnings inequality in Brazil between 1996 and 2018. To this end, we combine administrative and survey data with an equilibrium model of the Brazilian labor market. Our results imply that the minimum wage has far-reaching spillover effects on wages higher up in the distribution, accounting for 45 percent of a large fall in earnings inequality over this period. At the same time, the effects of the minimum wage on employment and output are muted by reallocation of workers toward more productive firms.

Keywords: Earnings Inequality, Wage Distribution, Minimum Wage, Worker and Firm Heterogeneity, Equilibrium Search Model, Monopsony, Spillover Effects, Reallocation, Employment, Brazil, Linked Employer-Employee Data

JEL classification: E24, E25, E61, E64, J31, J38

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1 Introduction

In light of historically high levels of income inequality in many places, understanding the effects of labor market policies on the distribution of income and employment is seen as increasingly important. Several countries have recently implemented higher minimum wages in an attempt to aid low-income workers. Yet the benefits and costs of minimum wage policies remain controversial. In the U.S., for example, there is an active debate over the connection between the decline in the real minimum wage and the rise in income inequality over the last decades. Maybe less known, Brazil—among other Latin American countries—has seen a remarkable decline in income inequality since the 1990s. Over the same period, Brazil's real minimum wage more than doubled. This raises the question: Is the minimum wage an effective tool to reduce income inequality?

The main contribution of our paper is to quantify the effects of a large increase in the minimum wage in Brazil from 1996 to 2018 on inequality and employment. By exploiting variation in the effective bindingness of the federal minimum wage across states (Lee, 1999; Autor et al., 2016), we show that a higher minimum wage is associated with compression throughout most of the wage distribution. At the same time, we find little evidence of negative effects of the minimum wage on employment. To understand these results, we develop an equilibrium model of a frictional labor market subject to a minimum wage, with a particular focus on the role played by heterogeneous firms in mediating such a policy. The minimum wage compresses firm pay differences and impacts wages higher up in the distribution. At the same time, it leads to worker reallocation from less to more productive employers, countering the effect of a (modest) employment decline on aggregate output. We conclude based on our reduced-form and structural analysis that the minimum wage was a key factor behind Brazil's remarkable decline in wage inequality over this period.

Our analysis proceeds in three steps. In the first step, we empirically dissect Brazil's inequality decline and link it to firm heterogeneity and the minimum wage. To this end, we decompose the variance of log wages using a variant of the two-way fixed effects model due to Abowd, Kramarz and Margolis (1999, henceforth AKM) estimated within separate time windows. This decomposition allows us to assess whether firms are a key channel through which the minimum wage may reshape the wage distribution. We find that declining firm pay heterogeneity for identical workers, which accounts for 26 percent of the variance of log wages around 1996, explains 43 percent of the reduction in the variance over time. To quantify the fraction of the aggregate decline in inequality that is accounted for by the minimum wage, we exploit cross-sectional variation in the effective bindingness of the federal minimum wage across states. Motivated by the fact that especially lower-tail inequality declined by more in initially lower-income regions, we estimate the effects of the minimum wage throughout the wage distribution building on the seminal econometric framework by Lee (1999) and the recent contribution by Autor et al. (2016). We find robust evidence of spillover effects of the minimum wage throughout most of the wage distribution and a large negative effect on the standard deviation of wages. At the same time, we find little effect of the minimum wage on employment, formality, and other labor market outcomes.

In the second step, we develop and estimate an equilibrium model of Brazil's labor market subject to a minimum wage to understand these patterns. Our model extends the popular Burdett and Mortensen (1998) framework to include unobserved worker heterogeneity, minimum wage jobs, and endogenous job creation in a tractable manner. We show that a relatively simple extension of this framework can be operationalized to speak to worker and firm pay differences in the data and to quantify the equilibrium effects of the minimum wage. In our model, workers permanently differ in their ability and value of leisure, as well as their time-varying on-the-job search efficiency and separation rate. They engage in random search in frictional labor markets segmented by worker type. Differentially productive firms operating a linear technology in labor chose what wage to offer and a recruiting intensity in each market. The model allows for a flexible account of worker and firm pay differences, including a mass point in the wage distribution at the minimum wage. We estimate the model via the Simulated Method of Moments (SMM) based on our linked employer-employee data and find that, despite its simplicity, it provides a parsimonious account of salient empirical patterns in Brazil.

In the third and final step, we use the model to quantify the effects of the observed increase in the minimum wage on the distribution of wages, employment, and aggregate output. To this end, we feed the empirical increase in Brazil's minimum wage between 1996 and 2018 into the estimated model. We find that the increased minimum wage reduces the variance of wages by 12 log points, or 45 percent of the empirical decline over this period. A critical factor behind these large effects on inequality is that the rise in the minimum wage induces firms above the new minimum wage to raise pay to maintain their rank in the wage distribution. Indeed, such spillover effects reach all the way to the top of the wage distribution, though the wage gain is a relatively modest six percent at the 50th percentile and two percent at the 75th percentile. We demonstrate that the magnitudes of our estimated effects of the minimum wage on inequality are driven by how binding the minimum wage is, together with the extent of firm productivity dispersion in Brazil. At the same time, we find muted negative effects of the minimum wage on employment and aggregate output due to the heterogeneous effects of the minimum wage across the firm productivity distribution. Lower-productivity firms cut vacancy creation as the minimum wage squeezes their profit margins. The easier recruiting environment in turn induces higher-productivity firms to increase hiring. As a result, the minimum wage primarily reallocates employment from lower- to higher-productivity firms rather than to unemployment.

Related literature. This paper contributes to three strands of the literature. First, much research has been devoted to the reduced-form measurement of minimum wage effects on labor market outcomes.[1] A large number of these studies are concerned with the employment effects of the minimum wage (e.g., Card and Krueger, 1994). A complementary set of papers assess the distributional consequences of the minimum wage in the U.S. and other high-income countries (Grossman, 1983; DiNardo et al., 1996; Machin et al., 2003; Teulings, 2003; Butcher et al., 2012; Fortin and Lemieux, 2015; Brochu et al., 2018; Firpo et al., 2018; Rinz and Voorheis, 2018; Cengiz et al., 2019; Fortin et al., 2021). In a seminal contribution to this literature, Lee (1999) finds significant effects of the minimum wage in the lower half of the U.S. wage distribution. By extending this methodology and data series, Autor et al. (2016) argue that spillover effects of the minimum wage are indistinguishable from measurement error using household survey data from the U.S. Current Population Survey (CPS). Relative to these papers, we exploit administrative data to quantify the effects of a large increase in the minimum wage in a developing country, Brazil. We find robust evidence of spillovers throughout large parts of the wage distribution, which we link to the relatively greater bindingness of the minimum wage and dispersion in firm pay policies in Brazil.

Second, a separate literature has developed and estimated structural models to assess the impacts of a minimum wage. Van den Berg and Ridder (1998), Bontemps et al. (1999, 2000), and Manning (2003) highlight the contribution of firms in imperfectly competitive labor markets toward wage dispersion for identical workers, based on the seminal framework by Burdett and Mortensen (1998). A theoretical prediction of this framework is that the minimum wage has spillover effects on higher wages through the equilibrium response of firm pay policies. Perhaps surprisingly, the magnitude of these spillover effects has, before our work, not been quantified using worker-firm linked data. Related research abstracts from firms and instead models match-level heterogeneity to study endogenous contact rates (Flinn, 2006) and the nature of wage setting (Flinn and Mullins, 2018) in the context of minimum wage policies. Relative to these works, we show that a model of multi-worker firms has distinct predictions for the reallocation of workers across heterogeneous employers and changes in firm pay policies in response to a minimum wage. In this sense, our findings connect to recent work on the reallocative effects of minimum wages (Aaronson et al., 2018; Berger et al., 2019, 2021; Harasztosi and Lindner, 2019; Dustmann et al., 2020; Clemens et al., 2021).[2] Our contribution is to show that a relatively simple extension of the seminal

[1] See Card and Krueger (1995) and Neumark and Wascher (2008) for comprehensive overviews of this literature.

[2] Other mechanisms that could give rise to spillover effects include skill assignments with comparative advantage (Teulings, 1995), hierarchical matching (Lopes de Melo, 2012), fairness considerations (Card et al., 2012), educational investment (Bárány,

framework by Burdett and Mortensen (1998) provides a strikingly good description of the Brazilian labor market and is well suited to incorporating minimum wages into the recent literature exploring the role of firms in labor market outcomes (Clemens, 2021).[3] The model also helps to reconcile our finding of large distributional consequences of the minimum wage with its small disemployment effects (Teulings, 2000) and sheds light on the determinants of the magnitude of these effects (Neumark, 2017).

Third, our paper relates to a literature that aims to understand the evolution of wage inequality in Brazil over the past decades, as summarized by Firpo and Portella (2019). Alvarez et al. (2018) document the role of falling firm pay differences in a large inequality decline in Brazil between 1996 and 2012, for which our current paper provides a structural explanation: the rise of the minimum wage. Previous reduced-form work by Fajnzylber (2001), Neumark et al. (2006), and Lemos (2009) studies the distributional effects of Brazil's minimum wage over an earlier period before the minimum wage rapidly increased. Subsequent work by Haanwinckel (2020) also quantifies the contribution of the minimum wage toward the decline in wage inequality in Brazil. Although his task-based model differs from ours in several dimensions, his main conclusion is consistent with our results on the inequality-reducing effect of the minimum wage through spillovers higher up in the wage distribution. Like in other developing countries, the informal sector plays an important role in the Brazilian labor market (Ulyssea, 2018, 2020; Dix-Carneiro et al., 2021). While our estimated model accounts for informality in a simple manner, the richer model by Meghir et al. (2015) allows for interactions between formal and informal firms, suggesting that policies like the minimum wage may affect pay and employment in both sectors (Jales, 2018).

Outline. The remainder of the paper is structured as follows. Section 2 introduces the data and dissects Brazil's inequality decline. Section 4 presents reduced-form evidence for the effects of the minimum wage on wages and employment. Section 5 develops a structural equilibrium model of Brazil's labor market subject to a minimum wage. Section 6 estimates the model. Section 7 uses the estimated model to quantify the effects of the minimum wage on the distribution of wages and employment. Finally, Section 8 concludes.

2016), hedonic compensation (Phelan, 2018), and the union threat (Taschereau-Dumouchel, 2020).

[3] See also Davis and Haltiwanger (1991), Abowd et al. (1999), Card et al. (2013), Barth et al. (2016), and Song et al. (2019) for empirical studies of firms in the labor market, and Postel-Vinay and Robin (2002), Dey and Flinn (2005), Cahuc et al. (2006), Lise and Robin (2017), Bilal et al. (2019), Elsby and Gottfries (2019), Gouin-Bonenfant (2020), Bilal and Lhuillier (2021), and Jarosch (2021) for recent structural advances in this area.

2 The decline in wage inequality in Brazil

2.1 Data

Our main data source is an administrative linked employer-employee data set that covers nearly the universe of formal sector workers between 1985 and 2014, called *Relação Anual de Informações Sociais* (RAIS) and administered by Brazil's Ministério da Economia (2020). It consists of annual employment records, which employers are required to report to the Ministry of the Economy (formerly the Ministry of Labor), and allows tracking workers across employers over time.[4] Our analysis also exploits two household surveys: the *Pesquisa Nacional por Amostra de Domicílios* (PNAD) administered by Instituto Brasileiro de Geografia e Estatística (2019) or IBGE in short, and the *Pesquisa Mensal de Emprego* (PME) administered by Instituto Brasileiro de Geografia e Estatística (2020). PNAD is a nationally representative household survey that covers all individuals, regardless of labor market status, in repeated cross sections between 1996 and 2012. PME is a longitudinal household survey that tracks individuals in a rotating monthly panel structure similar to the CPS in the U.S. It covers Brazil's six largest metropolitan regions between 2002 and 2012. Appendix A.1 discusses the three datasetes in more detail. Finally, time series data of Brazil's national minimum wage is obtained from Instituto de Pesquisa Econômica Aplicada (2022) or IPEA in short.[5]

Variables and sample selection. RAIS contains the start and end dates of all formal job spells during a given calendar year. We use as our income concept in RAIS the mean monthly earnings in multiples of the current minimum wage—henceforth referred to as wages. These are consistently reported over the period from 1985 to 2014. RAIS also contains unique individual and employer identifiers, gender, age, educational attainment, contractual weekly work hours, and six-digit occupation codes.

An important difference between the two household surveys, PNAD and PME, in comparison to RAIS is that they do not contain employer identifiers. Instead, they ask respondents questions about the job they held during a reference week preceding the interview, including their work status. Following Meghir et al. (2015), we classify as informal all self-employed and those in remunerated employment without an official work permit.

For our empirical analysis, we restrict attention to male workers between the ages of 18 and 54. We exclude women and individuals outside of this age range to focus on a subpopulation that is relatively attached to the (formal) labor market.[6] Among this subpopulation in RAIS, we restrict attention to

[4] All of our analysis is at the level of the establishment, which we interchangeably refer to as the firm or the employer.
[5] Further details of the datasets are relegated to the replication materials disseminated as Engbom and Moser (2022).
[6] For a separate study of men and women in Brazil's labor market, see Morchio and Moser (2020).

the largest leave-one-out connected set of workers and firms as in Kline, Saggio and Sølvsten (2020, henceforth KSS). A connected set is defined as a set of all workers and firms that are linked through worker mobility across firms during a given time period. A leave-one-out connected set is a connected set that remains connected when eliminating worker-firm matches one at a time. No such restriction is necessary or possible in PNAD or PME.[7]

Summary statistics. Table 1 summarizes our sample from the three datasets.[8] The RAIS data show that between 1996 and 2018, Brazil experienced a 29 log points increase in mean formal sector wages at the same time that there was a striking fall in inequality, with the standard deviation of wages declining by 19 log points. While the age distribution remained somewhat stable, there was a significant increase in educational attainment over this period. Using the PNAD survey data, we find congruent trends in the formal sector wage distribution. Relative to the formal sector, informal wages are initially characterized by lower levels but similar relative dispersion. Throughout 2012, the informal sector wage distribution saw an increase in its mean accompanied by mild compression. At the same time, the employment rate remained stable while the formal employment share rose by eight percentage points. Consistent with the increase in formality, the longitudinal PME data show a rise in the flow rate from formal into formal employment and a decline in the flow rate from formal into informal jobs.[9]

Panels A and B of Figure 1 show histograms of log wages in 1996 and 2018, respectively. Evidently, Brazil's inequality decline was associated with relatively greater compression in the left tail of the wage distribution over this period. Indeed, panel C shows that lower-tail wage inequality—as measured by the P50/P10 log wage percentile ratio—fell by significantly more compared to upper-tail inequality—as measured by the P90/P50 log wage percentile ratio. While both tails of the wage distribution experienced some compression, lower-tail inequality fell by almost 40 percent between 1996 and 2018, while upper-tail inequality fell by around 15 percent over the same period.

2.2 Dissecting Brazil's decline in earnings inequality: The role of firms

To understand the decline in wage inequality in Brazil, we follow Alvarez et al. (2018) in implementing a statistical decomposition of wages among formal sector workers in Brazil. Motivated by the fact that a large share of empirical wage dispersion is within detailed worker groups based on observ-

[7] The PME is the same data source as used in Meghir et al. (2015), though we apply slightly different selection criteria (e.g., age 18 to 54 instead of age 23 to 65), use a longer period (from 2002 to 2012 instead of from 2002 to 2007), and measure employment transitions slightly differently (counting any month-to-month transition over the 16-months rotating panel instead of counting months until the first transition or until four months without transition have passed).

[8] Additional summary statistics are presented in Appendix A.2.

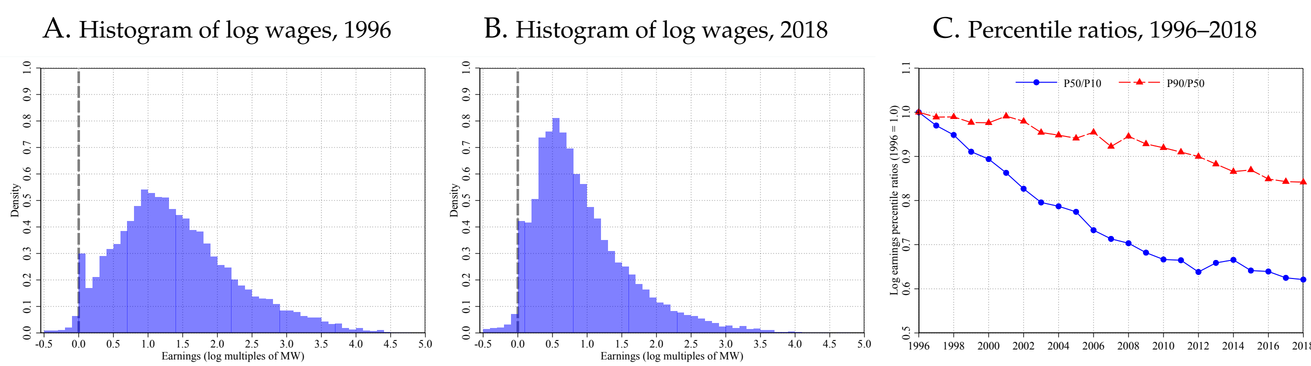
[9] In Appendix A.3, we show that official labor force statistics are compatible with the sample sizes in the RAIS.

Table 1. Summary statistics for three datasets, 1996 and 2018

	Mean	St.d.	Mean	St.d.
Panel A. Administrative linked employer-employee data (RAIS)	1996		2018	
Age	32.74	9.30	34.71	9.57
Years of education	8.90	3.92	11.06	2.93
Real wage (log real BRL)	7.31	0.86	7.60	0.67
Observations (millions)	17.20		27.60	
Panel B. Cross-sectional household survey data (PNAD)	1996		2012	
Real wage in formal sector (log real BRL)	7.01	0.81	7.13	0.62
Real wage in informal sector (log real BRL)	6.26	0.81	6.56	0.78
Employment rate	0.95		0.95	
Formal employment share	0.68		0.76	
Observations (thousands)	74.5		86.0	
Panel C. Longitudinal household survey data (PME)	2002		2012	
Transition rate nonemployed-employed	0.08		0.10	
Transition rate employed-nonemployed	0.05		0.04	
Observations (thousands)	94.3		121.2	

Notes: Years of education are set to 0 for illiterate, 3 for some primary school, 5 for primary school, 7.5 for some middle school, 9 for middle school, 11 for some high school, 12 for high school, 14 for some college, and 16 for at least a bachelor's degree. Real wage refers to mean actual (in RAIS) or usual (in PNAD) monthly earnings in constant December 2018 BRL. Employment comprises domestic workers, employees, and self-employed. Formal employment is employment with a legal work permit. Monthly transition rates are between employment (i.e., formal employment) and nonemployment (i.e., informal employment + unemployment). *Source:* RAIS, 1996 and 2018, PNAD, 1996 and 2012, and PME, 2002 and 2012.

Figure 1. Lower- and upper-tail inequality



Notes: Panels A and B show histograms of log wages in multiples of the current minimum wage based on 60 equispaced bins for population of male workers aged 18–54 for 1996 and 2018, respectively. Panel C plots lower- and upper-tail wage inequality, as measured by the P50/P10 and the P90/P50 log wage percentile ratios between 1996 and 2018, normalized to 1.0 in 1996. *Source:* RAIS, 1996–2018.

able characteristics—as demonstrated in Appendix A.4—we estimate two-way fixed effect specifications based on the econometric framework by AKM. The goal of the exercise is to assess whether firms are a key channel through which the distribution of wages may change over time, either through adjustments in firm pay policies or through worker reallocation across firms. Specifically, we decompose log wages w_{ijt} of individual i working at firm j in year t within five-year periods as

$$w_{ijt} = \alpha_i + \psi_j + X_{it}\beta + \varepsilon_{ijt}, \tag{1}$$

where α_i denotes a worker fixed effect, ψ_j denotes a firm fixed effect, X_{it} is a vector of time-varying worker characteristics—including education-specific age dummies restricted to be flat between ages 45 and 49, education-specific year dummies, contractual work hours dummies, and six-digit occupation dummies—and ε_{ijt} is a residual satisfying a strict exogeneity condition. Equation (1) is identified off workers switching employers within the largest set of firms connected through worker mobility. While ordinary least squares (OLS) estimates of individual coefficients in equation (1) are unbiased, the variance and covariance terms based on these coefficients generally are biased in finite samples. To correct for this bias, we adopt the leave-one-out estimator developed by KSS, which yields unbiased estimates of the variance components of log wages based on equation (1).[10]

Table 2 presents a decomposition of the variance of log wages based on the AKM wage equation (1), separately for a five-year period centered around 1996 (i.e., from 1994–1998) and a five-year period ending in 2018 (i.e., from 2014–2018). For each period, we report results from four estimations: one without KSS correction and without controls in columns (1) and (5), one with KSS correction and without controls in columns (2) and (6), one without KSS correction and with controls in columns (3) and (7), and one with KSS correction and with controls in columns (4) and (8). The last four columns report the change between periods for each of the four sets of estimates.

During 1994–1998 (columns 1–4), out of the total variance of wages of 70.9 log points, between 46 and 25 percent are attributable to the variance of person fixed effects. The inclusion of worker controls reduces this share by around one third, while the KSS correction further reduces it. Between 30 percent (column 1) and 26 percent (column 4) of the total variance of log wages are attributed to the firm pay component, with little variation in this share with and without KSS correction or controls. There is significant positive worker-firm sorting, as measured by the correlation between worker and firm fixed effects of 0.330 including the KSS correction and controls. The associated value of two times their covariance term equals 0.120, which accounts for an additional 17 percent of the total variance (column 4).

During 2014–2018 (columns 5–8), the total variance of wages is 44.4 log points, which is 26.5 log

[10] There has been a fruitful debate around the benefits and drawbacks of estimating AKM wage equations, including Andrews et al. (2008), Eeckhout and Kircher (2011), Lopes de Melo (2018), Card et al. (2018), Bonhomme et al. (2019), Bonhomme et al. (2020), and Borovičková and Shimer (2020). In related work, Alvarez et al. (2018) and Gerard et al. (2021) present a battery of robustness checks, which suggest that the AKM equation is well suited for describing the Brazilian data during this period.

Table 2. Decomposition of the variance of log wages over time

	Variance (%), 1994–1998				Variance (%), 2014–2018				Change (%), 1994–1998 to 2014–2018			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(5)−(1)	(6)−(2)	(7)−(3)	(8)−(4)
$Var(w_{ijt})$	0.709	0.709	0.709	0.709	0.444	0.444	0.444	0.444	-0.265	-0.265	-0.265	-0.265
	(100%)	(100%)	(100%)	(100%)	(100%)	(100%)	(100%)	(100%)	(100%)	(100%)	(100%)	(100%)
$Var(\hat{\alpha}_i)$	0.323	0.279	0.217	0.176	0.264	0.241	0.173	0.154	-0.059	-0.038	-0.044	-0.022
	(46%)	(39%)	(31%)	(25%)	(59%)	(54%)	(39%)	(35%)	(22%)	(14%)	(17%)	(8%)
$Var(\hat{\psi}_j)$	0.212	0.198	0.201	0.187	0.083	0.076	0.078	0.072	-0.129	-0.122	-0.123	-0.115
	(30%)	(28%)	(28%)	(26%)	(19%)	(17%)	(18%)	(16%)	(49%)	(46%)	(46%)	(43%)
$2 \times Cov(\hat{\alpha}_i, \hat{\psi}_j)$	0.140	0.163	0.098	0.120	0.081	0.092	0.061	0.070	-0.059	-0.071	-0.037	-0.050
	(20%)	(23%)	(14%)	(17%)	(18%)	(21%)	(14%)	(16%)	(22%)	(27%)	(14%)	(19%)
$Var(\hat{\varepsilon}_{ijt})$	0.034	0.070	0.033		0.017	0.036	0.016		-0.017	-0.034	-0.017	
	(5%)	(10%)	(5%)		(4%)	(8%)	(4%)		(6%)	(13%)	(6%)	
$Corr\left(\hat{\alpha}_i, \hat{\psi}_j\right)$	0.267	0.347	0.234	0.330	0.273	0.340	0.263	0.332				
R^2	0.951	0.902	0.953		0.961	0.919	0.965					
Obs. (mm)	67.8	67.8	67.8	67.8	131.9	131.9	131.9	131.9				
KSS correction	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Controls	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes

Notes: This table shows plug-in and bias-corrected variance components of log wages based on estimating AKM equation (1) for the population of male workers of age 18–54 in 1994–1998 and 2014–2018. $Var(w_{ijt})$ denotes the variance of log wages, $Var(\hat{\alpha}_i)$ denotes the variance of estimated person fixed effects, $Var(\hat{\psi}_j)$ denotes the variance of estimated firm fixed effects, $2 \times Cov(\hat{\alpha}_i, \hat{\psi}_j)$ denotes two times the sum of the covariance between estimated person fixed effects $\hat{\alpha}_i$ and estimated firm fixed effects $\hat{\psi}_j$, and $Var(\hat{\varepsilon}_{ijt})$ denotes the variance of estimated residuals. For columns (3)–(4) and (7)–(8), omitted terms include the variance of the estimated component of log wages due to observable worker characteristics, $Var(X_{it}\hat{\beta})$, and two times the sum of covariance terms involving observable worker characteristics. $Corr\left(\hat{\alpha}_i, \hat{\psi}_j\right)$ denotes the correlation between estimated person fixed effects α_i and estimated firm fixed effects ψ_j. Variance shares are in parentheses in columns (1)–(8). Share of total change in the variance of log wages is in parentheses in the last four columns. Observations are in millions of worker-years. KSS correction refers to leave-one-out estimators of variance components by Kline et al. (2020). The variance of estimated residuals, $Var(\hat{\varepsilon}_{ijt})$, and the coefficient of determination, R^2, are not reported in columns (4) and (8) due to their omission in the KSS leave-one-out estimation with controls. Controls include education-specific age dummies restricted to be flat between ages 45 and 49, education-specific year dummies, contractual work hours dummies, and occupation dummies. *Source:* RAIS, 1994–1998 and 2014–2018.

points lower relative to 1994–1998. While worker heterogeneity is the most important factor behind the cross-sectional wage variance, a drop in the variance of firm fixed effects constitutes between 49 percent (comparing columns 5 and 1) and 43 percent (comparing columns 8 and 4) of the total decline. A lower variance of person fixed effects accounts for between 22 percent (comparing columns 5 and 1) and 8 percent (comparing columns 8 and 4) of the total decline. Lower covariance terms and residual variance account for the remaining decline. Between the two periods, the correlation between worker and firm fixed effects remained roughly constant, as did the coefficient of determination for the reported specifications.

In summary, Brazil saw a remarkable decline in wage inequality between 1996 and 2018, which was partly driven by a reduction in pay differences across firms for identical workers. We interpret this as evidence for the hypothesis that the decline in inequality over this period was the result of changes in firms' pay policies rather than solely due to changes in worker composition.

3 The minimum wage and other wage setting institutions in Brazil

3.1 Brazil's minimum wage

Brazil first adopted a regional minimum wage as part of the decree-law *Decreto-Lei No. 2.162* on May 1, 1940, under then-dictator and later-elected-president Getúlio Vargas. In 1984, the regional minimum wages were unified under a federal minimum wage. Over much of the period we study, the federal minimum wage was the only unconditional wage floor in place. However, since the passage of the labor law *Lei Complementar No. 103* on July 14, 2000, states are allowed to institute their own wage floors called *Pisos Salariais Estaduais*. Since then, five out of the 27 states have instituted such state-specific minimum wages (Corseuil et al., 2015; Saltiel and Urzúa, 2020).[11] These five states are located in the relatively high-income southern and southeastern regions of Brazil and comprise Rio de Janeiro and Rio Grande do Sul since 2001, Paraná since 2006, São Paulo since 2007, and Santa Catarina since 2010. Nevertheless, the federal minimum wage (henceforth referred to as the "minimum wage") remains the most important wage floor for the majority of the Brazilian population.

Brazil's minimum wage is stated in terms of a floor on monthly nominal earnings, with no provisions for legal subminimum wages or differentiated minimum wages across demographics or economic subdivisions (Lemos, 2004). The minimum wage applies to workers with full-time contracts of 44 hours per week, and is adjusted proportionately for part-time workers.[12]

3.2 Other wage setting institutions

While the minimum wage serves as an important reference point for wage setting in Brazil, a number of other labor market institutions complement its role. Industry- and occupation-specific trade unions regularly negotiate wage floors for members and other workers with coverage of collective bargaining agreements. During the hyperinflationary period of the early 1990s, wages were commonly expressed as multiples of the minimum wage, though its use as an explicit numeraire has been outlawed and, in practice, is greatly imperfect. Nevertheless, the minimum wage serves as a benchmark for unemployment and retirement benefits. Apart from providing a lower bound on permissible wages, the minimum leaves ample freedom for firms to pay above the minimum wage. In this way, the minimum wage serves as a reference point for wage negotiations.

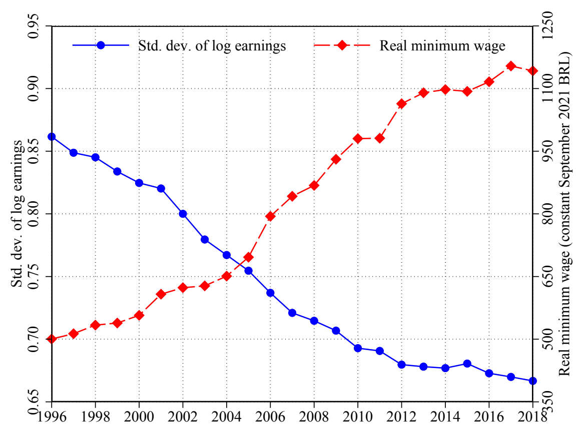
[11] Technically, the Federative Republic of Brazil consists of 26 states and one federal district, the *Distrito Federal*. For simplicity, we henceforth refer to all of Brazil's 27 federative units (i.e., the 26 states and the federal district) as "states."

[12] Using information on hours in the RAIS data, we find a relatively small share of part-time workers. Special labor contracts allow for parts of the minimum wage to be paid in-kind in the form of accommodation and food, although in the PNAD data only 0.8 percent of workers report receiving nonmonetary remuneration in 1996.

3.3 Evolution of Brazil's minimum wage over time

Motivated by the remarkable decline in wage inequality in Brazil, we now turn to a salient change in the labor market over this period: the rise in the minimum wage.[13] Brazil's real minimum wage deteriorated under high inflation between 1985 and 1995. A switch in government towards the end of this period ignited a gradual ascent of the wage floor from BRL 500.4 in 1996 to BRL 1,142.3 (both in constant September 2021 BRL) in 2018, which corresponds to a 128.3 percent increase in real terms. Accounting for aggregate productivity growth, this corresponds to a 58.6 log points real productivity-adjusted rise in the minimum wage over 23 years. To put these numbers into context, the minimum wage as a fraction of the median wage increased from around 30.3 percent in 1996 to around 55.6 percent in 2018. Figure 2 shows a strong negative comovement between the minimum wage and the standard deviation of log wages between 1996 and 2018, with a time series correlation of -0.973.[14]

Figure 2. Evolution of wage inequality and the real minimum wage



Notes: Statistics are for males of age 18–54. Real minimum wage is the annual mean of the monthly time series. The correlation between the two time series is -0.973. *Source:* RAIS and IPEA, 1996–2018.

4 Cross-sectional heterogeneity and the minimum wage

While the correlation between the minimum wage and aggregate wage inequality documented in the previous section is striking, we caution against interpreting this pattern as causal. For example, the changes in wage inequality over this period might have been driven by simultaneous changes in macroeconomic conditions or secular trends in the wage distribution unrelated to Brazil's federal minimum

[13] While Brazil enacted other social policies during the mid-2000s, such as a transfer program for needy families (*Bolsa Família*) launched in 2003, the minimum wage predates many of these policies.

[14] Appendix B.1 shows an equally striking comovement between earnings inequality and the minimum wage over the extended period from 1985–2018.

wage. We address this simultaneity problem by exploiting spatial variation in the bindingness of the federal minimum wage across states in Brazil, building on the seminal econometric framework by Lee (1999) and the recent contribution by Autor et al. (2016). This approach allows us to filter out changes in national macroeconomic conditions and secular trends. In this sense, the fact that inequality decreased in Brazil over this period is neither necessary nor sufficient for our conclusions regarding the effects of the minimum wage on wage inequality.

4.1 Motivating evidence on state-level heterogeneity

To motivate our econometric analysis, we start by noting that wage inequality—while declining overall during this period—fell disproportionately in initially lower-income regions for which the federal minimum wage was relatively more binding. Figure 3 plots normalized wage inequality measures between 1996 and 2018 for the three lowest-income states and three highest-income states in Brazil in 1996.[15] Panel A shows that the variance of log wages drops by more than half in initially low-income states, but by less than one-fifth in initially high-income states. Panel B shows that lower-tail inequality drops especially in initially low-income states, with the P50–P10 and P50–P25 for this group declining by 50 and 40 percent, respectively, but by markedly less for initially high-income states. In contrast, upper-tail inequality, measured by the P75–P50 or the P90–P50, falls only in initially low-income states, as shown in panel C.[16]

These empirical patterns yield three take-aways. First, Brazil's inequality decline was due to factors that matter more at lower income levels. Second, the inequality decline was associated with compression particularly in the bottom of the wage distribution. Third, the compression in the wage distribution reaches from the bottom to above the median of the wage distribution. This motivates our study of the minimum wage.

4.2 Econometric framework

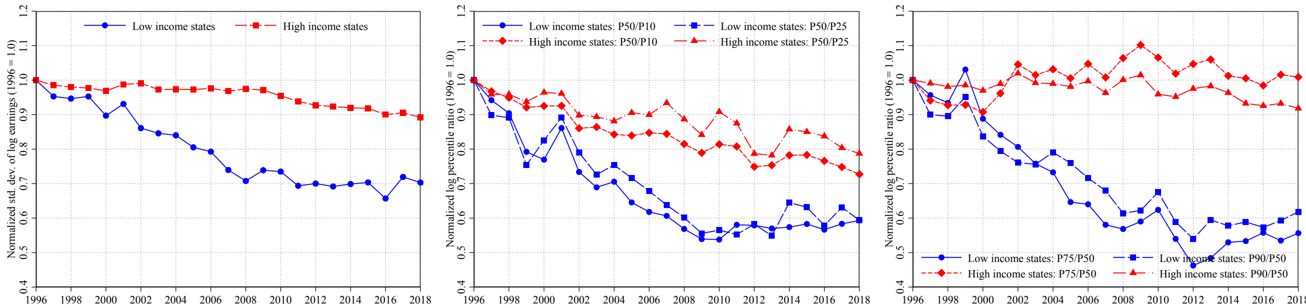
To correlate the minimum wage with wage inequality, we follow Lee (1999) and Autor et al. (2016) in exploiting heterogeneous exposure across states that differ in their bindingness with respect to Brazil's federal minimum wage. To this end, we define the *Kaitz-p index* for state s in year t as $kaitz_{st}(p) \equiv \log w_t^{min} - \log w_{st}^{\mathrm{P}p}$. That is, the Kaitz-$p$ index is the log difference between the federal minimum wage

[15] The three low-income states are Maranhão, Piauí, and Paraíba, while the three high-income states are Rio de Janeiro, São Paulo, and Distrito Federal.

[16] Appendix B.5 shows that the inverse relationship between the effective bindingness of the minimum wage and wage inequality generalizes to the full set of states.

Figure 3. Evolution of wage inequality across rich and poor states

A. Overall inequality | B. Lower-tail inequality | C. Upper-tail inequality



Notes: For this figure, we assign the three lowest-income states and three highest-income states states in Brazil in 1996 into a "low income" group and a "high income" group, respectively. The three low-income states are Maranhão, Piauí, and Paraíba, while the three high-income states are Rio de Janeiro, São Paulo, and Distrito Federal. The three panels then plot various wage inequality measures by state group between 1996 and 2018, normalized to 1.0 in 1996. panel A shows the variance of log wages, panel B shows lower-tail percentile ratios (P50/P10 and P50/P25) of log wages, and panel C shows upper-tail percentile ratios (P75/P50 and P90/P50) of log wages. *Source:* RAIS, 1996–2018.

prevailing in year t, w_t^{min}, and the pth percentile of the log wage distribution of state s in year t, w_{st}^{Pp}.[17] We are interested in how various inequality measures at the state-year level covary with the Kaitz-p index, for high enough p such that the pth percentile of the wage distribution is not (directly or indirectly) affected by the minimum wage. To assess this, we regress outcome variable $y_{st}(p';p)$ specific to wage percentile p' with respect to some base percentile p in state s and year t on the Kaitz-p index, using the same base percentile p, and state-year controls:

$$y_{st}(p';p) = \sum_{n=1}^{N} \beta_n(p') \times kaitz_{st}(p)^n + \gamma_s(p') + \delta_s(p') \times t + \varepsilon_{st}(p'), \tag{2}$$

where $y_{st}(p';p)$ may stand in for the log ratio of wage percentile p' over wage percentile p in state s and year t, N denotes the order of the polynomial in the Kaitz-p index, $\beta_n(p')$ is the percentile p'-specific coefficient on the nth power of the Kaitz-p index, $\gamma_s(p')$ is a set of state dummies for each percentile p', and $\delta_s(p') \times t$ is a set of state-specific linear time trends for each percentile p'. Finally, $\varepsilon_{st}(p')$ is a percentile p'-specific error term, which we assume satisfies the strict exogeneity condition $\mathbb{E}[\varepsilon_{st}(p')|kaitz_{st}(p), \ldots, kaitz_{st}(p)^n, \gamma_s(p'), \delta_s(p') \times t] = 0$.

After estimating equation (2) separately for each wage percentile p' using a baseline percentile p, we estimate the marginal effect of the minimum wage throughout the wage distribution,

$$\rho(p', p) \equiv \sum_{n=1}^{N} n\beta_n(p') \times kaitz_{st}(p)^{n-1}, \tag{3}$$

[17] Figure B.10 in Appendix B.4 shows that variation across Brazilian states in the Kaitz-p index, for $p \in \{50, 90\}$, is large initially and decreases as the minimum wage increases, while approximately preserving the ranking of states over time.

evaluated at the worker-weighted median value of the Kaitz-p index across states and years. Allowing for polynomials of order $N \geq 2$ is important to capture the nonlinear effects of the minimum wage as it becomes more binding. After trying different values, we set $N = 2$.[18]

We first consider as outcome variables in equation (2) a set of global or local wage inequality measures. To capture the effects of the minimum wage on global wage inequality, we consider a variant of equation (2) that uses the standard deviation of log wages as the dependent variable. To capture the effects of the minimum wage on local wage inequality, we use—for various values of $p' \in \{10, 15, \ldots, 90\}$—the log ratio between wage percentile p' and a base percentile p, so that $y_{st}(p'; p) = \log[w_{st}(p')/w_{st}(p)]$. Here, p is the same percentile as in the Kaitz-p index. Ideally, p would be chosen high enough so as to be (directly and indirectly) unaffected by the minimum wage. Prior studies of the minimum wage in the U.S. context have used $p = 50$—i.e., the median—while appealing to the fact that, ex-post, their findings suggest insignificant spillover effects at or above that point in the wage distribution. For Brazil, where the minimum wage is more binding than in the U.S., we report results for the same value of $p = 50$ and consistently find a statistically significant correlation with outcomes above the median of the wage distribution.[19] Therefore, we also report results for an alternative, preferred normalization using $p = 90$.

When analyzing the correlation between the minimum wage and log wage percentile ratios, the inclusion of the pth wage percentile in both the dependent and the independent variable may induce a spurious correlation that results in biased estimates of the coefficient $\beta_n(p')$, and thus the marginal effect $\rho(p', p)$, in the presence of measurement error or other transitory shocks (Autor et al., 2016). While measurement error is plausibly a lesser concern in large administrative data such as ours, we address this issue by implementing a variant of the solution proposed by Autor et al. (2016). Specifically, we adopt an instrumental variables (IV) strategy that predicts the Kaitz-p index and its square based on an instrument set that consists of the log real statutory minimum wage, its square, and the log real statutory minimum wage interacted with the mean of the log real pth percentile of the wage distribution for each state over the full sample period. The motivation for this instrument set is that the current level of the statutory minimum wage in relation to the long-term average income level within a state affects the concurrent bindingness of the minimum wage (i.e., instrument relevance) and has an effect on concurrent wage inequality only through its effect on the concurrent bindingness of the minimum wage (i.e., the exclusion restriction) by being essentially decoupled from transitory wage fluctuations. Since

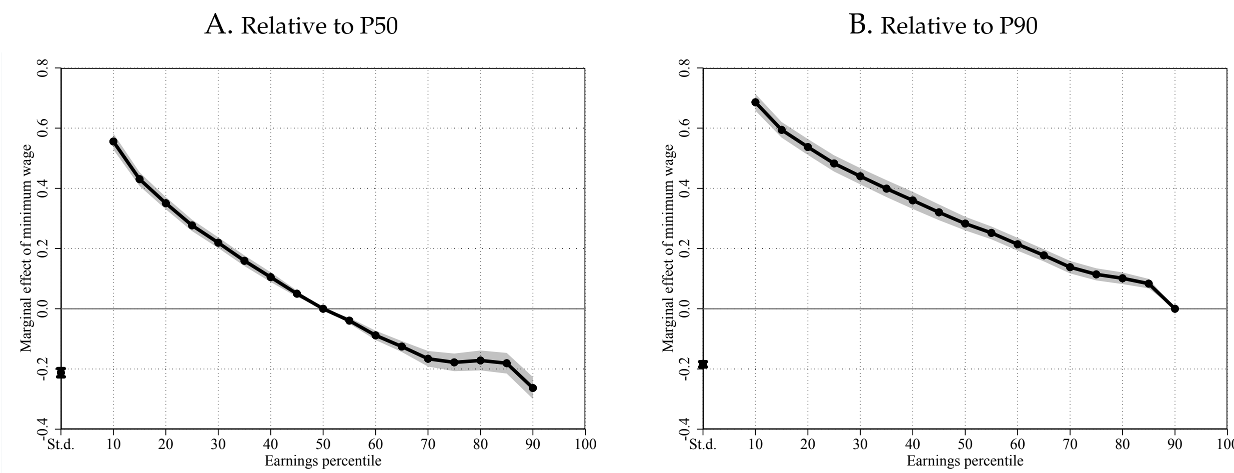
[18] Using polynomials of order $N > 2$ yields results that are substantially the same as those presented below.

[19] See Appendix B.12 for a comparison of the relative bindingness of the minimum wage, as proxied by left-tail wage inequality, between Brazil and the U.S.

we study states' differential exposure to the federal minimum wage, rather than state-level minimum wages that are more likely to be endogenous to local economic conditions, we include as controls in our IV specification state-specific linear time trends instead of a set of year dummies as in Autor et al. (2016).

Result 1: Effects of the minimum wage on wage inequality. Figure 4 shows the results obtained from estimating equation (2) over the sample period from 1996 to 2018. We report results for our baseline specifications with state fixed effects and state-specific linear time trends, estimated via OLS in levels across Brazil's 27 states, with the base percentile being either $p = 50$ (panel A) or $p = 90$ (panel B). The shaded areas represent 99 percent confidence intervals based on regular (i.e., not clustered) standard errors. In each panel, we report the estimated marginal effect on the standard deviation of log wages ("St.d." on the x-axis) and on wages between the 10th and the 90th percentiles of the wage distribution ("10" to "90" on the x-axis) relative to the base wage p.

Figure 4. Estimated minimum wage effects on the distribution of wages



Notes: Figure plots estimated marginal effects from equation (3) based on the regression framework in equation (2). Each panel shows the results from a baseline specification, with estimated marginal effects shown as black circles connected by lines and standard error bands shown as bars or shaded areas. The baseline specification includes state fixed effects in addition to state-specific linear time trends and is estimated using ordinary least squares (OLS). Each value on the horizontal axis corresponds to a separate regression for a specific dependent variable, which can be either the standard deviation of log wages ("St.d." on the x-axis) or wages between the 10th and the 90th percentiles of the wage distribution ("10" to "90" on the x-axis) relative to some base wage p. Panel A uses the 50th percentile as the base wage (i.e., $p = 50$), while panels B uses the 90th percentile as the base wage (i.e., $p = 90$). Both panels are estimated across Brazil's 27 states. The bars and four shaded areas represent 99 percent confidence intervals based on regular (i.e., not clustered) standard errors. *Source:* RAIS, 1996–2018.

The results show a strong correlation between the minimum wage and inequality throughout the wage distribution. Using the median as a base percentile (panel A), the estimated marginal effects of the minimum wage are monotonically decreasing between the 10th and the 75th percentile, and statistically significant at the one percent level throughout. The marginal effects are also tightly estimated.

The statistically significant correlation between the minimum wage and inequality outcomes above the median motivates our alternative normalization using the 90th wage percentile (panel B). Inspecting these results, we estimate monotonically decreasing and statistically significant marginal effects of the minimum wage up to the 90th percentile. Again, the marginal effects are tightly estimated.

In terms of the correlation between the minimum wage and the standard deviation of log wages, our estimates across the two base wages in panels A and B of Figure 4 yield consistent results, with an estimated semi-elasticity of around -0.20. This means that a one percent increase in the nominal minimum wage, holding fixed the median 90th percentile of wages, is associated with a decrease in the standard deviation of wages of around 20 log points. Although caution is warranted when extrapolating from cross-sectional regressions to aggregate trends, these estimates suggest a decline in the standard deviation of wages of around 11.7 log points, compared to the actual decline in the standard deviation of wages of 19.3 log points in the raw data, in response to the 58.6 log point labor productivity-adjusted increase in the minimum wage seen in Brazil between 1996 and 2018.

We conduct a battery of robustness checks and consistently find that spillovers reach up to or above the 75th percentile of the earnings distribution. This is significantly higher than previous evidence on the reach of minimum wage spillovers in the US due to Lee (1999), who finds significant effects up to the median of the wage distribution, and Autor et al. (2016), who find spillovers in the lowest quintile of the wage distribution. Importantly, Autor et al. (2016)'s concern that measurement error may bias estimates of the effect of the minimum wage does not seem to drive our finding, as Appendix B.6 shows by presenting similar results from the IV specification described above.[20] In this way, our results complement recent evidence by Fortin et al. (2021) that relies on a method robust to the type of measurement error problem described in Autor et al. (2016) and finds spillover effects similar to those of Lee (1999) for the same period of the 1980s in the US.

Our robust finding of a correlation between the minimum wage and inequality outcomes up to the 90th percentile of the wage distribution may seem surprising. For comparison, Autor et al. (2016) show spillovers up to the 20th percentile of the wage distribution in the U.S. In light of this, we make five

[20] Appendix B.6 also shows similar results from OLS and IV specifications in differences, though with significantly larger standard error bounds. In Appendix B.7, we find similar results using alternative sets of controls, including only state fixed effects, only year fixed effects, state and year fixed effects, and state and year fixed effects in addition to state-specific linear trends. Appendix B.8 shows that these results are not unique to the 1996–2018 period we study, since we find similar results for the period 1985–2007 and the complete set of years 1985–2018. Notably, spillover effects are not markedly stronger during the early period of 1985–1995, though the right tail of our estimates suggests that there were significant transitory state-level shocks not related to the minimum wage during this high-inflation period. Appendix B.9 shows similarly strong spillover effects when controlling for state-specific quadratic or cubic time trends. Although the number of states (27) falls below conventional thresholds for clustering (Cameron and Miller, 2015), Appendix B.10 also presents results with standard errors clustered at the state level and a separate specification estimated at the level of mesoregions (of which there are 137) with standard errors clustered at the mesoregion level. Finally, in Appendix B.11 we show that similar insights are obtained from a set of specifications and controls replicating those in complementary work by Haanwinckel (2020), the relation to which we discuss in some detail in Appendix B.11.

observations. First, our large-scale administrative data plausibly admit less measurement error than the CPS, alleviating concerns about bias in the estimates of $\beta_n(p)$ in equation (2) and allowing us to measure spillover effects with greater accuracy than previously possible. Second, the minimum wage in Brazil during this period was more binding compared to that in the U.S. over the last decades (Autor et al., 2016), which due to the nonlinear nature of spillover effects is expected to lead to greater effects throughout the wage distribution.[21] Third, while a relatively small fraction of Brazilian workers earn the minimum wage in any given year during our sample period, we find that a significant fraction of workers throughout the wage distribution ever (currently, in the past, or in the future) earn the minimum wage during our sample period. This may suggest that the minimum wage in Brazil acts as an important stepping stone, even for workers that eventually find themselves high up in the wage distribution.[22] Fourth, the minimum wage in Brazil is particularly salient given Brazil's volatile economic history. While indexation of wages to the minimum wage is not allowed by Brazilian labor laws and not supported by the government, the minimum wage still serves as an important reference point in wage setting mechanisms (Neri and Moura, 2006).[23] Fifth and finally, compared to the U.S., Brazil's workforce is heavily skewed toward low-skill workers as measured by educational attainment. It is around the 75th–90th percentile of the wage distribution where there is a sharp increase in the share of workers with either a high school or a college degree, and also where (log) wages increase sharply across wage quantiles.[24] Therefore, we would naturally expect the minimum wage to have a greater impact among lower-skill workers, which make up a relatively larger population share in Brazil compared to the U.S.

Result 2: Effects of the minimum wage on employment. So far, we have focused on the correlation between the minimum wage and inequality. We now extend our regression framework to investigate the link between the minimum wage and employment outcomes—including formal and informal sectors—over our period of study. To this end, we supplement the administrative data from RAIS with household survey data from PNAD and PME, based on which we estimate variants of the specification in equation (2) with a dependent variable y_{st} that captures employment outcomes at the region-year level. [25]

[21] Appendix B.12 shows that between 1996 and 2018, the minimum wage in Brazil relative to that in the U.S. has gone from less binding to significantly more binding.

[22] Appendix B.2 shows that a relatively small fraction of Brazilian workers have wages exactly equal to, less than, or around the minimum wage at any given point in time between 1996 and 2018. Appendix B.3 studies characteristics of minimum wage earners.

[23] Our model in Section 5 rationalizes the view of the minimum wage as a reference point as an equilibrium outcome due to frictional inter-firm competition for workers. In the data, like in our model, the link between the minimum wage and the wage distribution is imperfect—not all wages move one-for-one with the minimum wage. Thus, the wage distribution compresses as the minimum wage is increased. Appendix B.13 compares the distribution of (changes in) wages in nominal values and in multiples of the current minimum wage.

[24] See Appendix A.2 for details.

[25] A region corresponds to Brazil's 27 states in RAIS and PNAD and to one of the six largest metropolitan areas in PME.

For simplicity, we present results based on specifications that use the Kaitz-50 index, though we obtain similar results when using the Kaitz-90 index.

Consistent with previous evidence by Lemos (2009), results from the PNAD survey data in panel A in Table 3 show that the minimum wage has precisely estimated zero effects on the population size, labor force participation rate, employment rate, and formal employment share, all of which are insignificant at conventional levels. Specifically, there is little evidence of cross-state differences in population or labor force dynamics linked to the minimum wage—if anything, the rise in the minimum wage is associated with a rise in log population size that is statistically significant only at the ten percent level. Results from the PME data in panel B show small estimated marginal effects of the minimum wage on transition rates from nonformal to formal as well as from formal to nonformal employment. While both point estimates are negative, they are also statistically insignificant at conventional levels.[26] Finally, panel C shows the estimated effects of the minimum wage on other labor market outcomes in RAIS. Mean hours worked show a significant correlation of mild magnitude with the relative bindingness of the minimum wage, suggesting that the intensive margin of hours adjustments in response to the minimum wage (Doppelt, 2019) is not of prime importance in the Brazilian context. Mean firm size correlates strongly positively with the minimum wage, consistent with the idea that the minimum wage induces small firms to shrink or exit in favor of larger competitors. The estimated effect on the probability of remaining employed at the same firm until next year is negative and significant, suggesting that some jobs are destroyed as the minimum wage increases. However, together with our findings of constant labor force participation, employment, and formality rates in response to the minimum wage increase, this suggests that the effect of the minimum wage is primarily to reallocate workers across firms rather than a reduction in overall employment.[27]

4.3 A call for an equilibrium model

The above findings suggest that Brazil's minimum wage has had far-reaching effects on the wage distribution. That the inequality-decreasing effects of the minimum wage are so large may seem surprising in light of past findings of smaller effects in the U.S. by Lee (1999) and Autor et al. (2016). Yet there exists little theoretical guidance on how strong we should expect spillover effects of the minimum wage to be and at what cost they may come. Furthermore, reduced-form estimates based on cross-sectional variation recover only the relative, but not the absolute, effects of the minimum wage—a problem that

[26] An increase in the minimum wage may affect both formal and informal employment, as studied by Jales (2018). Unfortunately, the condition of no spillover effects imposed by Jales (2018) does not hold in our context.

[27] See also Appendix B.14 for a more detailed analysis of the correlation between the minimum wage and hours worked.

Table 3. Effects of the minimum wage on employment worker transitions

	Marginal effect (standard error)
Panel A. Cross-sectional household survey data (PNAD)	
Log population size	0.057 (0.030)
Labor force participation rate	0.009 (0.016)
Employment rate	0.014 (0.015)
Formal employment share	0.024 (0.020)
Panel B. Longitudinal household survey data (PME)	
Transition rate nonformal-formal	−0.003 (0.017)
Transition rate formal-nonformal	−0.005 (0.009)
Panel C. Administrative linked employer-employee data (RAIS)	
Mean log hours worked	0.043 (0.003)
Mean log firm size	0.433 (0.055)
Probability of remaining employed at the same firm until next year	−0.111 (0.011)

Notes: This table shows the predicted marginal effects with standard errors in parentheses evaluated at the worker-weighted mean across Brazil's 27 states. Each cell corresponds to the estimated coefficient and standard error from one regression with the relevant dependent variable (row). The underlying regressions are variants of equation (2) including state fixed effects and state-specific linear time trends. *Source:* PNAD, 1996–2012, PME, 2002–2012, and RAIS, 1996–2018.

is compounded if spillovers are present throughout most of the wage distribution.[28] Finally, there may remain concerns about confounding factors not controlled for in our econometric analysis, such as the concurrent rollout of social security programs and the expansion of education in Brazil.

To address these issues, we develop and estimate an equilibrium model of the Brazilian labor market subject to a minimum wage. Such a model, while based on certain assumptions, can lend additional credibility to our reduced-form estimates, which rely on a very different set of assumptions. Another benefit of a structural model is that it can aggregate the effects of the minimum wage estimated based on cross-sectional variation in the data, while shedding light on the mechanisms by which the minimum wage impacts the labor market through counterfactual simulations.

5 Equilibrium model of a labor market subject to a minimum wage

We now develop an equilibrium model of the Brazilian labor market subject to a minimum wage. Our framework is essentially a series of heterogeneous Burdett and Mortensen (1998) economies separated by worker types. Our contribution is to provide empirical content to this framework by integrating unobserved worker heterogeneity, minimum wage jobs, and endogenous job creation in a tractable manner.

[28]This is a variant of the "missing intercept" problem highlighted in a recent micro-to-macro literature (Nakamura and Steinsson, 2018).

The extended framework is geared toward estimation on linked employer-employee data and an analysis of the equilibrium effects of the minimum wage on the distribution of wages and employment.

5.1 Environment

Consider a continuous-time economy in steady state populated by a unit mass of workers and a mass M of firms, both infinitely-lived and with risk-neutral preferences over consumption discounted at rate ρ.

Worker types. At any point in time, a worker can be either employed or nonemployed. We think of nonemployment as a simple way of capturing either unemployment or informal employment with associated utility flow value $ab(a)$ that depends on permanent worker ability $a \sim \Psi(\cdot)$, with $a \in [\underline{a}, \overline{a}]$. That the informal market offers a constant flow utility simplifies the analysis substantially. We think of the dependence of this flow utility on ability a as reflecting individual traits that are valued not just in formal employment but also in informal employment or home production. This ability parameter corresponds to both observable and unobservable worker characteristics, which Appendix A.4 shows matter for explaining empirical wage dispersion.

Workers also differ in their relative on-the-job search efficiency, $s \in [\underline{s}, \overline{s}]$. In particular, an employed worker of type (a, s) becomes nonemployed at Poisson rate $\delta(a, s)$, at which point her search efficiency is updated according to a first-order Markov process with transition probability $\pi(s'|a, s)$.[29] We think of this assumption as reflecting in reduced-form different propensities to switch employers, for instance due to family circumstances preventing a geographic move.[30] As will become clear, it allows the model to match the modest spike in the wage distribution at the minimum wage in Brazil (that being said, we show in Appendix E.7 that our main results are not sensitive to the particular value for $\pi(s'|a, s)$).

Technology. Firms are heterogeneous in their permanent productivity $z \sim \Gamma(z)$, with $z \in [\underline{z}, \overline{z}]$. A firm that employs $l(a, s)$ workers of each type (a, s) produces output according to the linear technology

$$y\left(z, \{l(a,s)\}_{a,s}\right) = z \int_{\underline{a},\underline{s}}^{\overline{a},\overline{s}} a l(a,s) da ds.$$

[29]The assumption that search efficiency only updates when a worker transitions into nonemployment avoids added complexity from worker type transition hazards entering firms' problem.

[30]In a framework with endogenous search intensity as in Lentz (2010), we hypothesize that a rise in the minimum wage would have two opposing effects on incentives to search. On the one hand, it would render employment more attractive since it pays better on average, which incentivizes search. On the other hand, it flattens the wage ladder and reduces job vacancies, which disincentivizes search. Given these offsetting forces and existing evidence that worker search effort is rather inelastic (Engbom, 2020), we focus here on a model with exogenous search effort.

To hire workers, firms post vacancies v in each market (a, s) at a strictly convex, increasing cost $c(v|a, s)$, which reflects the cost of advertising the job, screening applicants and training workers for the job.

Search and matching. Both nonemployed and employed workers search for jobs at random in labor markets that are segmented by worker type, (a, s). Let $p(a, s)$ denote the Poisson arrival rate of job offers per unit of search efficiency in market (a, s). A job offer is an opportunity to work for a fixed piece rate w for the duration of a job. Therefore, a worker of ability a employed at piece rate w receives flow value wa. Let $F(w|a, s)$ denote the cumulative distribution function (cdf) of piece rates offered in market (a, s). While workers take offer arrival rates and the offer distribution as given, both are determined in equilibrium by firms' vacancy and wage posting decisions. In particular, if firms post total vacancies $V(a, s)$ in a given market (a, s) and workers's aggregate search intensity is $S(a, s) = u(a, s) + se(a, s)$, where $u(a, s)$ is the number of nonemployed workers and $e(a, s)$ is the number of employed workers of type (a, s), then the total number of worker-firm contacts in market (a, s) is given by $\chi V(a, s)^{\alpha} S(a, s)^{1-\alpha}$. Here, $\chi > 0$ is the match efficiency and $\alpha \in (0, 1)$ is the match elasticity with respect to aggregate vacancies.

5.2 Worker's problem and the distribution of workers over the job ladder

Let $U(a, s)$ denote the value to an nonemployed worker with ability a and search efficiency s. Let $W(w, a, s)$ be the value to a worker with ability a and search efficiency s from being employed at piece rate w. The value $U(a, s)$ satisfies the following Hamilton-Jacobi-Bellman (HJB) equation:

$$\rho U(a,s) = ab(a) + p(a,s) \int_{\underline{w}(a,s)}^{\overline{w}(a,s)} \max\{W(w,a,s) - U(a,s), 0\}\, dF(w|a,s) \tag{4}$$

For nonemployed workers, there exists a reservation threshold $r(a, s)$ such that $W(r(a, s), a, s) = U(a, s)$. A nonemployed worker of type (a, s) accepts any piece rate offer $w \geq r(a, s)$ and rejects any offer $w < r(a, s)$. In equilibrium, firms only make offers with $w \geq r(a, s)$.

The value $W(w, a, s)$ of a worker of type (a, s) employed at piece rate w is given by the HJB equation:

$$\begin{aligned} \rho W(w,a,s) &= wa + sp(a,s) \int_{w}^{\overline{w}(a,s)} \left(W(w',a,s) - W(w,a,s)\right) dF(w'|a,s) \\ &+ \delta(a,s) \left(\int_{\underline{s}}^{\overline{s}} U(a,s')\, \pi(s'|a,s) ds' - W(w,a,s) \right) \end{aligned} \tag{5}$$

A worker of type (a, s) employed at piece rate w receives outside offers at rate $sp(a, s)$, which they accept if the associated piece rate offer w' satisfies $w' > w$. If an employed worker rejects an outside offer, they remain employed in their current job. Employed workers become nonemployed at exogenous rate $\delta(a,s)$, in which case the worker's search efficiency updates according to the Markov process $\pi(s'|a,s)$.

Let $G(w|a,s)$ denote the steady-state cdf of employed workers of type (a,s) over piece rates w. Appendix C shows that this distribution satisfies:

$$G\left(w|a,s\right) \quad = \quad \frac{p(a,s)F\left(w|a,s\right)}{\delta(a,s)+sp(a,s)\left(1-F\left(w|a,s\right)\right)}\frac{u(a,s)}{e(a,s)}. \tag{6}$$

5.3 Firms' problem

Under the assumption that the discount rate tends to zero, $\rho \rightarrow 0$, firms' dynamic problem reduces to maximizing flow profits. Firms choose, market by market, how many job openings to advertise, $v \geq 0$, and what piece rate to pay, w, subject to a minimum wage constraint, $wa \geq w^{\min}$:

$$\max_{w \geq w^{min}/a, v} \left\{a\left(z-w\right)l\left(w,v|a,s\right)-c(v|a,s)\right\}, \tag{7}$$

where $l(w,v|a,s)$ is the number of workers of type (a,s) that a firm posting piece rate w and vacancies v attains in equilibrium. In particular, Appendix C.2 shows that:

$$l\left(w,v|a,s\right) \quad = \quad \frac{vu(a,s)p(a,s)}{V(a,s)}\frac{\delta(a,s)+sp(a,s)}{\left(\delta(a,s)+sp(a,s)(1-F(w|a,s))\right)^2} \tag{8}$$

Let $v(z|a,s)$ denote the optimal vacancy policy of a firm with productivity z in market (a,s) and $w(z|a,s)$ its optimal wage policy. Given these policies, the equilibrium offer distribution is given by:

$$F(w(z|a,s)|a,s) \quad = \quad \frac{M}{V(a,s)}\int_{\underline{z}}^{z} v(\tilde{z}|a,s)d\Gamma(\tilde{z}), \qquad \text{where} \quad V(a,s) \quad = \quad M\int_{\underline{z}}^{\overline{z}} v(\tilde{z}|a,s)d\Gamma(\tilde{z})$$

Henceforth, we assume that the vacancy cost takes an isoelastic form, $c(v,a,s) = ac(a,s)v^{1+\eta}/(1+\eta)$. Define $h(z|a,s) = F(w(z|a,s)|a,s)$ as the vacancy-weighted cdf of firms over productivity, so that $f(w(z|a,s)|a,s) = h'(z|a,s)/w'(z|a,s)$.

5.4 Equilibrium

Appendix C defines the equilibrium, which market by market can be characterized as a system of two first-order ordinary differential equations in the wage policy, $w(z|a,s)$, and the cdf of firms, $h(z|a,s)$:

$$
\begin{aligned}
w'(z|a,s) &= (z - w(z|a,s)) \frac{2sp(a,s)h'(z|a,s)}{\delta(a,s) + sp(a,s)\,(1 - h(z|a,s))}, \qquad (9) \\
h'(z|a,s) &= \gamma(z) \frac{M}{V(a,s)} \left(\frac{1}{c(a,s)} (z - w(z|a,s)) \frac{u(a,s)}{V(a,s)} p(a,s) \frac{\delta(a,s) + sp(a,s)}{(\delta(a,s) + sp(a,s)(1 - h(z|a,s)))^2} \right)^{\frac{1}{\eta}},
\end{aligned}
$$

subject to the initial value conditions $w(\underline{z}(a,s)|a,s) = \max\{r(a,s), w^{\min}/a\}$ and $h(\underline{z}(a,s)|a,s) = 0$, where $\underline{z}(a,s)$ is the lowest productivity active in market (a,s), so $\underline{z}(a,s) = \max\{\underline{z}, \max\{r(a,s), w^{\min}/a\}\}$. Equilibrium requires that the total number of vacancies, $V(a,s)$, is such that $\lim_{z \to \bar{z}} h(z|a,s) = 1$.

6 Estimation

We estimate the model by targeting empirical moments from the preperiod 1994–1998. The goal is to use the estimated model to quantify the equilibrium effects of the observed increase in the minimum wage.

6.1 Estimation strategy

To accommodate unobserved heterogeneity among workers and firms, our model features a continuum of parameters. To reduce the dimensionality of the estimation problem, we make some simplifying assumptions. We first discretize both worker ability a and firm productivity p. We then parameterize how worker heterogeneity varies across ability levels a and how firm productivity p is distributed. Subsequently, we proceed in three steps. First, we preset three parameters based on standard values in the literature. Second, we directly infer three parameters, which the model maps one-to-one to three empirical moments. Third, we estimate 12 remaining parameters using the SMM via indirect inference.

Preset parameters. We adopt a monthly frequency and set the discount rate to the equivalent of an annual real interest rate of five percent. We normalize matching efficiency to $\chi = 1$, since without data on vacancies it is not separately identified from the intercept in the vacancy cost function. Based on standard values in the literature (Petrongolo and Pissarides, 2001), we set the elasticity of matches with respect to vacancies to $\alpha = 0.5$, which is at the upper end of the range considered by Meghir et al. (2015). For robustness, we consider alternative values for α and other key parameters in Appendix E.7.

Directly inferred parameters. The mass of firms, M, can be directly chosen to target a mean firm size of 11.8 workers in RAIS. Under the assumption that the separation rate of workers with zero on-the-job search efficiency, $\delta(a, 0)$, is constant across ability levels, we can equate this parameter to the empirical separation rate of workers earning the minimum wage, which equals 6.5 percent per month. We assume that the job finding rate $p(a, s) = \lambda$ is independent of worker ability a and relative on-the-job search efficiency s. We set the auxiliary parameter λ to target a monthly nonemployment-to-employment (NE) rate of 4.4 percent.[31] Of course, λ is an equilibrium outcome, but we can treat it as an auxiliary parameter since the cost of creating jobs, $c(a, s)$, can be chosen to rationalize any positive value of λ in equilibrium. Hence, we pin down the structural parameters $c(a, s)$ flexibly in each market such that the equilibrium job finding rate is λ.

Internally estimated parameters. We estimate the remaining model parameters by the SMM via indirect inference. Specifically, we choose the parameter vector $\mathbf{p}^* \in \mathscr{P}$ that minimizes the sum of weighted squared percentage deviations between a set of moments in the model and in the data:

$$\mathbf{p}^* = \arg\min_{\mathbf{p}} \sum_{p \in \mathscr{P}} \sum_{m \in \mathscr{M}(p)} w_m \left(\frac{m^{\text{model}} - m^{\text{data}}}{m^{\text{data}}} \right)^2$$

While all parameters are jointly determined, we assign to each parameter p a set of moments $\mathscr{M}(p)$ that are particularly informative for p as we compare the model-based moments m^{model} against their data equivalent m^{data} with weight w_m. We discuss our choice of moments and weights in greater detail below.

To further simplify the problem, we impose some flexible parametric restrictions based on inspection of the data vis-à-vis the model output. We assume that log worker ability is distributed according to a double exponential distribution with mean μ and shape parameter σ. Firm productivity is Pareto distributed with shape parameter ζ and a scale parameter normalized to one.

We restrict search efficiency to fluctuate between $s = 0$ and a positive value $s(a) > 0$ that depends on ability a. In equilibrium, firms offer the reservation wage $r(a, s)a$ to workers with $s = 0$ who do not search on the job (Diamond, 1971). If the minimum wage binds with $w^{min} = r(a, s)a$ for a positive measure of workers, then our model produces a spike at the minimum wage in the wage distribution. We assume that an employed worker with search efficiency $s(a) > 0$ who becomes unemployed transitions

[31] Brazil's NE rate is low in an international comparison (Engbom, 2021), likely because we include informal workers in our definition of nonemployment. This is not a prime concern for us, however, because the key factor affecting firm wages is how fast workers move up and fall off the job ladder, which relates to job-to-job (EE) and employment-to-nonemployment (EN) rates. In contrast, the NE rate impacts the economy primarily through the stock of nonemployed, as we confirm in robustness exercises in Section 7.4.

to $s(a) = 0$ with probability π and retains $s(a)$ with complementary probability $1 - \pi$.[32] A worker with $s(a) = 0$ who becomes unemployed transitions to $s(a) > 0$ with probability 1. That is,

$$\pi(x|a, s(a) > 0) = \begin{cases} 1-\pi & \text{if } x = s(a) \\ \pi & \text{if } x = 0 \\ 0 & \text{otherwise} \end{cases} \qquad \pi(x|a, 0) = \begin{cases} 1 & \text{if } x = s(a) \\ 0 & \text{otherwise} \end{cases}$$

For a worker with search efficiency $s(a) > 0$, the exogenous separation rate is assumed to be an affine transformation of a worker's ability rank, $\delta(a, s) = \delta_0(1 + \delta_1 \Psi(a))$. The relative on-the-job search efficiency among workers in the regular state is $s(a) = \phi_0(1 + \phi_1(\exp(\Psi(a)) - 1))$. These parametric forms are guided by what appears to fit the data well.

Next, we posit a reduced-form relationship for the reservation wage among workers with positive search efficiency given by $ar(a, s > 0) = r_0 + r_1(a - \underline{a})$. The reservation wage is an endogenous outcome, but the flow value of leisure $b(a)$ is a free parameter, allowing us to treat $r(a, s > 0)$—or, in this case, r_0 and r_1—as auxiliary parameters to be estimated. We then choose $b(a)$ so as to reproduce the estimated reservation piece rate $r(a, s)$ as an equilibrium outcome.[33] This approach allows us to solve the model using the system of differential equations in (9) without reference to workers' value functions (4)–(5), which leads to a great reduction in computational time.

Model solution, simulation, and estimation. We solve the model in continuous time over 50 grid points for ability and 500 grid points for productivity. We then simulate the model at monthly frequency over a period of five years for a large number of workers, starting from the ergodic distribution. To match the empirical residual wage dispersion conditional on worker and firm heterogeneity, we assume that the logarithm of measured wages, $\log \tilde{w}$, equals the sum of the logarithm of the true wage, $\log w$, and measurement error, κ, so $\log \tilde{w} = \log w + \kappa$. We let $\kappa \sim \mathcal{N}(0, \varepsilon)$ with variance ε and values drawn independently and identically distributed across worker-firm matches. Motivated by the empirical existence of a (relatively small) spike in the wage distribution at the minimum wage, we assume that measurement error is identically zero for minimum wage jobs. One interpretation of this is that employers offering exactly the minimum wage are well aware of its statutory level and the penalties for violations, which

[32] While the probability of transiting to $s = 0$ upon separating to unemployment is independent of a, our model features a lower incidence of minimum wage jobs among higher-ability workers since they are less likely to separate to unemployment.

[33] We verify that all worker types $(a, s = 0)$ prefer being employed at the minimum wage over unemployment under our estimated parameter values. Note that in markets where the minimum wage is binding, the minimum wage provides an upper bound on the latent reservation wage. Since the impact of a simulated minimum wage increase—unlike in the case of a decrease—is invariant to the level of the flow value of leisure, $b(a)$, in markets where the minimum wage is initially binding, we assume that $b(a)$ equated to the value of unemployment in those markets.

induces them to make accurate reports. We construct monthly and annual data sets based on model simulations, using the same sample selection criteria and variable construction as in the data.

These assumptions leave us with a vector $\mathbf{p}$ of 12 parameters to be estimated using the SMM via indirect inference:[34]

$$\mathbf{p} = \{\mu, \sigma, \zeta, \eta, \varepsilon, \delta_0, \delta_1, \phi_0, \phi_1, \pi, r_0, r_1\}$$

While all parameters are jointly determined, it is useful to provide a heuristic discussion of what data moments are particularly informative for each parameter. We verify this intuition in Appendix D.3. The scale of the ability distribution, μ, is informed by the log ratio of the median to minimum wage. Greater μ means that wage distribution is further removed from the wage floor. This moment plays a key role in our analysis and we assign it a weight of $w_m = 5$. For the ability shape parameter, σ, we target log wage percentile ratios relative to the median in increments of five (i.e., P5-50, P10-50, ..., P95-P50). We assign each of the 18 percentile ratios a weight of $w_m = 1$.

For the remaining parameters, we connect our equilibrium model to reduced-form estimates from the AKM wage equation in Section 2.2. The AKM wage equation does not have a structural interpretation in our framework. Nevertheless, Appendix D.3 shows that this indirect inference approach disciplines the distributions of unobserved worker and firm heterogeneity in our model vis-à-vis the data.[35]

The shape of the Pareto distribution for firm productivity, ζ, is informed by the standard deviation of AKM firm fixed effects. Lower values of ζ are associated with greater dispersion in productivity and firm pay. We match the curvature of the vacancy cost, η, to the share of employment at firms with 50 or more workers. For lower values of η, it is cheaper for firms to scale up vacancies, which results in more productive firms growing relatively larger. Both moments are assigned a weight of $w_m = 1$.

The variance of measurement error $w_m = 1$ intuitively maps into the variance of residuals in the AKM wage equation. We assign this moment a weight of $w_m = 1$.

For the separation rate's intercept, δ_0, and slope, δ_1, we target the EN rate by AKM worker fixed effect deciles. The intercept δ_0 steers the average EN rate, while the slope in ability, δ_1, steers heterogeneity in EN rates across AKM worker fixed effects. Moments for each of the then AKM worker fixed effect deciles receives a weight of $w_m = 1/10$, which results in a unit cumulative weight.

The intercept, ϕ_0, and slope, ϕ_1, of the relative on-the-job search intensity, $s(a)$ maps into the EE rate

[34] Recall that our directly inferred estimate of λ is associated with an implied vacancy cost scalar $c(a, s)$ for each market (a, s) and each value of $r(a, s > 0)$ corresponding to our estimates of (r_0, r_1) is associated with an implied flow value of leisure $b(a)$.

[35] For this indirect inference estimation step, both in our model and in the data, we drop minimum wage workers, do not apply a KSS bias correction, and do not include additional controls. Importantly, we treat the model and the model identically.

by AKM worker fixed effect decile. Again, each of these 10 moments receives a weight of $w_m = 1/10$.

The probability $\pi(0|a,s)$ that a displaced worker transitions from $s > 0$ to $s = 0$ maps into the spike at the minimum wage in the wage distribution. This moment also receives a weight of $w_m = 1$.

For the auxiliary parameters governing reservation wages, r_0 and r_1, we target the P5 of log wages by AKM worker fixed effect decile. Intuitively, r_0 guides the minimum wage bindingness for all markets, while r_1 guides the relative bindingness across AKM worker fixed effect deciles. Again, each of these 10 moments receives a weight of $w_m = 1/10$, which results in a unit cumulative weight.

6.2 Parameter estimates and model fit

Table 4 presents the three preset, three directly inferred, and 12 internally estimated parameter values along with their targeted moments. A few comments are in order, beginning with the set of parameters related to the wage distribution. The model closely replicates the empirical median-to-minimum log wage ratio (related to $\mu = 0.960$) and the general shape of the log wage distribution (related to $\sigma = 0.258$) shown in Figure 6 and to be discussed shortly. A tail index of the firm productivity distribution of $\zeta = 3.503$ allows the model to match well the variance of AKM firm fixed effects. To match the share of workers employed at firms with at least 50 employees, the model requires a relatively low curvature of the vacancy cost, $1 + \eta = 1.467$.[36] Finally, most of the AKM residual variance is accounted for by measurement error, $\varepsilon = 0.215$, as opposed to violations of log additivity of the wage equation.

We now turn to a set of parameters related to employment transitions. In the RAIS data, around four percent of workers leave formal employment in the subsequent month, which is close to the EN rate in the U.S. Note that this number includes workers who leave for informal employment not recorded in RAIS. Furthermore, the data show a steep negative gradient between the EN rate and AKM person fixed effect deciles. Together, these empirical moments lead us to estimate $\delta_0 = 0.074$ and $\delta_1 = -0.815$—see Figure D.3A in Appendix D.2 for details. Next, an average of 1.8 percent of workers make an EE transition each month, which is again close to the corresponding number in the U.S.[37] Because the EE rate is high relative to the NE rate in Brazil, we infer a high average relative search efficiency, $s(a)$. This

[36] Because η also governs the elasticity of vacancy creation with respect to firm profitability, a low value of η implies that firms' employment responds relatively flexibly to the minimum wage—see Figure D.4D in Appendix D.3 for details.

[37] Using survey data from the PME, Meghir et al. (2015) report a quarterly EE rate of 1.58 percent and 2.49 percent, respectively, in the Brazilian metropolitan regions of São Paulo and Salvador. There are several differences between the way we estimate EE transitions for our purposes compared to Meghir et al. (2015). Our estimates are based on a different data set, RAIS, which has wider geographic coverage. RAIS, unlike PME, also records the exact employment start and end dates, mitigating concerns about time aggregation bias (Shimer, 2012). Compared to survey data like PME, reporting issues are likely also a lesser concern in administrative data like RAIS. Finally, regarding right censoring, the RAIS data allow us to estimate transition rates over a longer panel of sixty months, compared to the four-month panel in PME. See Engbom et al. (2021) for a detailed comparison between the PME and RAIS datasets.

does not mean that Brazilian labor markets are highly efficient but merely that EE transitions are not as rare as NE transition rates may suggest.The resulting parameter estimates $\phi_0 = 0.436$ and $\phi_1 = 1.055$ match the empirical EE transition rates shown in Figure D.3B of Appendix D.2. The estimated value of the transition rate to minimum wage jobs, $\pi = 0.019$, leads our model to generate a realistic spike in the wage distribution at the minimum wage.

The two remaining parameters relate to workers' outside option value. The parameters $r_0 = -0.078$ and $r_1 = 1.127$ capture the empirical feature of the P5 of log wages rising steeply across AKM person fixed effect deciles—see Panel D of Figure D.3 in Appendix D.2.

Table 4. Parameter estimates

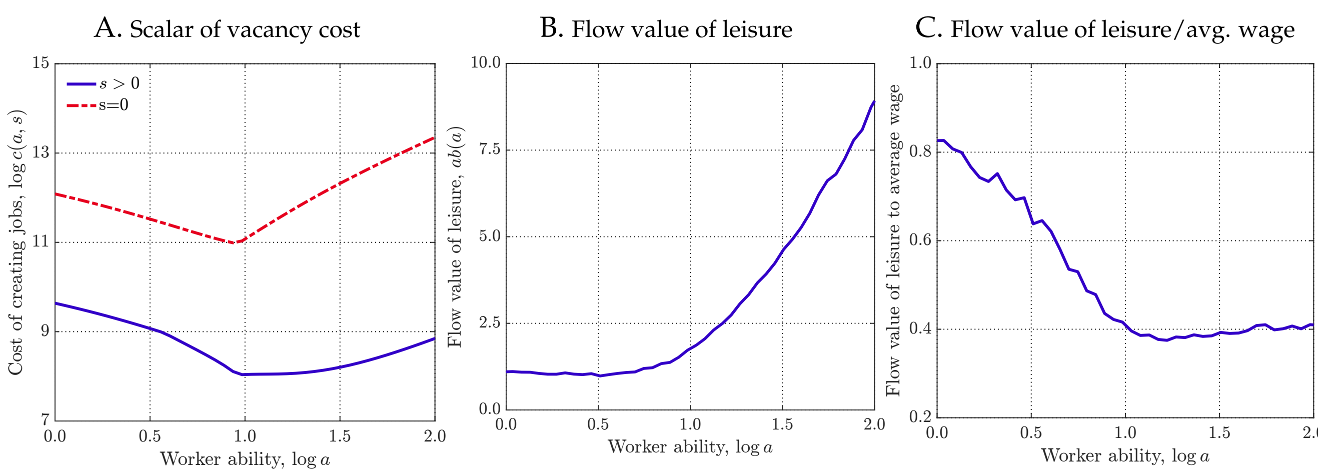
Parameter		Estimate	Targeted moment	Data	Model
	Panel A. Pre-determined parameters				
ρ	Discount rate	0.004	4% annual real interest rate		
χ	Matching efficiency	1.000	Normalization		
α	Elasticity of matches w.r.t. vacancies	0.500	Petrongolo and Pissarides (2001)		
	Panel B. Structural and auxiliary parameters calibrated offline				
M	Mass of firms	0.069	Average firm size	11.787	13.085
$\delta(a,0)$	Separation rate of those with $s=0$	0.065	EN rate from MW jobs	0.064	0.065
λ	Job finding rate	0.044	NE rate	0.044	0.044
	Panel C. Internally estimated structural parameters				
μ	Mean of worker ability	0.960	Median to minium wage	1.224	1.192
σ	Shape of worker ability	0.258	Percentiles of wage distribution	See figure 6	
ζ	Shape of productivity distribution	3.503	Variance of AKM firm FEs	0.217	0.195
η	Curvature of vacancy cost	0.467	Employment share of firms with 50+ empl.	0.588	0.583
ϵ	Variance of noise	0.215	Variance of AKM residual	0.032	0.035
δ_0	Separation rate, intercept	0.074	EN rate	See figure D.3	
δ_1	Separation rate, slope	-0.815	EN rate	See figure D.3	
ϕ_0	Relative search intensity, intercept	0.436	JJ rate	See figure D.3	
ϕ_1	Relative search intensity, slope	1.055	JJ rate	See figure D.3	
π	Transition rate to MW	0.019	Share of employed earning the MW	0.012	0.011
	Panel D. Internally estimated auxiliary parameters				
r_0	Reservation wage, intercept	-0.078	5th wage percentile	See figure D.3	
r_1	Reservation wage, slope	1.127	5th wage percentile	See figure D.3	

Notes: Parameter estimates are expressed at a monthly frequency, when applicable. *Source:* Model and RAIS, 1994–1998.

We now discuss the mapping between the estimated auxiliary parameters (λ, r_0, r_1) and the corresponding structural parameters of the model. Panel A of Figure 5 plots the implied vacancy cost scalars $c(a,s)$ across markets (a,s). The implied per-ability-unit vacancy cost is nonmonotonic, initiall decreasing in ability, and subsequently increasing. Because the overall recruiting cost for workers of type (a,s) equals $ac(a,s)$, the overall recruiting cost turns out to be relatively flat among low ability levels and then sharply increasing toward higher ability levels. Conditional on worker ability a, recruiting costs are uniformly higher in the markets with $s = 0$.

Panel B of Figure 5 shows the flow value of leisure $b(a)a$ across ability types a, which is first flat and then upward-sloping, consistent with the idea that higher-ability workers are also better at home production or at work in the informal sector. Panel C shows for each ability type the flow value as a fraction of mean wages, $\overline{w}(a)$, which varies from around 80 percent among low ability levels to around 40 percent at medium and high ability levels. Appendix D.1 shows that these estimates give rise to a model-implied mean-to-min wage ratio (Hornstein et al., 2011) of between 1.3 at low ability levels and 3.0 at the top. Thus, the estimated model suffers less from the critique raised by Hornstein et al. (2011) that many search models require unrealistically low (or indeed negative) flow values of leisure to generate realistic levels of frictional wage dispersion. This result obtains for two reasons. First, the high relative on-the-job search efficiency means that job acceptance out of unemployment forgoes a lesser option value. Second, a large share of the variance of wages in our linked employer-employee data is due to unobserved worker heterogeneity, corresponding to ability differences in our model. Conventional survey data would attribute this variation partly to residual, or frictional, wage dispersion—see Appendix A.4 for details.

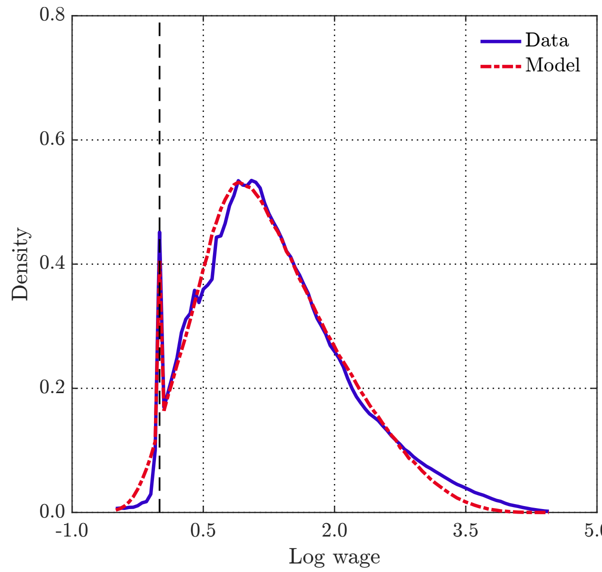
Figure 5. Estimated vacancy costs and flow values of leisure



Notes: Parameter estimates are expressed at a monthly frequency, when applicable. Panel A shows the scalar $c(a,s)$ of the vacancy cost function $ac(a,s)v^{1+\eta}/(1+\eta)$. Panel B shows the flow value of leisure $b(a)a$ that workers of ability a receive when not formally employed. Panel C shows the flow value of leisure, $b(a)$, relative to the ability specific average wage, $\overline{w}(a) = \int_s \int_z w(z|a,s)dG(z|a,s)d\Phi(s|a)$, where $\Phi(s|a)$ is the conditional distribution of workers of ability a over search efficiency, s. *Source:* Model.

We now turn to an important dimension of our model's performance, namely its fit vis-à-vis the empirical wage distribution. Figure 6 compares the distribution of log wages in the data and the model. Overall, the model-generated wage distribution matches several salient features of the empirical wage distribution. These include its mode, dispersion, skewness, a spike at the minimum wage, and a mass below the minimum wage. At the same time, the model fit is less than perfect. For example, the model underpredicts the mass in the far right tail of the wage distribution. It also overpredicts the number of workers below the minimum wage. While the model matches well the spike exactly at the minimum wage—see Table 4 above—it slightly understates the number of workers earning just above the minimum wage.[38] We postulate that more flexible parametric forms or a richer wage setting mechanisms such as that in Flinn and Mullins (2018) would help match these features.[39] We note, however, that such extensions would come at a significant increase in computational time, which is already substantial.[40]

Figure 6. Distribution of wages in estimation period, model vs. data



Notes: Log monthly earnings, expressed as a multiple of the current minimum wage, and constructed as the sum of earnings from a given employer over the five year sample period divided by the sum of months worked for that employer over the five year sample period. Sample selection and variable construction criteria for the model are chose to match those of the data. *Source:* Model and RAIS, 1994–1998.

[38] Appendix E.7 shows that our results are robust to varying parameters to better fit these features of the data in isolation.

[39] Flinn and Mullins (2018) show that the presence of wage bargaining, in addition to wage posting, can change the predicted spillover effects of the minimum wage. We think that our wage posting model provides a good approximation for our problem at hand for two reasons. First, low-skill workers have been shown to be less likely to bargain over wage in the U.S. (Hall and Krueger, 2012). Given that the average skill level is significantly lower in Brazil, it is reasonable to expect wage bargaining to be relatively rare for most of Brazil's labor force. Second, we show in Section 7.1 that our model predicts minimum wage spillovers in line with our reduced-form estimates for most of the wage distribution, suggesting that an added degree of freedom from integrating a parameter that guides the trade-off between posting and bargaining would marginally improve the model's predictive power in our context.

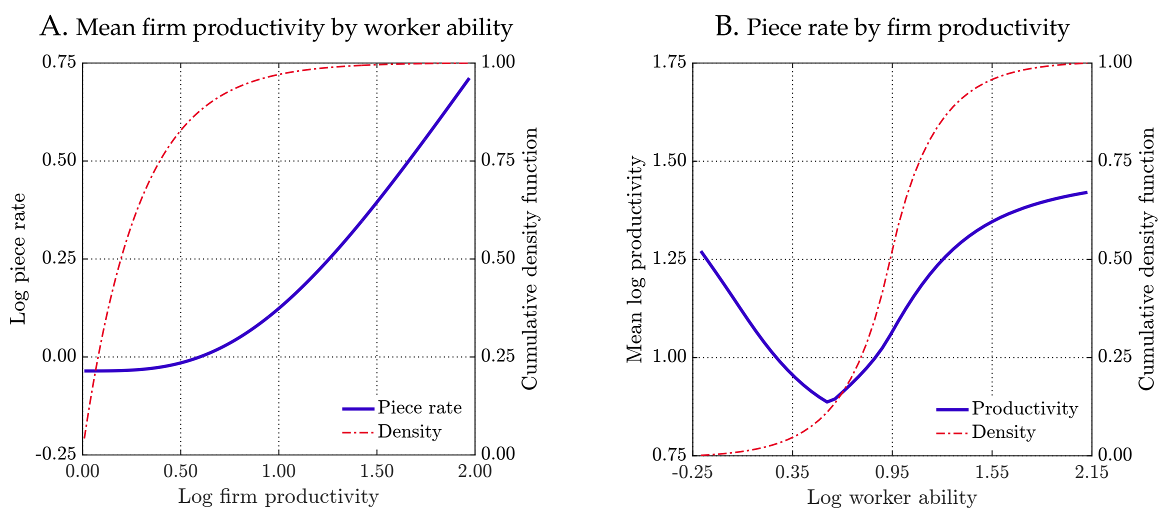
[40] Appendix D.2 presents further details of the model's fit to the data. Appendix D.3 contains additional estimation diagnostics. We find that most of the parameters are well identified. The only exception is the intercept in the reservation wage, r_0, which Appendix E.7 shows has a negligible impact on the predicted effects of the minimum wage.

6.3 Worker-firm sorting and firm pay

It will be instructive to lay out the mechanics of the estimated model with regards to worker-firm sorting and firm pay. Regarding sorting, panel A of Figure 7 shows that higher-ability workers work at more productive firms, which rationalizes the positive correlation between AKM worker and firm fixed effects we documented in Section 2.2. This is the case even absent log-complementarities in the production technology, since we estimate that higher-skill workers are more efficient at climbing the job ladder. However, a binding minimum wage causes the assortative matching to be negative near the bottom of the ability distribution because it renders matches between low-skill workers and low-productivity firms unviable. Figure D.8 in Appendix D.4 provides reduced-form evidence consistent with this prediction.

Panel B of Figure 7 shows piece rates across firm productivity levels for a group of workers most affected by the minimum wage—specifically, the first percentile of worker ability. More productive firms pay identical workers more to grow larger. At the same time, pay increases less than one-for-one with productivity. Consequently, higher productivity firms have a lower labor share (Gouin-Bonenfant, 2020).

Figure 7. Model mechanics



Notes: Panel A shows the average log firm productivity by worker ability, $\int_{\underline{z}}^{\overline{z}} \log z dG(z|a,s)$, in $s(a) > 0$ market by worker ability. Panel B shows log piece rates, $\log w(z|a,s)$, offered by firms to the first percentile of the worker ability distribution in market for $s(a) > 0$ workers. *Source:* Model.

7 The equilibrium effects of the minimum wage

Having estimated the model to the preperiod from 1994–1998, we compare the model-implied impact of an increase in the minimum wage with that estimated in the Brazilian data across space and time.

7.1 The impact of the minimum wage on wage inequality

Our main interest lies in the impact of the minimum wage on wage inequality. To assess this, we start by comparing the model-predicted effects of the minimum wage on inequality with the estimates from our reduced-form approach following Lee (1999) and Autor et al. (2016). To that end, we simulate "state-year-level" data from our estimated model by varying only the level of the minimum wage relative to mean worker ability in order to replicate the empirical distribution of Kaitz-p indices across Brazil's 27 states over time.[41] We then run the same regression (2) on our model simulations as we did on the data in Section 4.2.

Figure 8 shows that the estimated effect of the minimum wage in the model matches well that based on estimated across states and time in the data. For parsimony, we focus here on our preferred specification that uses an OLS strategy, state fixed effects, and state-specific linear time trends.[42] In the specification relative to the 50th percentile, the point estimates in the model fall within the 99 percent confidence interval of the empirical estimates for the bottom 60 percent of the wage distribution. Above the 60th percentile, the model estimates are somewhat more pronounced than in the data. In the specification relative to the 90th percentile, the point estimates in the model are somewhat smaller than the data.

We next turn to the aggregate time trend in Brazil between 1996 and 2018. To that end, we feed in the observed increase in the effective minimum wage in Brazil between 1996 and 2018. Specifically, we consider a productivity-adjusted increase in the minimum wage of 57.7 log points, which corresponds to the rise in the productivity growth-adjusted real minimum wage between 1996 and 2018. Holding all other parameters fixed, we contrast the impact of the increase in the minimum wage on inequality in the model with the aggregate time trend over this period.

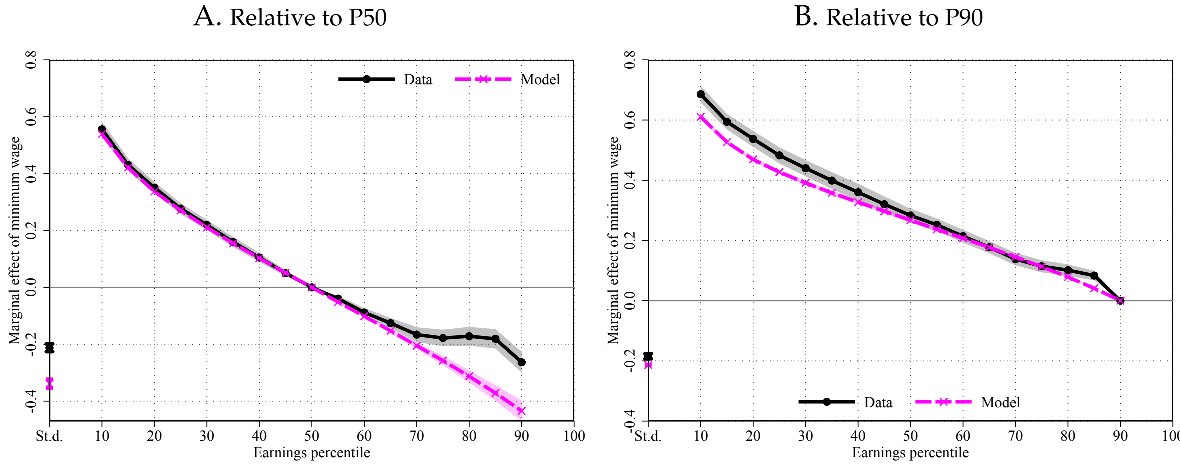
Figure 9 illustrates the impact of the minimum wage increase on wages throughout the distribution. Panel A shows that the cdf in 2018 first-order stochastically dominates that in 1996. The right shift of the cdf is particularly evident for the lower half of the wage distribution, reflecting the bottom-driven impact of the minimum wage.[43] Panel B plots the difference in log wages between 1996 and 2018 conditional on the cdf in each year. Naturally, the minimum wage pushes up wages one-for-one at the bottom of the distribution. More surprisingly, it also impacts wages strictly above the bottom. The wage increase is around 28, 15, 6, 2 and 1 percent at the 10th, 25th, 50th, 75th and 90th percentile, respectively. Neverthe-

[41] We treat each model state as its own, isolated economy, with no worker or firm mobility between them. An interesting avenue for future work would be to incorporate into our model a richer spatial structure, as in Zhang (2018).

[42] Appendix E.1 compares predicted spillover effects based on the model and the data under additional IV specifications.

[43] The reason why the wage cdf in 2018 appear to start at the same point as that in 1996 is the assumed measurement error in wages. Because measurement error is normal and hence unbounded, there are always some workers who have very low measured pay, regardless of the prevailing minimum wage.

Figure 8. Model vs. data: Estimated minimum wage effects throughout the wage distribution



Notes: Figure plots estimates of the marginal effects from equation (3) based on the regression framework in equation (2) estimated across Brazil's 27 states. Results from four separate estimates are shown, namely the combination of two base percentiles—P50 (panel A) and P90 (panel B)—and two sources—the RAIS data (black circles and solid lines) and model-simulated data (magenta crosses and dashed lines). All estimates use a specification that includes state fixed effects in addition to state-specific linear time trends, estimated using OLS. Within each panel, the estimated marginal effect of the minimum wage on the standard deviation of log earnings ("St.d." on the x-axis) and on wages between the 10th and the 90th percentiles of the wage distribution ("10" to "90" on the x-axis) relative to some base wage p are shown. Panel A uses the 50th percentile as the base wage (i.e., $p = 50$), while panel B uses the 90th percentile as the base wage (i.e., $p = 90$). The four error bars and four shaded areas represent 99 percent confidence intervals based on regular (i.e., not clustered) standard errors. *Source:* RAIS, 1996–2018, and model.

less, while spillover effects of the minimum wage are far-reaching, their absolute magnitude is moderate above the median.[44]

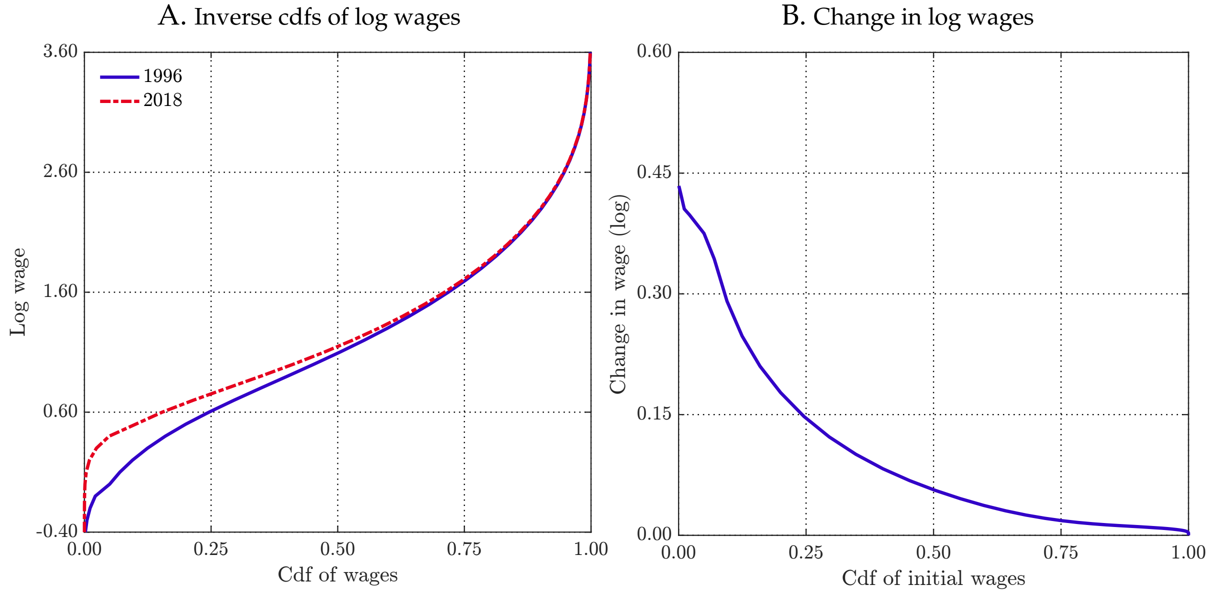
Table 5 compares the model-implied effects of the minimum wage on wage inequality with the raw data in 1996 and 2018. The rise in the minimum wage accounts for 45 percent of the empirical decline in the variance of log wages over this period.[45] Consistent with the observed data pattern, the minimum wage causes a greater absolute reduction in lower-tail inequality relative to upper-tail inequality. It also accounts for a larger share of the decline in lower-tail inequality measures, varying from 73 percent of the P5-P50 log wage percentile ratio to 49 percent of the P25-P50 log wage percentile ratio. The minimum wage still has effects on upper-tail inequality, explaining 18 percent of the empirical compression in P50-P90 log wage percentile ratio. The reason for this is that spillover effects reach above the median of the wage distribution.

One potential concern may be that the job ladder model captures well the labor market experiences of young workers, but is a worse description of the dynamics of older workers. To speak to such concerns,

[44] The reason why the effect of the minimum wage in Figure 8 appears to be close to linear while that in panel B of Figure 9 is distinctly convex is because the former plots the marginal effect while the latter shows the (nonlinear) total effect.

[45] Appendix E.2 shows the contribution of the minimum wage toward changes over time in an AKM wage decomposition. Through the lens of the reduced-form AKM wage equation, the minimum wage acts through a combination of compression in person fixed effects, compression in firm fixed effects, and a declining covariance between the two.

Figure 9. Impact of the minimum wage throughout the wage distribution in the model



Notes: Impact of a 57.7 log point increase in the minimum wage in the estimated model. Panel A shows the cdfs of log wages in 1996 and 2018, respectively, conditional on wages at or above the minimum wage. Panel B shows the change in log wages due to the minimum wage conditional on the cdf in each year. *Source:* Model.

Table 5. Total impact of the minimum wage on wage inequality, model versus data

	1996		2018		Change		
	Data	Model	Data	Model	Data	Model	**Due to MW**
Variance	0.704	0.600	0.436	0.478	-0.268	-0.121	**45.3%**
P5-50	-1.086	-1.092	-0.606	-0.743	0.480	0.349	**72.7%**
P10-50	-0.894	-0.874	-0.524	-0.650	0.370	0.224	**60.6%**
P25-50	-0.488	-0.484	-0.304	-0.394	0.184	0.090	**48.9%**
P75-50	0.614	0.600	0.451	0.563	-0.163	-0.037	**23.0%**
P90-50	1.301	1.195	1.049	1.150	-0.252	-0.045	**17.8%**
P95-50	1.737	1.532	1.493	1.486	-0.244	-0.047	**19.2%**

Notes: Table shows estimated impact of a 57.7 log point increase in the minimum wage in the model as well as the raw data. Percentile ratios of log wages, constructed as the sum of wages from a given employer over the five year sample period divided by the sum of months worked for that employer over each five year period. Model and data sample selection and variable construction is identical. See text for detail. *Source:* Model and RAIS.

Appendix E.3 reestimates the model for the population of only young workers aged 18–36, and resimulates the effects of the same minimum wage increase as previously considered. We reach qualitatively similar conclusions for the set of young workers and, if anything, find more far-reaching spillover effects of the minimum wage, as expected given the relatively high bindingness of the minimum wage among young workers.

7.2 Understanding the distributional effects of the minimum wage

To understand the impact of the minimum wage on wage inequality, we write the variance of log wages as the sum of between- and within-worker components:

$$
\begin{aligned}
Var(w) &= \int_{a,s}\int_{z} \Big(w(z|a,s) - \overline{w}\Big)^2 dG(z|a,s)\frac{e(a,s)}{E} d\Omega(a,s) \qquad (10)\\
&= \underbrace{\int_{a,s} \Big(\overline{w}(a,s) - \overline{w}\Big)^2 \frac{e(a,s)}{E} d\Omega(a,s)}_{\text{between-worker component}} + \underbrace{\int_{a,s}\int_{z} \Big(w(z|a,s) - \overline{w}(a,s)\Big)^2 dG(z|a,s)\frac{e(a,s)}{E} d\Omega(a,s)}_{\text{within-worker component}},
\end{aligned}
$$

where $\Omega(a,s)$ is the joint distribution over worker ability a and search efficiency s, $E = \int_{a,s} e(a,s)d\Omega(a,s)$ is aggregate employment, $\overline{w} = \int_{a,s}\int_{z} w(z|a,s)dG(z|a,s)(e(a,s)/E)d\Omega(a,s)$ is the population mean log wage, and $\overline{w}(a,s) = \int_{z} w(z|a,s)dG(z|a,s)$ is the mean log wage of type-(a,s) workers. The between-worker component captures average differences across worker types, while the within-worker component reflects wage differences among workers of the same type due to employer heterogeneity.

Building on the decomposition in equation (10), we consider two counterfactual experiments. First, fixing the initial allocation of workers, $e(a,s)$ and $g(z|a,s)$, we let firms' wage policies given by $w(z|a,s)$ adjust in response to the minimum wage. We label this the rent channel because it captures redistribution of rents from firms to workers. Second, fixing firms' wage policies, $w(z|a,s)$, we let the allocation of workers given by $e(a,s)$ and $g(z|a,s)$ adjust to the higher minimum wage. We call this the reallocation channel because it reflects changes in the wage distribution due to worker reallocation across firms.

Table 6 presents the results from these counterfactual exercises.[46] We find that 61 percent of the overall variance of log wages is between worker types, while 39 percent is within worker types across firms. The higher minimum wages causes both the between- and the within-worker components to decline, making up 87 and 13 percent, respectively, of the overall decline. The rent channel—firms raising pay for identical workers—is the most important factor behind compression in both the within- and the between-worker components. The reallocation channel also matters for the compression in the between-worker component but less so for the compression in the within-worker component.

To shed further light on the rent and reallocation channels of the minimum wage, we zoom in on a group of workers most affected by the minimum wage—specifically, the first percentile of worker ability. Figure 10 plots changes in firms' piece rate offers and vacancies against log firm productivity. Panel A shows that the minimum wage causes all firms to raise pay. Because low-ability workers' pay rises

[46]Numbers presented here are based on the analytical solution for wages in the model, while Table 5 uses simulated data.

Table 6. Decomposition of effect of minimum wage on wages, model

	1996	2018	Change
Total variance	**0.608**	**0.481**	**-0.127**
Rent channel (change in firm wage policy only, fixed allocation)	–	0.496	-0.112
Reallocation channel (reallocation only, fixed firm wage policy)	–	0.562	-0.046
Between variance	**0.369**	**0.258**	**-0.110**
Rent channel (change in firm wage policy only, fixed allocation)	–	0.285	-0.084
Reallocation channel (reallocation only, fixed firm wage policy)	–	0.321	-0.048
Within variance	**0.239**	**0.223**	**-0.016**
Rent channel (change in firm wage policy only, fixed allocation)	–	0.219	-0.020
Reallocation channel (reallocation only, fixed firm wage policy)	–	0.241	0.002

Notes: Table shows estimated impact of a 57.7 log point increase in the minimum wage. Decomposition of log wages based on (10) using exact (nonsimulated) model wages (i.e. without measurement error κ and not aggregated to the annual level following our empirical approach). The rent channel is the counterfactual impact of letting the wage policies $w(z|a,s)$ adjust while holding fixed the allocation of workers $\{g(z|a,s), e(a,s)\}$. The reallocation channel is the counterfactual impact of letting the allocation of workers $\{g(z|a,s), e(a,s)\}$ adjust, while holding fixed wage policies $w(z|a,s)$. *Source:* Model.

across the board, between-worker inequality falls. Moreover, low-productivity firms raise pay by more than high-productivity firms, consistent with the empirical decline in pass-through from firm productivity to pay over this period (Alvarez et al., 2018). Therefore, the minimum wage also reduces the within-component of wage inequality. Panel B shows that low-productivity firms cut vacancy creation, as their profit margins are squeezed. In contrast, the most productive firms actually increase their recruiting intensity, for reasons that we discuss below. Consequently, employment reallocates toward more productive, higher-paying firms. Since this leads to less positive assortative matching between workers and firms in lower-skill markets, between-worker inequality also falls.[47]

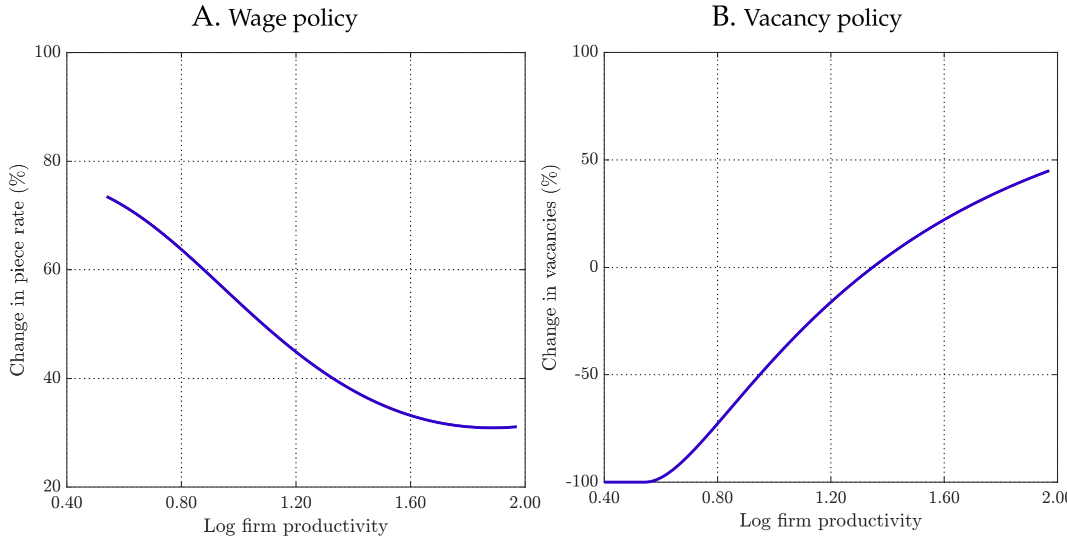
7.3 Aggregate effects of the minimum wage

Having understood the changes in rent sharing and worker reallocation at the micro level, we now turn to the aggregate consequences of the minimum wage. Table 7 shows that the aggregate employment rate falls, consistent with the intuition that a higher wage floor discourages job creation. However, the fall is a modest 0.7 percent.[48] At the same time, aggregate output and labor productivity increase by one and three percent, respectively. Aggregate costs of recruiting rise modestly, as vacancy creation shifts toward more productive firms who have a higher marginal cost of a vacancy. The total wage bill increases by

[47] We provide empirical support for this model prediction in Appendix E.4.

[48] This number masks significant heterogeneity. Among the lowest-skill workers, employment falls by over 15 percent, while employment is essentially unaffected for workers in the top half of the ability distribution. See Appendix E.7 for details.

Figure 10. Changes in firms' wage and vacancy policy in low-ability market, model



Notes: Impact of a 57.7 log point (i.e. 55.9 percent) increase in the minimum wage in the estimated model among workers with positive search efficiency, $s(a) > 0$, in the first percentile of the worker ability distribution. Panel A shows the percentage change in firms' wage policy, $w(z|a,s)$, by unweighted (i.e., not employment-weighted) productivity, z. Panel B shows the percentage change in firms' vacancy policy, $w(z|a,s)$, by unweighted (i.e., not employment-weighted) productivity, z. *Source:* Model.

two percent.[49] Profits decrease by less than 0.1 percent. As a result, the labor share increases by a modest 0.4 percent.

To summarize, labor reallocation across firms mediates the effects of the minimum wage in three ways. First, it buffers the disemployment effects. Second, it increases employment-weighted productivity and output. Third, it shifts workers to firms with higher profits and lower labor shares. As a consequence, the aggregate effects of the minimum wage are relatively muted. These rich predictions regarding worker reallocation depend critically on our model incorporating firms and would be missed by a one-worker-per-firm matching model of the labor market.

To understand why the muted employment effects of the minimum wage, it is useful to note that the change in a firm's vacancy creation in market (a,s) with respect to the minimum wage can be written as

$$\underbrace{\frac{d\log v(z|a,s)}{d\log w^{min}}}_{\text{firms' recruiting response}} = \underbrace{\frac{1}{\eta}\frac{d\log\left(z - w(z|a,s)\right)}{d\log w^{min}}}_{\text{profit channel}} + \underbrace{\frac{1}{\eta}\frac{d\log\left(q(a,s)\left(\frac{u(a,s)}{S(a,s)} + \frac{se(a,s)}{S(a,s)}G(z|a,s)\right)\right)}{d\log w^{min}}}_{\text{fill channel}} \tag{11}$$

$$+ \underbrace{-\frac{1}{\eta}\frac{d\log\left(\delta(a,s) + sp(a,s)(1 - F(z|a,s))\right)}{d\log w^{min}}}_{\text{retention channel}}.$$

[49] As shown in Figure 9B, wages increase by much more at the bottom. However, the aggregate wage bill is dominated by the top of the distribution, where wages change by little.

Table 7. Impact of minimum wage on aggregate outcomes, model

	1996	2018	**Due to MW**
Employment rate, $E = \int e(a,s)d\Omega(a,s)$	0.549	0.542	**-0.007**
Aggregate output, $\log Y = \log\left(\int azdG(z\|a,s)e(a,s)d\Omega(a,s)\right)$	1.747	1.758	**0.012**
Labor productivity, $\log(Y/E)$	2.379	2.407	**0.028**
Aggregate cost of recruiting, $\log C = \log\left(M\int ac(a,s)\frac{v(z\|a,s)^{1+\eta}}{1+\eta}d\Gamma(z)dads\right)$	0.258	0.269	**0.011**
Aggregate output minus recruiting costs, $\log(Y-C)$	1.491	1.503	**0.012**
Total wage bill, $\log W = \log\left(\int aw(z\|a,s)dG(z\|a,s)e(a,s)d\Omega(a,s)\right)$	1.082	1.101	**0.019**
Total profits, $\log(Y-W-C)$	0.399	0.398	**-0.001**
Labor share, W/Y	0.515	0.518	**0.004**

Notes: Table shows estimated impact of a 57.7 log point increase in the minimum wage on aggregate outcomes in the simulated economy. Employment rate is $E = \int e(a,s)d\Omega(a,s)$. Aggregate output is $\log Y = \log\left(\int azdG(z|a,s)e(a,s)d\Omega(a,s)\right)$. Log labor productivity is $\log(Y/E)$. Log aggregate recruiting cost is $\log C = \log\left(M\int ac(a,s)\frac{v(z|a,s)^{1+\eta}}{1+\eta}d\Gamma(z)dads\right)$. Log aggregate output minus recruiting costs is $\log(Y-C)$. Log wage bill is $\log W = \log\left(\int aw(z|a,s)dG(z|a,s)e(a,s)d\Omega(a,s)\right)$. Log profits, $\log(Y-W-C)$. Labor share is W/Y *Source:* Model.

Because our estimated curvature of the vacancy cost function is rather low with $\eta \approx 0.5$ and optimal vacancies scale with $1/\eta$, firms' recruiting response to the minimum wage is relatively elastic. In spite of this, we find a quantitatively small response of firm-level employment to the minimum wage due to three offsetting channels in equation (11). The first is the profit channel, which captures changes in pay at firms with constant productivity, which affect profits. The second is the fill channel, which captures changes in the fill rate of jobs due to interfirm competition. The fill rate depends on the rate $q(a,s) = (V(a,s)/S(a,s))^{\alpha-1}$ at which a vacancy contacts a worker, the unemployed share $u(a,s)/S(a,s)$, and the employed share's earnings distribution $G(z|a,s)$. The third is the retention channel, which captures changes in match duration due to changes in the rate of poaching by other firms, $sp(a,s)(1-F(z|a,s))$.

Panel A of Figure 11 shows the results from decomposing firms' recruiting response to the minimum wage based on equation (11) across productivity levels. To illustrate the forces at work, we focus again on a group of workers most affected by the minimum wage—specifically, the first percentile of worker ability. The profit channel reduces vacancy creation for all firms for low-productivity firms with smaller profit margins to begin with. The fill rate channel is positive throughout, U-shaped, and varies less across productivity levels. Finally, the retention channel varies in sign, follows an inverse-U shape, and not far from zero throughout. Summing over all three channels, firms' recruiting response to the minimum wage is increasing and concave, negative at the bottom, and positive at higher productivity levels.

Turning next to the aggregate response of employment in market (a,s), it writes identically as

$$\underbrace{\frac{d\log e(a,s)}{d\log w^{min}}}_{\text{aggregate employment reponse}} = \underbrace{\frac{d\log e(a,s)}{d\log p(a,s)}}_{\text{job finding channel}} \times \underbrace{\frac{d\log p(a,s)}{d\log V(a,s)}}_{\text{congestion channel}} \times \underbrace{\frac{d\log V(a,s)}{d\log w^{min}}}_{\text{vacancy channel}}. \tag{12}$$

Hence, the minimum wage impacts aggregate employment through three channels. First, the job finding channel captures the impact of a change in the job finding rate, $p(a,s)$, on employment, $e(a,s)$. Under the simplifying assumption that the probability of a type transition upon job loss is small ($\pi \to 0$),

$$\frac{d\log e(a,s)}{d\log p(a,s)} = \frac{\delta(a,s)}{\delta(a,s)+p(a,s)} \approx 0.6,$$

assuming approximations of $\delta(a,s) \approx 0.07$, and $p(a,s) \approx 0.04$. Second, the congestion channel captures the impact of aggregate vacancies, $V(a,s)$, on the job finding rate, $p(a,s)$. Simplifying,

$$\frac{d\log p(a,s)}{d\log V(a,s)} = \alpha \frac{1}{\left(1-\alpha\frac{(1-s(a))\delta(a,s)p(a,s)}{(\delta(a,s)+s(a)p(a,s))(\delta(a,s)+p(a,s))}\right)} \approx \alpha = 0.5,$$

assuming an approximation of $s(a) \approx 1.0$ and using $\alpha = 0.5$. Third, the vacancy channel captures the impact of the minimum wage w^{min} on aggregate vacancies, $V(a,s)$. This channel simply equals the integral over firms' recruiting responses to the minimum wage corresponding to equation (11) above.

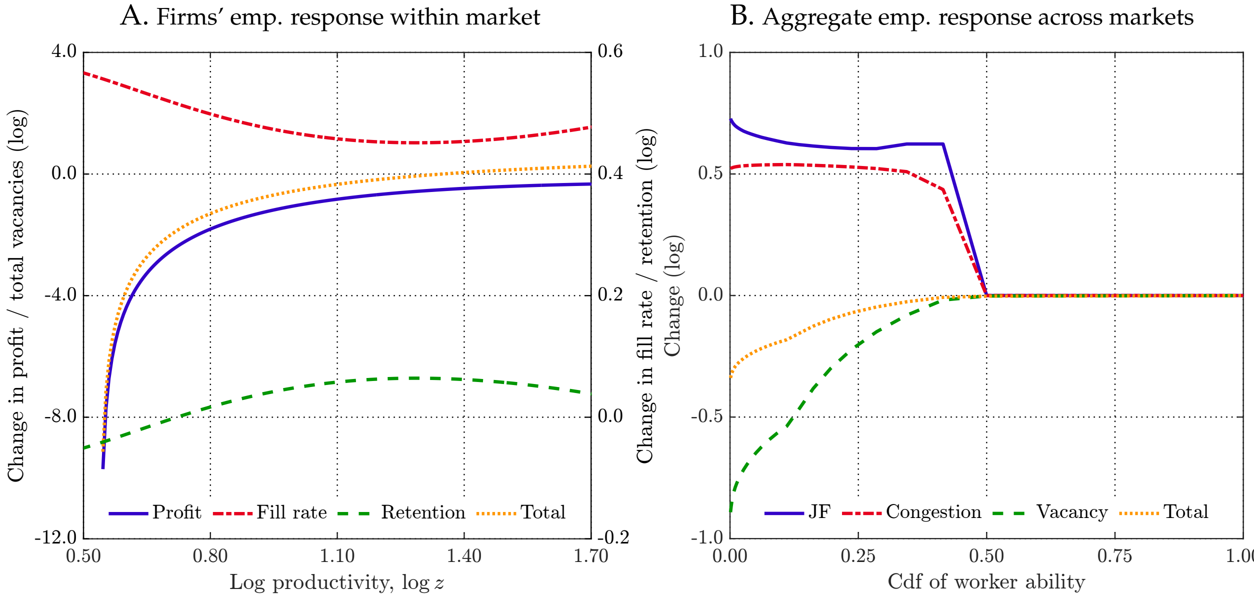
Panel B of Figure 11 shows the results from decomposing the aggregate employment response to the minimum wage based on equation (12) across ability ranks. Only workers in the bottom half of the ability distribution are affected. The job finding and congestion channels are roughly constant and positive. The vacancy channel is negative and increases from around -0.8 to 0.0. Combining the channels yields an aggregate employment response that ranges from around -0.3 to 0.0 log points.

In light of the decompositions (11)–(12), Appendix E.6 assesses the robustness of our estimated modest employment response to the increase in the minimum wage with respect to the underlying structural parameters. Over plausible ranges, the estimated employment response remains modest.

7.4 When are the effects of the minimum wage on wage inequality large?

Maybe our most striking finding is the large inequality reduction due to the minimum wage. This result is so striking because previous work on the distributional effects of the minimum wage has found smaller effects in the U.S. (Lee, 1999; Autor et al., 2016; Fortin et al., 2021), Canada (Fortin and Lemieux, 2015; Brochu et al., 2018), and the U.K. (Butcher et al., 2012). To reconcile these differences, we explore the

Figure 11. Decomposing the effect on employment



Notes: Panel A shows a decomposition of firms' recruiting response to a 57.7 log point increase in the minimum wage based on equation (11) for the market with $(a = \underline{a}, s > 0)$. Panel B shows a decomposition of the aggregate employment response across ability markets based on equation (12) for $s > 0$. Both panels show log changes in each component (e.g., $0.2 \approx 20$ percent). JF stands for job finding. *Source:* Model.

sensitivity of our results with respect to four model parameters—the mean of worker ability, μ, the tail index of the productivity distribution, ζ, the separation rate intercept, δ_0, and the job finding rate, λ.[50]

Panel A of Figure 12 shows that a higher mean worker ability, μ, significantly reduces the distributional effects of the minimum wage. Higher values of μ imply that the minimum wage is less binding initially, so the marginal effect of an increase in the minimum wage is smaller. In Appendix B.12, we show that the bindingness of the minimum wage, measured by the P10-P50 log wage percentile ratio, is up to 26 log points higher in Brazil compared to the U.S. Counterfactually reducing μ by 26 log points to mimic the U.S. moment indicates that the effects on the variance of log wages are around 50 percent higher in Brazil compared to the U.S. due to the relatively greater initial bindingness of the minimum wage in Brazil.[51]

Panel B shows a weaker inequality-reducing effect of the minimum wage for higher values of the productivity tail parameter ζ. While our estimate of $\zeta = 3.5$ corresponds to a variance of AKM firm fixed effects of 19.5 log points, Song et al. (2019) report that variance to be 6.7 log points in the U.S. from 1994–2000. For our model to replicate the U.S. moment would require $\zeta = 5.8$ (see panel B of Appendix

[50] Appendix E.7 shows the same comparative statics results with respect to other model parameters. Naturally, our analysis comes with the caveat that, for these experiments, we are considering a movement in only one parameter while holding all other parameters fixed at their estimated values.

[51] Note that due to spillover effects of the minimum wage, μ would need to change by even more than 26 log points in order to change the P10-P50 log wage percentile ratio by 26 log points.

Figure D.6), which would imply that the effects on the variance of log wages are around 18 percent higher in Brazil compared to the U.S. due to the relatively greater productivity dispersion in Brazil.

Panel C shows that a higher job finding rate λ amplifies the effects of the minimum wage on inequality, although the gradient is flatter than in the previous two cases. By comparison, the inequality reduction due to the minimum wage is relatively invariant to the separation rate intercept δ_0 (panel D).

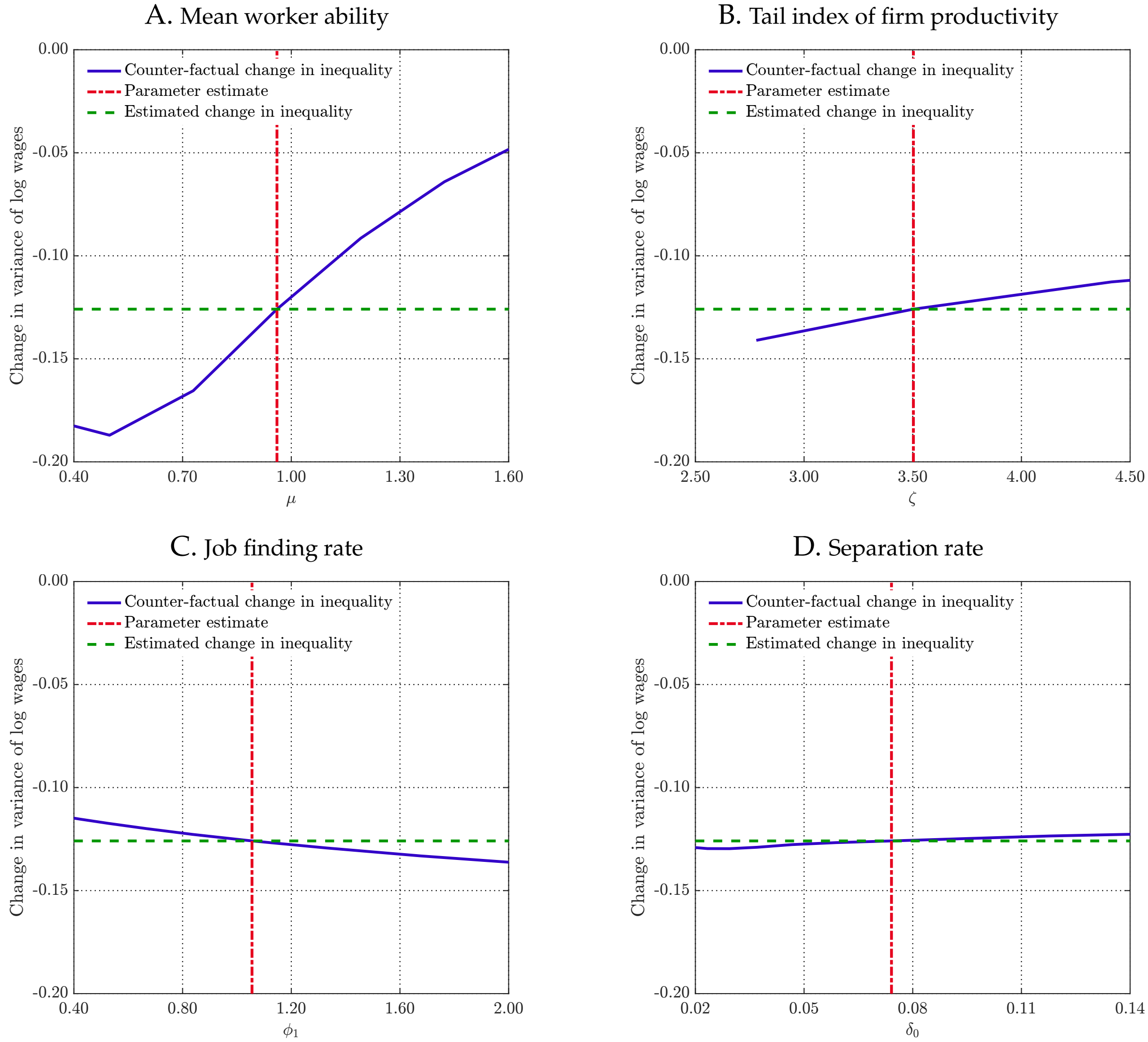
Besides our parameter estimates discussed above, other reasons for why we find relatively large effects of the minimum wage on inequality in Brazil may include the nature of wage setting. Our model assumes that all wages are posted, which is consistent with existing evidence that lower-skill jobs are more likely to post—rather than bargain over—wages (Hall and Krueger, 2012). In related work, Flinn and Mullins (2018) show that spillover effects of the minimum wage can be smaller in an economy where wages are sometimes bargained over, which is likely more so the case in the U.S. than in Brazil.

8 Conclusion

There remains a great debate over the potential for labor market institutions to affect wage inequality. In this paper, we study a large increase in the minimum wage in Brazil using rich administrative and household survey data together with an equilibrium model to shed new light on this debate. Both our reduced-form analysis, based on variation in the bindingness of the minimum wage across Brazilian states, and our estimated structural model indicate significant scope for the minimum wage to compress the distribution of wages, while having only modest disemployment effects. Through the lens of our equilibrium model and consistent with our reduced-form findings, these results are due to far-reaching spillover effects of the minimum wage on firm pay policies as well as worker reallocation across firms.

Our study points to several fruitful avenues for future research. First, while our structural model incorporates a rather simple view of informality, it would be interesting to quantify spillovers of the minimum wage in Brazil's formal sector to jobs in the informal sector, which is not directly constrained by the policy—what Neri and Moura (2006) call the lighthouse effect. Second, given our findings on the prominent role played by firms in the labor market, it is worth revisiting the effects of other labor market policies and institutions—including unions, unemployment benefits, and noncompete agreements—on the distribution of pay and employment in other settings. While such labor market institutions and policies may only affect a small share of workers directly, they may lead to sizable equilibrium effects of the kind we find in Brazil. Finally, our work stops short of an analysis of optimal minimum wage policies in a frictional environment, though our results will be an important ingredient for any such venture.

Figure 12. Minimum wage effects on wage inequality across selected model parameters



Notes: Estimated impact of a 57.7 log point increase in the minimum wage across different parameter values, varying one parameter at a time and holding fixed all other parameters at their estimated values. *Source:* Model.

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