

DISCUSSION PAPER SERIES

DP16143
(v. 2)

Earnings Inequality and the Minimum Wage: Evidence from Brazil

Niklas Engbom and Christian Moser

DEVELOPMENT ECONOMICS

LABOUR ECONOMICS

MACROECONOMICS AND GROWTH

PUBLIC ECONOMICS

CEPR

Earnings Inequality and the Minimum Wage: Evidence from Brazil

Niklas Engbom and Christian Moser

Discussion Paper DP16143
First Published 12 May 2021
This Revision 14 December 2021

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

This Discussion Paper is issued under the auspices of the Centre's research programmes:

- Development Economics
- Labour Economics
- Macroeconomics and Growth
- Public Economics

Any opinions expressed here are those of the author(s) and not those of the Centre for Economic Policy Research. Research disseminated by CEPR may include views on policy, but the Centre itself takes no institutional policy positions.

The Centre for Economic Policy Research was established in 1983 as an educational charity, to promote independent analysis and public discussion of open economies and the relations among them. It is pluralist and non-partisan, bringing economic research to bear on the analysis of medium- and long-run policy questions.

These Discussion Papers often represent preliminary or incomplete work, circulated to encourage discussion and comment. Citation and use of such a paper should take account of its provisional character.

Copyright: Niklas Engbom and Christian Moser

Earnings Inequality and the Minimum Wage: Evidence from Brazil

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.

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

Keywords: Inequality, Wage distribution, minimum wage, Worker and Firm Heterogeneity, Equilibrium Search Model, monopsony, spillover effects, reallocation, employment, Brazil

Niklas Engbom - nengbom@stern.nyu.edu
New York University and NBER and CEPR

Christian Moser - c.moser@columbia.edu
Columbia University and Federal Reserve Bank of Minneapolis and CEPR

Acknowledgements

We thank the editor and three anonymous referees for constructive comments that helped to significantly improve the paper. We are extremely grateful to Mark Aguiar, Mike Golosov, Nobu Kiyotaki, and Richard Rogerson for invaluable advice and encouragement. We also thank Jim Albrecht, Jorge Alvarez, Adrien Auclert, Anmol Bhandari, David Card, Carlos Carrillo-Tudela, Mark Colas, Olivier Darmouni, Cynthia Doniger, David Dorn, Andres Drenik, Christian Dustmann, Henry Farber, Fatih Guvenen, Kyle Herkenhoff, Oleg Itskhoki, Gregor Jarosch, Leo Kaas, Greg Kaplan, Fatih Karahan, Loukas Karabarbounis, Alan Krueger, Per Krusell, Rasmus Lentz, Ilse Lindenlaub, Attila Lindner, Jeremy Lise, Alan Manning, Alex Mas, Ellen McGrattan, Guido Menzio, Virgiliu Midrigan, Ben Moll, Simon Mongey, Giuseppe Moscarini, Andreas Mueller, Joseph Mullins, Makoto Nakajima, Emi Nakamura, Fabrizio Perri, Fabien Postel-Vinay, Todd Schoellman, Uta Schönberg, Jón Steinsson, Venky Venkateswaran, Gianluca Violante, Jonathan Vogel, Susan Vroman, Till von Wachter, Randall Wright, Pierre Yared, and numerous participants at seminars and conferences. Special thanks go to the research staff at IPEA, IBGE, and the Brazilian Ministry of the Economy for facilitating data access. We thank Data Zoom, developed by the Department of Economics at PUC-Rio, for providing the codes for processing IBGE microdata. The authors gratefully acknowledge financial support from CEPR PEDL. Moser benefitted from financial support by the Ewing Marion Kauffman Foundation and the Richard Paul Richman Center for Business, Law, and Public Policy at Columbia University. The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System. Any errors are our own.

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 of the wage distribution up to at least the 75th percentile. At the same time, we find little evidence of negative effects on employment. To understand the impact of the minimum wage, 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 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) in separate time windows. While firms account for 26 percent of the variance of log wages around 1996, 43 percent of the reduction in the variance over time was due to declining firm pay differences for identical workers. To assess what fraction of the aggregate decline in inequality 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 up to at least the 75th wage percentile and a large negative effect on the variance of wages. At the same time, we find no significant effects 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, firm productivity dispersion, 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 operate a linear technology in labor, and choose recruiting intensity and what wage to offer 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 13 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. Finally, we confront the model-implied effects of the minimum wage with cross-sectional evidence, which lends additional support to

our model predictions.

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

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

²Other 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, 2016](#)), hedonic compensation ([Phelan, 2018](#)), and the union threat ([Taschereau-Dumouchel, 2020](#)).

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 paper proceeds 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. Section 8 validates our model predictions using cross-sectional evidence. Finally, Section 9 concludes.

³See 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). 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) and the *Pesquisa Mensal de Emprego* (PME). 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 datasets in more detail.

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.⁵ Among this subpopulation in RAIS, we restrict attention to 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

⁴All of our analysis is at the level of the establishment, which we interchangeably refer to as the firm or the employer.

⁵For a separate study of men and women in Brazil’s labor market, see [Morchio and Moser \(2020\)](#).

necessary or possible in PNAD or PME.⁶

Summary statistics. Table 1 summarizes our sample from the three datasets.⁷ 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.⁸

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 observable characteristics—as demonstrated in Appendix A.4—we estimate two-way fixed effect specifications based on the econometric framework by AKM. Specifically, we decompose log wages w_{ijt} of individual

⁶The 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).

⁷Additional summary statistics are presented in Appendix A.2.

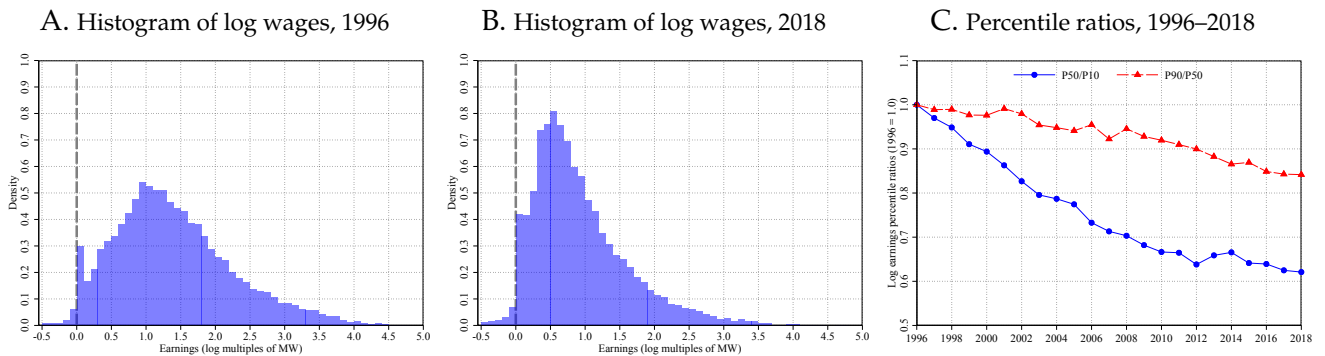
⁸In Appendix A.3, we show that official labor force statistics are compatible with the sample sizes in the RAIS.

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

	Mean	St.d.	Mean	St.d.
<i>Panel A. Administrative linked employer-employee data (RAIS)</i>				
	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	
<i>Panel B. Cross-sectional household survey data (PNAD)</i>				
	1996		2012	
Real wage (log real BRL, formal sector)	7.01	0.81	7.13	0.62
Real wage (log real BRL, informal sector)	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	
<i>Panel C. Longitudinal household survey data (PME)</i>				
	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 equi-spaced 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.

i working at firm j in year t within five-year periods as

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

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).⁹

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 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

⁹There 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. \(2020\)](#) 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 (100%)	0.709 (100%)	0.709 (100%)	0.709 (100%)	0.444 (100%)	0.444 (100%)	0.444 (100%)	0.444 (100%)	-0.265 (100%)	-0.265 (100%)	-0.265 (100%)	-0.265 (100%)
$Var(\hat{\alpha}_i)$	0.323 (46%)	0.279 (39%)	0.217 (31%)	0.176 (25%)	0.264 (59%)	0.241 (54%)	0.173 (39%)	0.154 (35%)	-0.059 (22%)	-0.038 (14%)	-0.044 (17%)	-0.022 (8%)
$Var(\hat{\psi}_j)$	0.212 (30%)	0.198 (28%)	0.201 (28%)	0.187 (26%)	0.083 (19%)	0.076 (17%)	0.078 (18%)	0.072 (16%)	-0.129 (49%)	-0.122 (46%)	-0.123 (46%)	-0.115 (43%)
$2 \times Cov(\hat{\alpha}_i, \hat{\psi}_j)$	0.140 (20%)	0.163 (23%)	0.098 (14%)	0.120 (17%)	0.081 (18%)	0.092 (21%)	0.061 (14%)	0.070 (16%)	-0.059 (22%)	-0.071 (27%)	-0.037 (14%)	-0.050 (19%)
$Var(\hat{\varepsilon}_{ijt})$	0.034 (5%)	0.070 (10%)	0.033 (5%)		0.017 (4%)	0.036 (8%)	0.016 (4%)		-0.017 (6%)	-0.034 (13%)	-0.017 (6%)	
$Corr(\hat{\alpha}_i, \hat{\psi}_j)$	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. $Corr(\hat{\alpha}_i, \hat{\psi}_j)$ 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.

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).¹⁰ 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.¹¹

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.

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.¹² Brazil’s real minimum wage

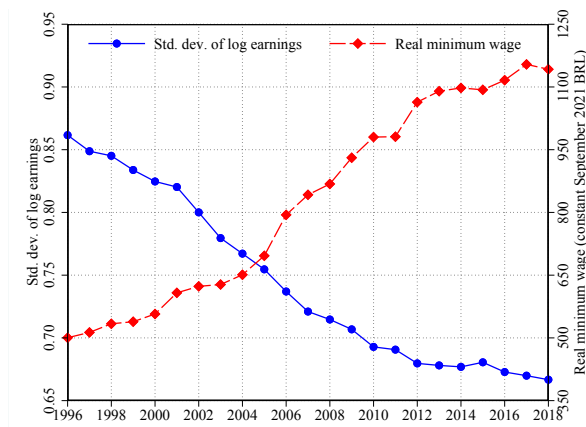
¹⁰Technically, the Federative Republic of Brazil consists of 26 states and one federal district, the *Distrito Federal*. For simplicity, we henceforth refer to all of Brazil’s 27 federative units (i.e., the 26 states and the federal district) as “states.”

¹¹Using 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.

¹²While 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.

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 .¹³

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 Evidence on the effects of the minimum wage in Brazil

4.1 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 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

¹³Appendix B.1 shows an equally striking comovement between earnings inequality and the minimum wage over the extended period from 1985–2018.

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.

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 1996.¹⁴ 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.¹⁵

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.

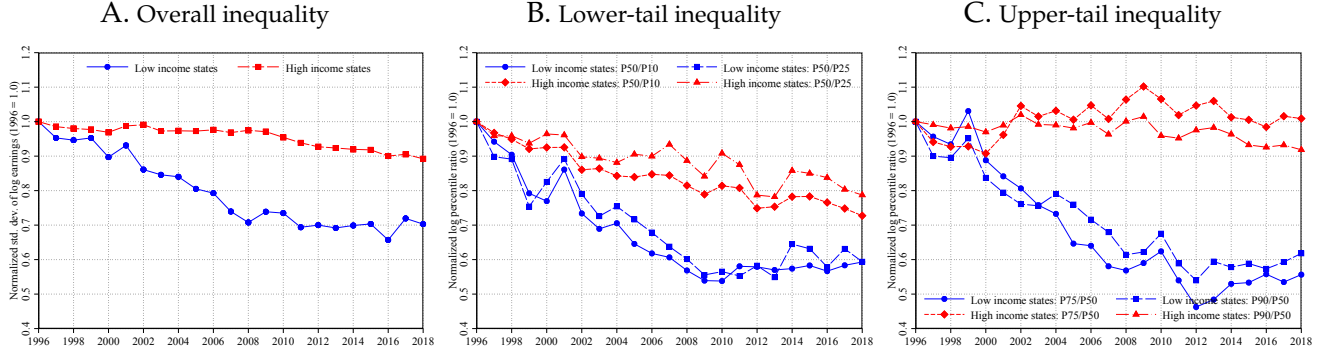
Econometric framework. To correlate the minimum wage with wage inequality, we follow Lee (1999) and Autor et al. (2016) in exploiting heterogeneous exposure across states that differ in their bindingness with respect to Brazil’s federal minimum wage. To this end, we define the *generalized Pp-Kaitz index* for state s in year t as $gkaitz_{st}(p) \equiv \log w_t^{min} - \log w_{st}^{Pp}$. That is, the Pp-Kaitz index is the log difference between the federal minimum wage prevailing in year t , w_t^{min} , and the p th percentile of the log wage distribution of state s in year t , w_{st}^{Pp} .¹⁶ We are interested in how various inequality measures at the state-year level covary with the generalized Pp-Kaitz index, for high enough p such that the p th 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

¹⁴The three low-income states are Maranhão, Piauí, and Paraíba, while the three high-income states are Rio de Janeiro, São Paulo, and Distrito Federal.

¹⁵Appendix 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.

¹⁶Figure B.10 in Appendix B.4 shows that variation across Brazilian states in the generalized Pp-Kaitz 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.

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



Notes: For this figure, we assign the three lowest-income states and three highest-income 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.

in state s and year t on the generalized Pp -Kaitz index, using the same base percentile p , and state-year controls:

$$y_{st}(p'; p) = \sum_{n=1}^N \beta_n(p') gk_{aitz}_{st}(p)^n + \gamma_{st}(p') + \varepsilon_{st}(p'), \quad (2)$$

where N is the polynomial order of the generalized Pp -Kaitz index, $\beta_n(p')$ is the percentile p' -specific coefficient on the n th power of the generalized Pp -Kaitz index, $\gamma_{st}(p')$ denotes a set of percentile p' -specific state-year controls—state dummies and state-specific linear time trends in our baseline specification—and $\varepsilon_{st}(p')$ is a percentile p' -specific error term, which we assume satisfies the strict exogeneity condition $\mathbb{E}[\varepsilon_{st}(p') | gk_{aitz}_{st}(p), \dots, gk_{aitz}_{st}(p)^n, \gamma_{st}(p')] = 0$.

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,

$$\rho(p', p) \equiv \sum_{n=1}^N n \beta_n(p') gk_{aitz}_{st}(p)^{n-1}, \quad (3)$$

evaluated at the worker-weighted median value of the generalized Pp -Kaitz 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 $N = 2$.¹⁷

We first consider as outcome variables in equation (2) a set of measures of global or local wage inequality. As a global inequality measure, we consider the variance of log wages, $y_{st}(p'; p) = \text{Var}(w_{st})$.

¹⁷Using polynomials of order $N > 2$ yields results that are substantially the same as those presented below.

As local inequality measures, we use, for various values of p' , 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 generalized Pp -Kaitz index, with p chosen to be 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.¹⁸ Therefore, we also report results for an alternative, preferred normalization using $p = 90$.

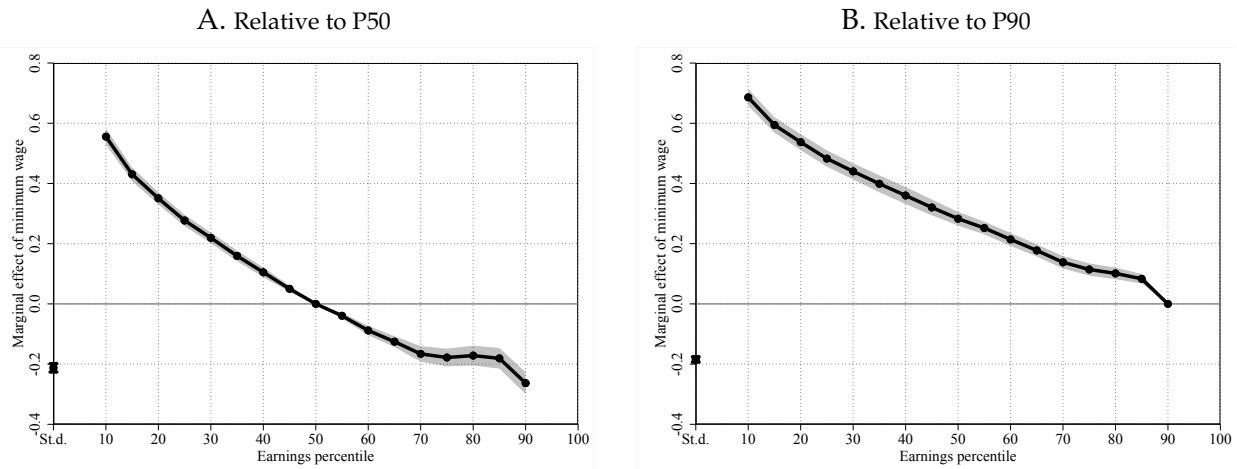
When analyzing the correlation between the minimum wage and log wage percentile ratios, the inclusion of the p th wage percentile in both the dependent and the independent variable may induce a spurious correlation that results in biased estimates of the coefficient $\beta_n(p')$, and thus the marginal 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 generalized Pp -Kaitz 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 median wage 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 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

¹⁸See 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.

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.¹⁹ 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 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.²⁰ 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

¹⁹[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](#).

²⁰[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.

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.²¹ 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).²² 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.²³ 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 to estimate variants of the specification in equation (2) with the dependent variable $y_{st}(p'; p) = y_{st}$ varying only at the region-year level.²⁴

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

²¹Appendix 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.

²²Our 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.

²³See Appendix A.2 for details.

²⁴A region corresponds to Brazil’s 27 states in RAIS and PNAD and to one of the six largest metropolitan areas in PME.

estimates are negative, they are also statistically insignificant at conventional levels.²⁵ 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 Kaitz index, suggesting that the intensive margin of hours adjustments in response to the minimum wage (Doppelt, 2019) is not of prime importance for understanding 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, more productive competitors. The estimated effect on the probability of a worker remaining employed until next year is negative, suggesting that there is some relocation of workers in response to minimum wage increases.²⁶

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

	Marginal effect (standard error)
<i>Panel A. Cross-sectional household survey data (PNAD)</i>	
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)
<i>Panel B. Longitudinal household survey data (PME)</i>	
Transition rate nonformal-formal	−0.003 (0.017)
Transition rate formal-nonformal	−0.005 (0.009)
<i>Panel C. Administrative linked employer-employee data (RAIS)</i>	
Mean log hours worked	0.043 (0.003)
Mean log firm size	0.433 (0.055)
Probability of remaining employed	−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.

4.2 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

²⁵An 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.

²⁶See also Appendix B.14 for a more detailed analysis of the correlation between the minimum wage and hours worked.

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 is compounded if spillovers are present throughout most of the wage distribution.²⁷ 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. 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 $a \in [\underline{a}, \bar{a}]$. 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

²⁷This is a variant of the “missing intercept” problem highlighted in a recent micro-to-macro literature ([Nakamura and Steinsson, 2018](#)).

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, $s \in [\underline{s}, \bar{s}]$. 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 $\pi(s'|a, s)$.²⁸ 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.²⁹ 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.5 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 $z \in [\underline{z}, \bar{z}]$. A firm that employs $l(a, s)$ workers of each type (a, s) produces output according to the linear technology

$$y\left(z, \{l(a, s)\}_{a, s}\right) = z \int_{\underline{a}, \underline{s}}^{\bar{a}, \bar{s}} al(a, s)dad s.$$

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 distribution 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.

²⁸The assumption that search efficiency only updates when a worker transitions into nonemployment avoids added complexity from worker type transition hazards entering firms' problem.

²⁹In 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.

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

Let $U(a, s)$ denote the value to a 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:

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

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:

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

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 distribution of employed workers of type (a, s) over piece rates w . Appendix C shows that this distribution satisfies

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

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, $wa \geq w^{\min}$:

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

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

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

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

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

Henceforth, we assume that the vacancy cost takes an isoelastic form, $c(v, a, s) = ac(a, s)v^{1+\eta}/(1+\eta)$. Define $h(z|a, s) = F(w(z|a, s)|a, s)$ 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 is characterized by a system of differential equations,

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

subject to boundary conditions $\lim_{z \rightarrow \underline{z}(a, s)} w(z|a, s) = \max\{r(a, s), w^{\min}/a\}$ and $\lim_{z \rightarrow \underline{z}(a, s)} h(z|a, s) = 0$, 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 $\lim_{z \rightarrow \bar{z}} h(z|a, s) = 1$.

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.5.

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.³⁰ 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 $\mathbf{p}^* \in \mathcal{P}$ that minimizes the sum of weighted squared percentage deviations between a set of moments in the model and in the data:

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

³⁰Brazil'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.

While all parameters are jointly determined, we assign to each parameter p a set of moments $\mathcal{M}(p)$ 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 $w^{\text{min}} = r(a, s)a$ 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 to $s(a) = 0$ with probability π and retains $s(a)$ with complementary probability $1 - \pi$.³¹ A worker with $s(a) = 0$ who becomes unemployed transitions to $s(a) > 0$ with probability 1. That is,

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

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 $r(a, s > 0) = r_0 + r_1(a - \underline{a})$. 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.³² This approach allows us to solve the model using the system of differential equations in (9) without reference to workers' value functions (4)–(5),

³¹While 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.

³²We 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.

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, $\log \bar{w}$, equals the sum of the logarithm of the true wage, $\log w$, and measurement error, κ , so $\log \bar{w} = \log w + \kappa$. 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 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 12 parameters to estimate by the SMM via indirect inference:³³

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

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.³⁴

The shape of the Pareto distribution for firm productivity, ζ , is informed by the standard deviation

³³Recall 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 $b(a)$.

³⁴For 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.

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 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, $1 + \eta = 1.467$.³⁵ 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

³⁵Because 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.

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 NE rates 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.³⁶ Because the EE rate is high relative to the NE rate in Brazil, we infer a high average relative search efficiency, $s(a)$. This 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 Figure D.3D in Appendix D.2.

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, initially 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, $\bar{w}(a)$, 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)

³⁶Using 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.

Table 4. Parameter estimates

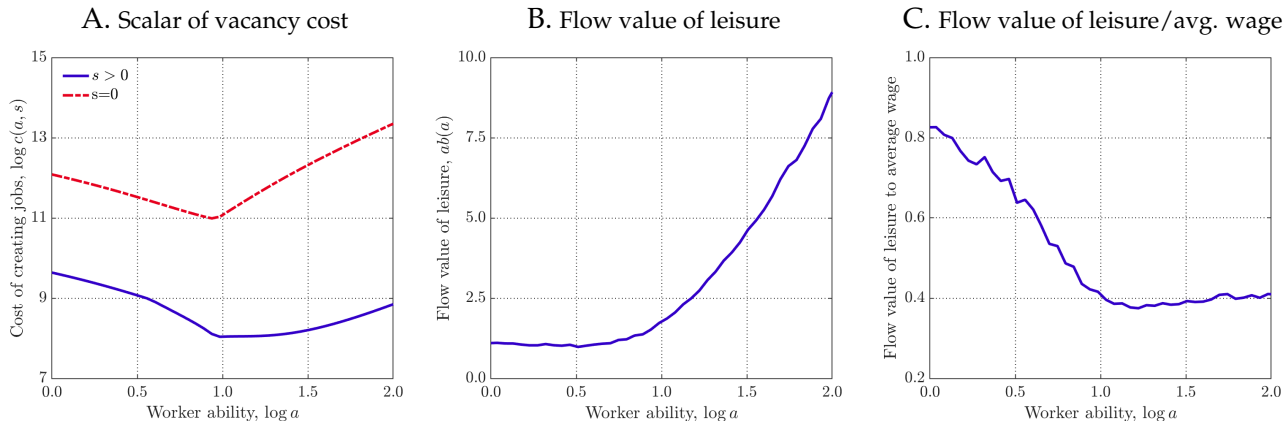
Parameter	Description	Estimate	Targeted moment	Data	Model
<i>Panel A. Preset parameters</i>					
ρ	Discount rate	0.004	Annual real interest rate of 4 percent		
χ	Matching efficiency	1.000	Normalization		
α	Elasticity of matches w.r.t. vacancies	0.500	Petrongolo and Pissarides (2001)		
<i>Panel B. Directly inferred structural and auxiliary parameters</i>					
M	Mass of firms	0.069	Average firm size	11.8	13.1
$\delta(a, 0)$	Separation rate of those with $s = 0$	0.065	EN rate from minimum wage jobs	0.065	0.065
λ	Job finding rate	0.044	NE rate	0.044	0.044
<i>Panel C. Internally estimated structural and auxiliary parameters</i>					
μ	Mean of worker ability	0.960	Median to minimum 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.	0.589	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	EE rate	See Figure D.3	
ϕ_1	Relative search intensity, slope	1.055	EE rate	See Figure D.3	
π	Transition rate to $s = 0$	0.019	Share of employment at minimum wage	0.012	0.011
r_0	Reservation wage, intercept	-0.078	P5 of log wages	See Figure D.3	
r_1	Reservation wage, slope	1.127	P5 of log wages	See Figure D.3	

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

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.

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 mini-

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, $\bar{w}(a) = \int_s \int_z w(z|a,s)dG(z|a,s)d\Phi(s|a)$, where $\Phi(s|a)$ is the conditional distribution of workers of ability a over search efficiency, s . Source: Model.

imum wage.³⁷ 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.³⁸ We note, however, that such extensions would come at a significant increase in computational time, which is already substantial.³⁹

6.3 Worker-firm sorting and firm pay

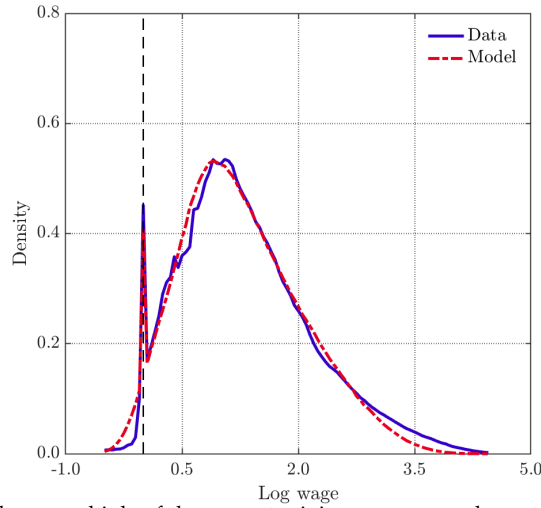
It will be instructive to lay out the mechanics of the estimated model with regards to worker-firm sorting and firm pay. Regarding sorting, panel A of Figure 7 shows that higher-ability workers work at more productive firms, which rationalizes the positive correlation between AKM worker and firm fixed 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.

³⁷ Appendix E.5 shows that our results are robust to varying parameters to better fit these features of the data in isolation.

³⁸ [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 8.1 that our model predicts minimum wage spillovers in line with our reduced-form estimates, 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 for our context.

³⁹ 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.5 shows has a negligible impact on the predicted effects of the minimum wage.

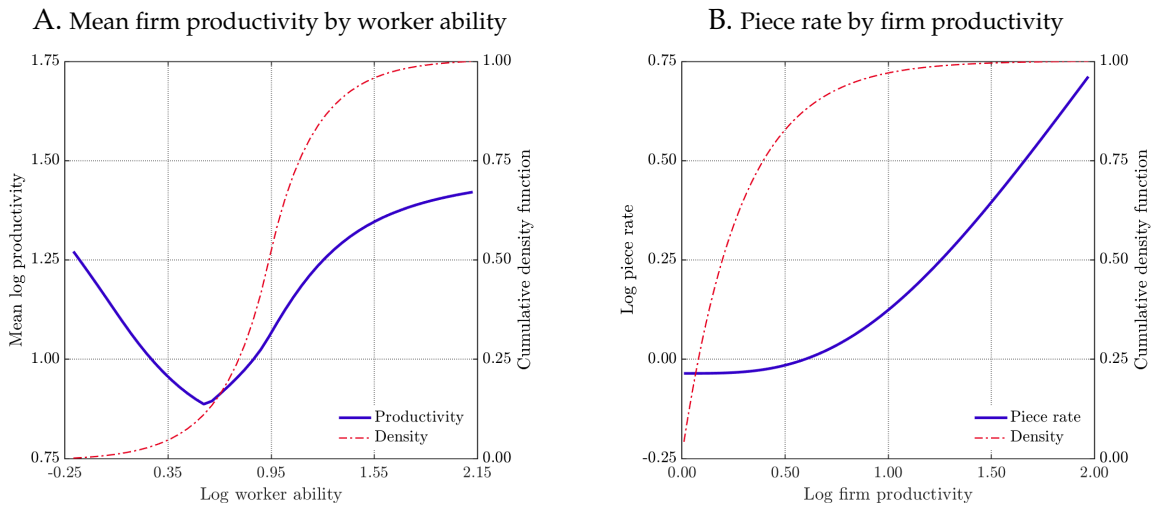
Figure 6. Distribution of wages in estimation period, model vs. data



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.

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, $\int_{\underline{z}}^{\bar{z}} \log z dG(z|a, s)$, 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 a preperiod from 1994–1998, we simulate the equilibrium effects of 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 by 57.7 log points, which corresponds to the rise in the productivity growth-adjusted real minimum wage between 1996 and 2018.

7.1 The impact of the minimum wage on wage inequality

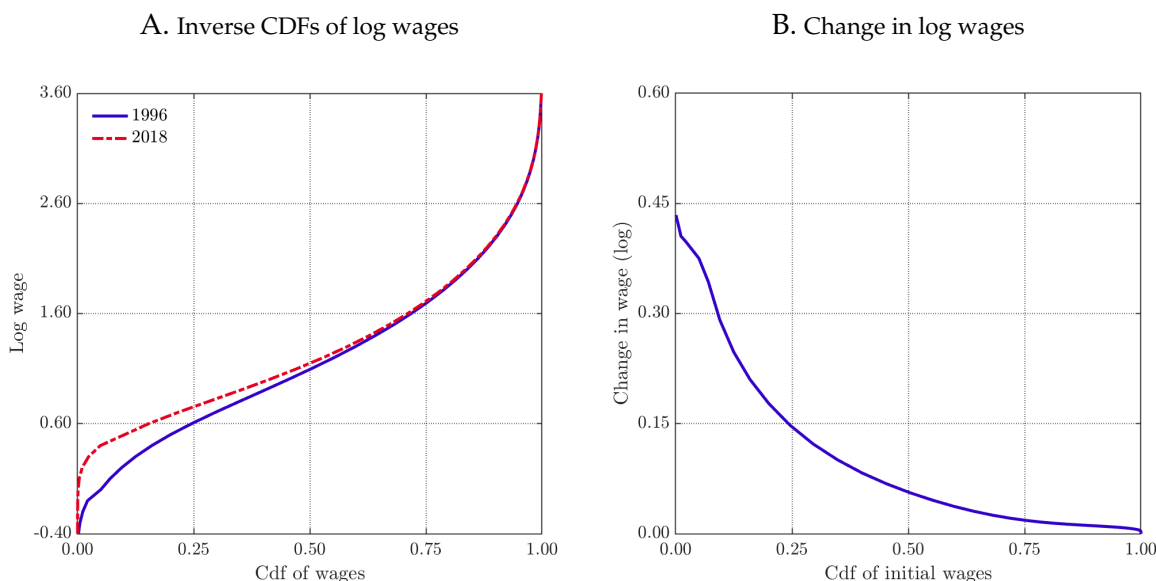
Our main interest lies in the impact of the minimum wage on wage inequality. Figure 8 illustrates the impact of the minimum wage increase on wages throughout the distribution. Panel A shows that the cumulative distribution function (CDF) in 2018 first-order stochastically dominates that in 1996. The 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.⁴⁰ 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. Nevertheless, while spillover effects of the minimum wage are far-reaching, their absolute magnitude is moderate above the median.

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.⁴¹ 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.

⁴⁰The 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 (combined with numerical approximation associated with binning by wage on the x-axis). Because measurement error is normal and hence unbounded, there are always some workers who have very low recorded pay.

⁴¹Appendix E.1 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 8. 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.

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:

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

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, $\bar{w} = \int_{a,s} \int_z w(z|a,s) dG(z|a,s) (e(a,s)/E) d\Omega(a,s)$ is the population mean log wage, and $\bar{w}(a,s) = \int_z w(z|a,s) dG(z|a,s)$ 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.⁴² 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 9 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

⁴²Numbers 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
<i>Rent</i> channel (change in firm wage policy only, fixed allocation)	–	0.496	-0.112
<i>Reallocation</i> channel (reallocation only, fixed firm wage policy)	–	0.562	-0.046
Between variance	0.369	0.258	-0.110
<i>Rent</i> channel (change in firm wage policy only, fixed allocation)	–	0.285	-0.084
<i>Reallocation</i> channel (reallocation only, fixed firm wage policy)	–	0.321	-0.048
Within variance	0.239	0.223	-0.016
<i>Rent</i> channel (change in firm wage policy only, fixed allocation)	–	0.219	-0.020
<i>Reallocation</i> 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.⁴³

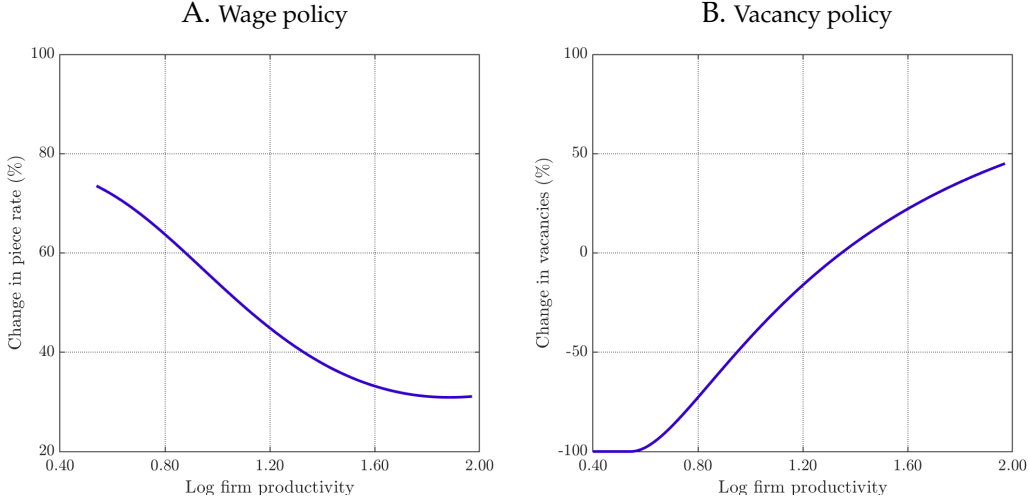
7.3 Aggregate effects of the minimum wage

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.⁴⁴ 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

⁴³We provide empirical support for this model prediction in Appendix E.

⁴⁴This 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.5 for details.

Figure 9. 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, $v(z|a, s)$, by unweighted (i.e., not employment-weighted) productivity, z . Source: Model.

two percent.⁴⁵ 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

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

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

⁴⁵As shown in Figure 8B, 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, $\log Y = \log (\int azdG(z a, s)e(a, s)d\Omega(a, s))$	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, $\log W = \log (\int aw(z a, s)dG(z a, s)e(a, s)d\Omega(a, s))$	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 $\log Y = \log (\int azdG(z|a, s)e(a, s)d\Omega(a, s))$. 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 $\log W = \log (\int aw(z|a, s)dG(z|a, s)e(a, s)d\Omega(a, s))$. 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 10 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

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

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 ($\pi \rightarrow 0$),

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

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.

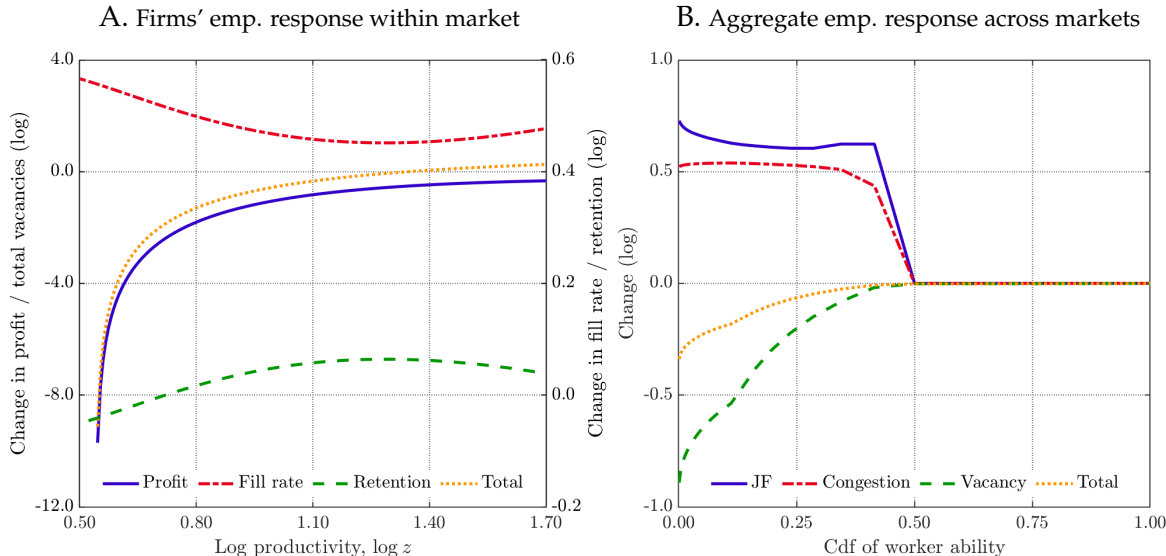
Panel B of Figure 10 shows the results from decomposing the aggregate employment response to the minimum wage based on equation (12) across ability ranks. Only workers in the bottom half of the ability distribution are affected. The job finding and congestion channels are roughly constant and positive. 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.4 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 10. 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 $(a = a, s > 0)$. 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 .⁴⁶

Panel A of Figure 11 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.⁴⁷

Panel B shows that the 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

⁴⁶Appendix E.5 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.

⁴⁷Note 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.

of Appendix 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 Confronting the model with cross-sectional evidence

We now confront the predictions of our structural model with cross-sectional evidence on the reach of spillover effects and the inequality-reducing effects of the minimum wage.

8.1 Spillover effects of the minimum wage in the model vs. data

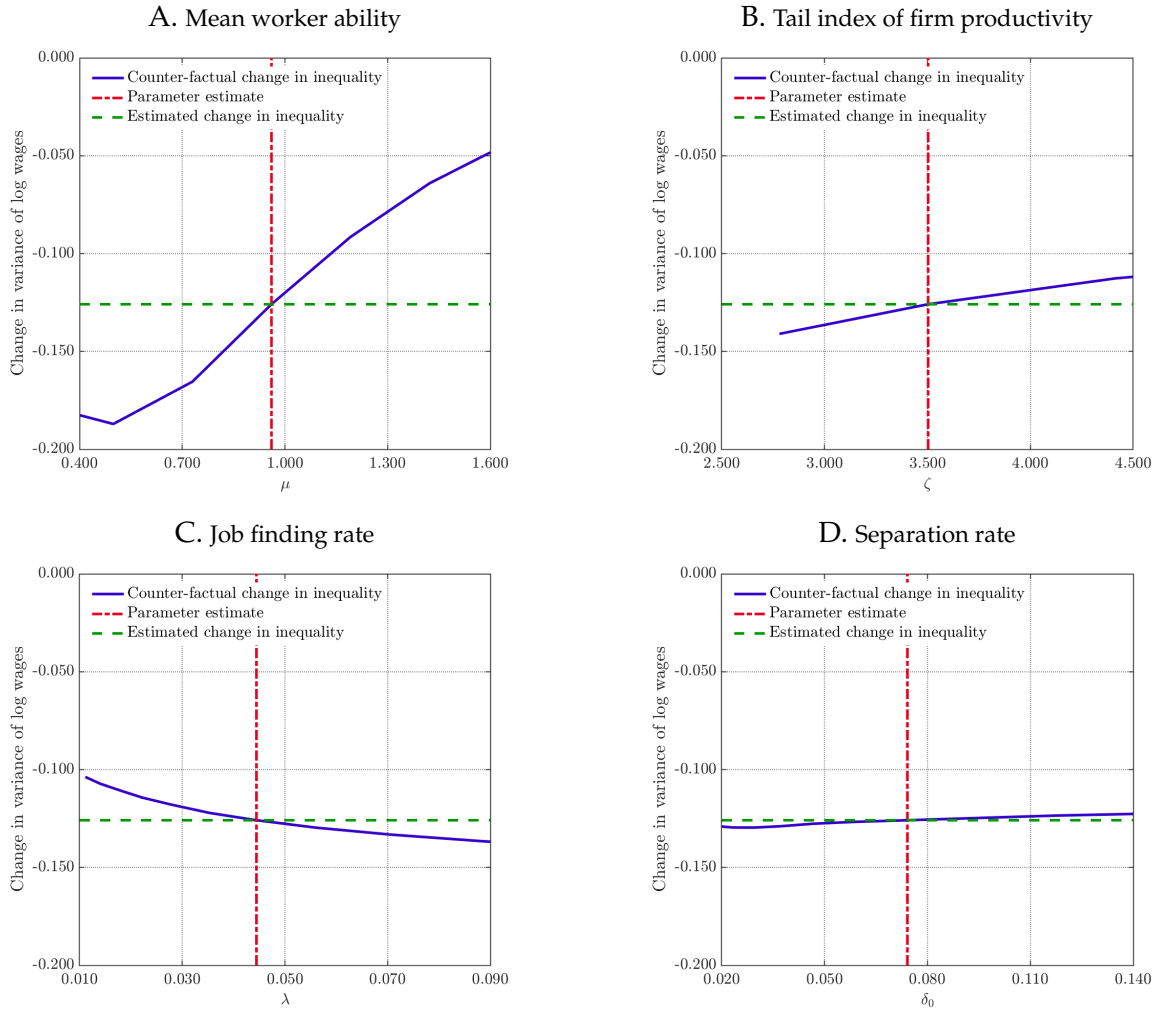
To compare the model-predicted effects of the minimum wage on inequality with estimates from our reduced-form approach following Lee (1999) and Autor et al. (2016), we simulate “state-year-level” data from our estimated model by varying only the level of the minimum wage relative to mean worker ability in order to replicate the empirical distribution of the Kaitz index across Brazil’s 27 states over time.⁴⁸ We then run the same regression (2) on our model simulations as we did on the data in Section 4.1.

Figure 12 shows that the estimated effects of the minimum wage broadly match between the model and the data. We focus on our preferred specification that uses an OLS strategy, state fixed effects, and state-specific time trends.⁴⁹ 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 as

⁴⁸We 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).

⁴⁹Appendix F.1 compares the model and the data under the four specifications from Section 4.1 and two additional difference specifications.

Figure 11. Minimum wage effects on wage inequality across selected model parameters



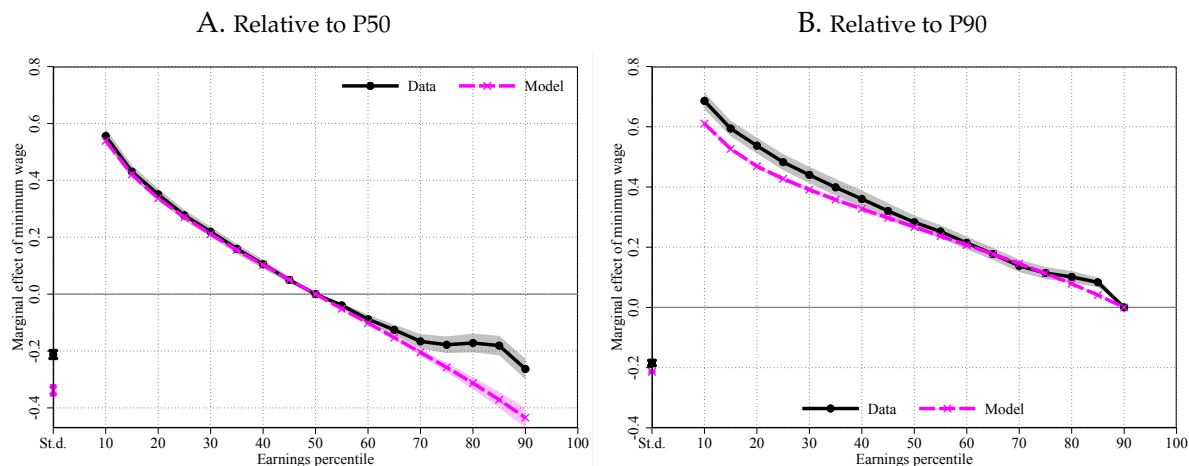
Notes: Estimated impact of a 57.7 log point increase in the minimum wage across different parameter values, varying one parameter at a time and holding fixed all other parameters at their estimated values. Source: Model.

somewhat smaller than the data. It is worth noting that these two sets of estimates were derived under very different assumptions and informed by different moments of the data.

8.2 Effects of the minimum wage on inequality in the model vs. data

To compare the model predictions regarding the determinants of the distributional effects of the minimum wage with the data, we study heterogeneity across simulations in our model and Brazilian states in RAIS. We show comparative statics with respect to the four structural parameters considered in Section 7.4: mean worker ability, μ , the productivity shape parameter, ζ , the job finding rate, λ , and the separation rate intercept, δ_0 . Corresponding to these four structural parameters, we compute four reduced-form

Figure 12. 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.

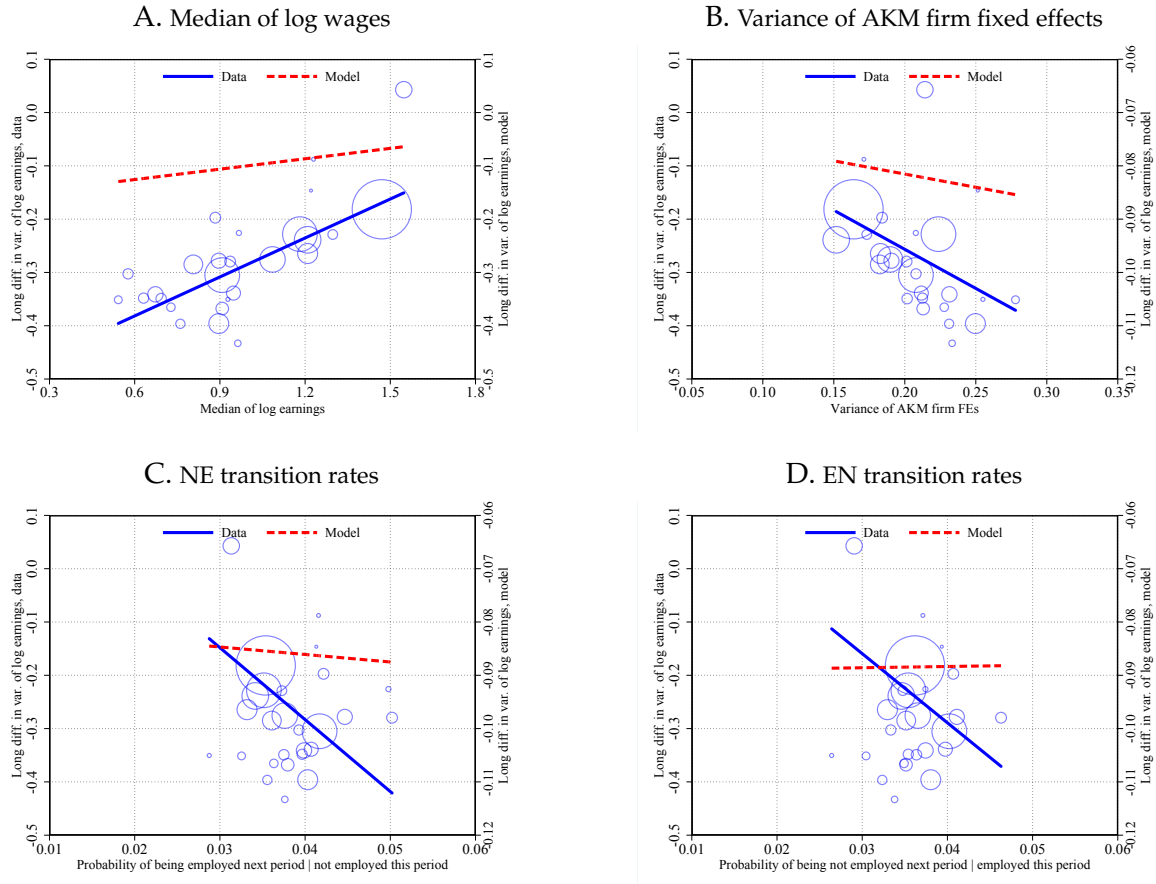
moments across states in 1994–1998: the median of log wages, the variance of AKM firm fixed effects, the probability of starting a formal job, and the probability of leaving a formal job. For each state, we also compute the long difference in the variance of log wages between 1996 and 2018.

Figure 13 compares the results for worker-year-weighted states in the data and equally-weighted “states” in the model for these four metrics.⁵⁰ First, the strongest model prediction is that a higher mean of worker ability, μ , leads to a smaller reduction in wage inequality. Panel A confirms this intuition by showing that the empirical decline in wage inequality was smaller in states with initially higher median log wages. Second, according to the model, lower values of the productivity tail parameter, ζ , are associated with a greater reduction in inequality. Panel B shows that, qualitatively, inequality declines by more in regions with higher dispersion in AKM firm fixed effects in the data as in the model. Quantitatively, however, the relationship is stronger in the data. Third, the model predicted that a high job finding rate, λ , means that the minimum wage has a greater negative impact on inequality. In the data, like in the model, we indeed find a negative relationship between initial EN transition rates and subsequent inequality changes, as shown in panel C. Again, the relationship is stronger in the data than in the model. Fourth, the model predicted a comparably flat relationship between the job separation

⁵⁰Appendix F.2 shows the same relationships with equal weights both in the data and in the model. Appendix F.3 shows analogous results for the comparative statics of the employment effects of the minimum wage in the data and in the model.

rate, δ , and the decline in wage inequality. Panel D paints a mixed picture of the relationship between EN transition rates and changes in inequality, with a negative estimated slope but lots of idiosyncratic dispersion in the data.⁵¹

Figure 13. Changes in inequality across observable labor market characteristics, model vs. data



Notes: Figure plots long differences between 1996 and 2018 in wage inequality—measured by the variance of log wages—across states in the data (blue solid line) and across simulations in the model (red dashed line). Variables on the x-axis are the median of log wages (panel A), the variance of AKM firm fixed effects (panel B) the probability of a transition from nonemployment into employment (panel C), and the probability of a transition from employment into nonemployment (panel D). The median of log wages is computed in 1996, while transition probabilities are computed in a balanced monthly panel from 1994 to 1998. States are represented as hollow circles, with their area proportional to their sample population in 1996. Linear best fit line is shown for the data (blue solid line) and the model (red dashed line), using OLS regression of inequality measures on the respective variable on the x-axis. Data is weighted by number of worker-years in each state, while model is equally weighted across states. Source: RAIS, 1994–1998 and 2018.

While key model predictions are consistent with the reduced-form evidence, our model misses other important features of the data. One reason for this might be that Brazil has seen a period of rapid formalization starting in the early 2000s, which our model has been silent on (Haanwinkel and Soares, 2020; Engbom et al., 2021). Another reason is that, over this period, educational attainment in Brazil rose

⁵¹One reason why the empirical relationship between EN (or NE) rates and the change in inequality might be less informative, is that we may misclassify true EE transitions in the data if they end (or start) in the informal sector.

rapidly for reasons entirely outside of our model (Binelli et al., 2008; Mak and Siow, 2017). Similarly, the country underwent rapid trade liberalization for unmodeled reasons (Dix-Carneiro, 2014; Dix-Carneiro and Kovak, 2017, 2019; Dix-Carneiro et al., 2018). Finally, the country has experienced rapid technological change and structural transformation that has also affected the organization of labor (Bustos et al., 2016). For these reasons, our model estimates should be interpreted as corresponding to a counterfactual in which none of these other changes happened concurrently.⁵² Nevertheless, we believe the exercises presented above are useful because they demonstrate empirical support for key mechanisms of our model while also pointing us in the direction of areas for further investigation.

9 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 and worker reallocation across heterogeneous 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.

⁵²Haanwinckel (2020) studies the effects of the Brazil minimum wage in a model that incorporates some of these additional features and reaches conclusions consistent with ours.

References

- Aaronson, Daniel, Eric French, Isaac Sorkin, and Ted To**, “Industry Dynamics and the Minimum Wage: A Putty-Clay Approach,” *International Economic Review*, 2018, 59 (1), 51–84.
- Abowd, John M, Francis Kramarz, and David N Margolis**, “High Wage Workers and High Wage Firms,” *Econometrica*, 1999, 67 (2), 251–333.
- Allegretto, Sylvia, Arindrajit Dube, Michael Reich, and Ben Zipperer**, “Credible Research Designs for Minimum Wage Studies: A Response to Neumark, Salas, and Wascher,” *ILR Review*, 2017, 70 (3), 559–592.
- Alvarez, Jorge, Felipe Benguria, Niklas Engbom, and Christian Moser**, “Firms and the Great Decline of Earnings Inequality in Brazil,” *American Economic Journal: Macroeconomics*, 2018, 10 (1), 149–189.
- Andrews, Martyn J., Leonard Gill, Thorsten Schank, and Richard Upward**, “High Wage Workers and Low Wage Firms: Negative Assortative Matching or Limited Mobility Bias?,” *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 2008, 171 (3), 673–697.
- Autor, David H., Alan Manning, and Christopher L. Smith**, “The Contribution of the Minimum Wage to US Wage Inequality over Three Decades: A Reassessment,” *American Economic Journal: Applied Economics*, 2016, 8 (1), 58–99.
- Bárány, Zsófia L.**, “The Minimum Wage and Inequality: The Effects of Education and Technology,” *Journal of Labor Economics*, 2016, 34 (1), 237–274.
- Barth, Erling, Alex Bryson, James C. Davis, and Richard Freeman**, “It’s Where You Work: Increases in the Dispersion of Earnings across Establishments and Individuals in the United States,” *Journal of Labor Economics*, 2016, 34 (S2), S67–S97.
- Berger, David, Kyle Herkenhoff, and Simon Mongey**, “Minimum Wages and Welfare,” Technical Report 2021.
- Berger, David W., Kyle F. Herkenhoff, and Simon Mongey**, “Labor Market Power,” Technical Report 2019.
- Bilal, Adrien and Hugo Lhuillier**, “Outsourcing, Inequality and Aggregate Output,” *Working Paper*, 2021.
- , **Niklas Engbom, Simon Mongey, and Giovanni L. Violante**, “Firm and Worker Dynamics in a Frictional Labor Market,” *Working Paper*, 2019.
- Binelli, Chiara, Costas Meghir, and Naercio Menezes-Filho**, “Education and Wages in Brazil,” *Working Paper*, 2008.
- Bonhomme, Stéphane, Kerstin Holzheu, Thibaut Lamadon, Elena Manresa, Magne Mogstad, and Bradley Setzler**, “How Much Should We Trust Estimates of Firm Effects and Worker Sorting?,” *NBER Working Paper No. 27368*, 2020.
- , **Thibaut Lamadon, and Elena Manresa**, “A Distributional Framework for Matched Employer Employee Data,” *Econometrica*, 2019, 87 (3), 699–739.
- Bontemps, Christian, Jean-Marc Robin, and Gerard J. van den Berg**, “An Empirical Equilibrium Job Search Model with Search on the Job and Heterogeneous Workers and Firms,” *International Economic Review*, 1999, 40 (4), 1039–1074.
- , –, and –, “Equilibrium Search with Continuous Productivity Dispersion: Theory and Nonparametric Estimation,” *International Economic Review*, 2000, 41 (2), 305–358.
- Borovičková, Katarína and Robert Shimer**, “High Wage Workers Work for High Wage Firms,” *Working Paper*, 2020.
- Brochu, Pierre, David A. Green, Thomas Lemieux, and James Townsend**, “The Minimum Wage, Turnover, and the Shape of the Wage Distribution,” *Working Paper*, 2018.
- Burdett, Kenneth and Dale T. Mortensen**, “Wage Differentials, Employer Size, and Unemployment,” *International Economic Review*, 1998, 39 (2), 257–273.
- Bustos, Paula, Bruno Caprettini, and Jacopo Ponticelli**, “Agricultural Productivity and Structural Transformation: Evidence from Brazil,” *American Economic Review*, 2016, 106 (6), 1320–65.
- Butcher, Tim, Richard Dickens, and Alan Manning**, “Minimum Wages and Wage Inequality: Some Theory and an Application to the UK,” *CEP Discussion Paper No. 1177*, 2012.
- Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin**, “Wage Bargaining with On-the-Job Search: Theory and Evidence,” *Econometrica*, 2006, 74 (2), 323–364.

- Cameron, A. Colin and Douglas L. Miller**, “A Practitioner’s Guide to Cluster-Robust Inference,” *Journal of Human Resources*, 2015, 50 (2), 317–372.
- Card, David, Alexandre Mas, Enrico Moretti, and Emmanuel Saez**, “Inequality at Work: The Effect of Peer Salaries on Job Satisfaction,” *American Economic Review*, 2012, 102 (6), 2981–3003.
- , **Ana Rute Cardoso, Joerg Heining, and Patrick Kline**, “Firms and Labor Market Inequality: Evidence and Some Theory,” *Journal of Labor Economics*, 2018, 36 (S1), S13–S70.
- and **Alan B. Krueger**, “Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania,” *American Economic Review*, 1994, 84 (4), 772–793.
- and – , *Myth and Measurement: The New Economics of the Minimum Wage*, Princeton, NJ: Princeton University Press, 1995.
- , **Jörg Heining, and Patrick Kline**, “Workplace Heterogeneity and the Rise of West German Wage Inequality,” *Quarterly Journal of Economics*, 2013, 128 (3), 967–1015.
- Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer**, “The Effect of Minimum Wages on Low-Wage Jobs,” *Quarterly Journal of Economics*, 2019, 134 (3), 1405–1454.
- Clemens, Jeffrey**, “How Do Firms Respond to Minimum Wage Increases? Understanding the Relevance of Non-employment Margins,” *Journal of Economic Perspectives*, 2021, 35 (1), 51–72.
- , **Lisa B. Kahn, and Jonathan Meer**, “Dropouts Need Not Apply? The Minimum Wage and Skill Upgrading,” *Journal of Labor Economics*, 2021, 39 (S1), S107–S149.
- Corseuil, Carlos Henrique, Miguel Foguel, and Marcos Hecksher**, “Efeitos dos Pisos Salariais Estaduais Sobre o Mercado de Trabalho: Uma Nova Abordagem Empírica,” *Economia Aplicada*, 2015, 19 (1), 131–169.
- Davis, Steve J. and John Haltiwanger**, “Wage Dispersion between and within U.S. Manufacturing Plants, 1963–86,” *Brookings Papers on Economic Activity. Microeconomics*, 1991, 1991, 115–200.
- Dey, Matthew S. and Christopher J. Flinn**, “An Equilibrium Model of Health Insurance Provision and Wage Determination,” *Econometrica*, 2005, 73 (2), 571–627.
- Diamond, Peter A.**, “A Model of Price Adjustment,” *Journal of Economic Theory*, 1971, 3 (2), 156–168.
- DiNardo, John E., Nicole M. Fortin, and Thomas Lemieux**, “Labor Market Institutions and the Distribution of Wages, 1973–1992: A Semiparametric Approach,” *Econometrica*, 1996, 64, 1001–1044.
- Dix-Carneiro, Rafael**, “Trade Liberalization and Labor Market Dynamics,” *Econometrica*, 2014, 82 (3), 825–885.
- and **Brian K. Kovak**, “Trade Liberalization and Regional Dynamics,” *American Economic Review*, 2017, 107 (10), 2908–2946.
- and – , “Margins of Labor Market Adjustment to Trade,” *Journal of International Economics*, 2019, 117 (C), 125–142.
- , **Pinelopi K. Goldberg, Costas Meghir, and Gabriel Ulyssea**, “Trade and Informality in the Presence of Labor Market Frictions and Regulations,” *NBER Working Paper No. 28391*, 2021.
- , **Rodrigo R. Soares, and Gabriel Ulyssea**, “Economic Shocks and Crime: Evidence from the Brazilian Trade Liberalization,” *American Economic Journal: Applied Economics*, 2018, 10 (4), 158–95.
- Doppelt, Ross**, “Minimum Wages and Hours of Work,” *Working Paper*, 2019.
- Dustmann, Christian, Attila Lindner, Uta Schönberg, Matthias Umkehrer, and Philipp vom Berge**, “Reallocation Effects of the Minimum Wage,” *Working Paper*, 2020.
- Eeckhout, Jan and Philipp Kircher**, “Identifying Sorting—In Theory,” *Review of Economic Studies*, 2011, 78 (3), 872–906.
- Elsby, Michael W. L. and Axel Gottfries**, “Firm dynamics, on-the-job search and labor market fluctuations,” 2019.
- Engbom, Niklas**, “Misallocative Growth,” *Working Paper*, 2020.
- , “Labor Market Fluidity and Human Capital Accumulation,” *Working Paper*, 2021.
- and **Christian Moser**, “Earnings Inequality and the Minimum Wage: Evidence from Brazil,” *Federal Reserve Bank of Minneapolis OIGI Institute Working Paper 7*, 2018.
- , **Gustavo Gonzaga, Christian Moser, and Roberta Olivieri**, “Earnings Inequality and Dynamics in the Presence of Informality: The Case of Brazil,” *Working Paper*, 2021.
- Fajnzylber, Pablo**, “Minimum Wage Effects throughout the Wage Distribution: Evidence from Brazil’s Formal and Informal Sectors,” *CEDEPLAR Working Paper No. 151*, 2001, (td151).

- Firpo, Sergio and Alysson Portella**, "Decline in Wage Inequality in Brazil: A Survey," *World Bank Policy Research Working Paper No. 9096*, 2019.
- Firpo, Sergio P., Nicole M. Fortin, and Thomas Lemieux**, "Decomposing Wage Distributions Using Recentered Influence Function Regressions," *Econometrics*, 2018, 6 (2).
- Flinn, Christopher J.**, "Minimum Wage Effects on Labor Market Outcomes under Search, Matching, and Endogenous Contact Rates," *Econometrica*, 2006, 74 (4), 1013–1062.
- , *The Minimum Wage and Labor Market Outcomes*, Cambridge, MA: MIT Press, 2010.
- and **Joseph Mullins**, "Firms' Choices of Wage-Setting Protocols in the Presence of Minimum Wages," *Working Paper*, 2018.
- Fortin, Nicole M. and Thomas Lemieux**, "Changes in Wage Inequality in Canada: An Interprovincial Perspective," *Canadian Journal of Economics*, 2015, 48 (2), 682–713.
- , –, and **Neil Lloyd**, "Labor Market Institutions and the Distribution of Wages: The Role of Spillover Effects," *NBER Working Paper No. 28375*, 2021.
- Gerard, François, Lorenzo Lagos, Edson Severnini, and David Card**, "Assortative Matching or Exclusionary Hiring? The Impact of Employment and Pay Policies on Racial Wage Differences in Brazil," *Working Paper*, 2020.
- Gouin-Bonenfant, Émilien**, "Productivity Dispersion, Between-Firm Competition, and the Labor Share," 2020.
- Grossman, Jean Baldwin**, "The Impact of the Minimum Wage on Other Wages," *Journal of Human Resources*, 1983, 18 (3), 359–378.
- Haanwinckel, Daniel**, "Supply, Demand, Institutions, and Firms: A Theory of Labor Market Sorting and the Wage Distribution," *Working Paper*, 2020.
- and **Rodrigo R. Soares**, "Workforce Composition, Productivity, and Labor Regulations in a Compensating Differentials Theory of Informality," *Working Paper*, 2020.
- Hall, Robert E. and Alan B. Krueger**, "Evidence on the Incidence of Wage Posting, Wage Bargaining, and On-the-Job Search," *American Economic Journal: Macroeconomics*, 2012, 4 (4), 56–67.
- Harasztosi, Peter and Attila Lindner**, "Who Pays for the Minimum Wage?," *American Economic Review*, 2019, 109 (8), 2693–2727.
- Hornstein, Andreas, Per Krusell, and Giovanni L. Violante**, "Frictional Wage Dispersion in Search Models: A Quantitative Assessment," *American Economic Review*, 2011, 101 (7), 2873–2898.
- Jales, Hugo**, "Estimating the effects of the minimum wage in a developing country: A density discontinuity design approach," *Journal of Applied Econometrics*, 2018, 33 (1), 29–51.
- Jarosch, Gregor**, "Searching for Job Security and the Consequences of Job Loss," *Working Paper*, 2021.
- Kline, Patrick, Raffaele Saggio, and Mikkel Sølvsten**, "Leave-Out Estimation of Variance Components," *Econometrica*, 2020, 88 (5), 1859–1898.
- Lee, David S.**, "Wage Inequality in The United States During The 1980s: Rising Dispersion Or Falling Minimum Wage?," *Quarterly Journal of Economics*, 1999, 114 (3), 977–1023.
- Lemos, Sara**, "The Effects of the Minimum Wage on Wages, Employment and Prices," *Working Paper*, 2004, (No. 1135).
- , "Minimum Wage Effects in a Developing Country," *Labour Economics*, 2009, 16 (2), 224–237.
- Lentz, Rasmus**, "Sorting by Search Intensity," *Journal of Economic Theory*, 2010, 145 (4), 1436–1452.
- Lise, Jeremy and Jean-Marc Robin**, "The Macrodynamics of Sorting between Workers and Firms," *American Economic Review*, 2017.
- Lopes de Melo, Rafael**, "Firm Heterogeneity, Sorting and the Minimum Wage," *Working Paper*, 2012.
- , "Firm Wage Differentials and Labor Market Sorting: Reconciling Theory and Evidence," *Journal of Political Economy*, 2018, 126 (1), 313–346.
- Machin, Stephen, Alan Manning, and Lupin Rahman**, "Where the Minimum Wage Bites Hard: Introduction of Minimum Wages to a Low Wage Sector," *Journal of the European Economic Association*, 2003, 1 (1), 154–180.
- Mak, Eric and Aloysius Siow**, "Occupational Choice and Matching in the Labor Market," *Working Paper*, 2017.
- Manning, Alan**, *Monopsony in Motion: Imperfect Competition in Labor Markets*, Princeton, NJ: Princeton University Press, 2003.

- Meghir, Costas, Renata Narita, and Jean-Marc Robin**, “Wages and Informality in Developing Countries,” *American Economic Review*, 2015, 105 (4), 1509–1546.
- Morchio, Iacopo and Christian Moser**, “The Gender Gap: Micro Sources and Macro Consequences,” *Working Paper*, 2020.
- Mortensen, Dale T. and Eva Nagypal**, “More on Unemployment and Vacancy Fluctuations,” *Review of Economic Dynamics*, 2007, 10 (3), 327–347.
- Nakamura, Emi and Jón Steinsson**, “Identification in Macroeconomics,” *Journal of Economic Perspectives*, August 2018, 32 (3), 59–86.
- Neri, Marcelo and Rodrigo Moura**, “Brasil: La Institucionalidad del Salario Mínimo,” in A. Marinakis and J.J. Velasco, eds., *¿Para Qué Sirve el Salario Mínimo? Elementos para Su Determinación de los Países del Cono Sur*, 2006, pp. 217–260.
- Neumark, David**, “The Employment Effects of Minimum Wages: Some Questions We Need to Answer,” 2017.
- and **William L. Wascher**, *Minimum Wages*, Cambridge, MA: The MIT Press, 2008.
- and **William Wascher**, “Reply to “Credible Research Designs for Minimum Wage Studies”,” *ILR Review*, 2017, 70 (3), 593–609.
- , **J. M. Ian Salas, and William Wascher**, “Revisiting the Minimum Wage-Employment Debate: Throwing Out the Baby with the Bathwater?,” *ILR Review*, 2014, 67 (3), 608–648.
- , **Wendy Cunningham, and Lucas Siga**, “The Effects of the Minimum Wage in Brazil on the Distribution of Family Incomes: 1996–2001,” *Journal of Development Economics*, 2006, 80 (1), 136–159.
- Petrongolo, Barbara and Christopher A. Pissarides**, “Looking into the Black Box: A Survey of the Matching Function,” *Journal of Economic Literature*, 2001, 39 (2), 390–431.
- Phelan, Brian J.**, “Hedonic-Based Labor Supply Substitution and the Ripple Effect of Minimum Wages,” *Working Paper*, 2018.
- Postel-Vinay, Fabien and Jean-Marc Robin**, “Equilibrium Wage Dispersion with Worker and Employer Heterogeneity,” *Econometrica*, 2002, 70 (6), 2295–2350.
- Rinz, Kevin and John Voorheis**, “The Distributional Effects of Minimum Wages: Evidence from Linked Survey and Administrative Data,” *CARRA Working Paper Series, Working Paper 2018-02*, 2018.
- Saltiel, Fernando and Sergio Urzúa**, “Does an Increasing Minimum Wage Reduce Formal Sector Employment? Evidence from Brazil,” *Working Paper*, 2020.
- Shimer, Robert**, “The Cyclical Behavior of Equilibrium and Vacancies Unemployment,” *American Economic Review*, 2005, 95 (1), 25–49.
- , “Reassessing the Ins and Outs of Unemployment,” *Review of Economic Dynamics*, 2012, 15 (2), 127–148.
- Song, Jae, David J. Price, Fatih Guvenen, Nicholas Bloom, and Till Von Wachter**, “Firming Up Inequality,” *Quarterly Journal of Economics*, 2019, 134 (1), 1–50.
- Taschereau-Dumouchel, Mathieu**, “The Union Threat,” *Review of Economic Studies*, 2020, 87 (6), 2859–2892.
- Teulings, Coen N.**, “The Wage Distribution in a Model of the Assignment of Skills to Jobs,” *Journal of Political Economy*, 1995, 103 (2), 280–315.
- , “Aggregation Bias in Elasticities of Substitution and the Minimum Wage Paradox,” *International Economic Review*, 2000, 41 (2), 359–398.
- , “The Contribution of Minimum Wages to Increasing Wage Inequality,” *Economic Journal*, 2003, 113 (490), 801–833.
- Ulysea, Gabriel**, “Firms, Informality, and Development: Theory and Evidence from Brazil,” *American Economic Review*, 2018, 108 (8), 2015–2047.
- , “Informality: Causes and Consequences for Development,” *Annual Review of Economics*, 2020, 12 (1), 525–546.
- U.S. Bureau of Labor Statistics**, “Characteristics of Minimum Wage Workers, 2016,” *Technical Report* 2017.
- van den Berg, Gerard J. and Geert Ridder**, “An Empirical Equilibrium Search Model of the Labor Market,” *Econometrica*, 1998, 66 (5), 1183–1221.
- Zhang, Weilong**, “Distributional Effects of Local Minimum Wage Hikes: A Spatial Job Search Approach,” *Working Paper*, 2018.

Online Appendix—Not for Publication

The overview of the appendices is as follows. Appendix [A](#) gives further details on the datasets introduced in Section [2](#). Appendix [B](#) presents additional empirical results building on Section [4](#). Appendix [C](#) adds to the description of our equilibrium model from Section [5](#). Appendix [D](#) provides more information on the model estimation routine and results extending what is presented in Section [6](#). Appendix [E](#) shows further results related to the simulated impact of the minimum wage that we consider in Section [7](#). Finally, Appendix [F](#) contains the results of additional model validation exercises complementing the materials in Section [8](#).

A Data Appendix

This appendix provides further details on the datasets introduced in Section 2, including subsections on further data description (Appendix A.1), additional summary statistics (Appendix A.2), a comparison of official labor force statistics and sample sizes in the RAIS administrative data (Appendix A.3), and an exploration of explained wage dispersion when (not) controlling for observable and unobservable heterogeneity (Appendix A.4).

A.1 Dataset description

Administrative linked employer-employee data (RAIS). Our main data source is the *Relação Anual de Informações Sociais* (RAIS), a linked employer-employee register by the Brazilian Ministry of the Economy (*Ministério da Economia*). We use the RAIS microdata with person and firm identifiers covering the period 1985–2018 available to us under a confidentiality agreement with the Brazilian ministry.

Firms’ survey response is mandatory, and misreporting is deterred through audits and threat of fines. The earliest available data go back to 1985, with coverage becoming near universal from 1994 onward. The data contain detailed information on job characteristics, with approximately 66 million formal sector employment spells recorded in 2018. Although reports are annual, we observe for every job spell the date of accession and separation in addition to average monthly earnings. We keep for each worker the highest-paid among each year’s longest employment spells. As Brazil’s minimum wage is set in terms of monthly earnings, henceforth we interchangeably refer to this income concept as “earnings” or “wages.”

The main text presents results of both plug-in and leave-one-out bias corrected variance components of log wages based, following the methodology and code by KSS. For our main analysis, we restrict attention to the largest leave-one-out connected set but do not impose any additional restrictions on either earnings, firm size, or the minimum number of switchers across firms. For a set of additional estimation results of the AKM wage equation (1), we keep workers with earnings not equal to or weakly above the minimum wage.

We devise our own cleaning procedure for these data, starting with the raw text files, benefiting from guidance by the data team at IPEA. Our cleaning procedure consists of three stages. The first stage reads in and standardizes the format of the raw data files that were transmitted to us at the region-year level, saving a set of compatible region-year files. The second stage reads in all region files within a year and applies a set of cleaning and recoding procedures to the data to make them consistent within each year, saving a set of yearly files. The third stage reads in all yearly files and applies a set of cleaning procedures to the data to make them consistent across years. Whenever possible, we use the official crosswalks provided by IBGE to convert industry (IBGE, CNAE 1.0, and CNAE 2.0 classifications), occupation (CBO 1994 and CBO 2002), and municipality codes (IBGE classification).

Cross-sectional household survey data (PNAD). A substantial fraction of Brazil’s working-age population is not formally employed and hence not covered by the RAIS. To address this gap, we complement our analysis using data from the *Pesquisa Nacional por Amostra de Domicílios* (PNAD), a nationally representative annual household survey from 1996 to 2012. Respondents are asked to produce a formal work permit (*Carteira de Trabalho e Previdência Social assinada*). Following Meghir et al. (2015), we classify as informal all self-employed and those in remunerated employment without a work permit.

The PNAD data collection consists of a double-stratified sampling scheme by region and municipality, interviewing a representative of households in Brazil. The survey asks the household head to respond on behalf of all family members and report a rich set of demographic and employment-related questions. In particular, the survey asks a question about whether the respondent holds a legal work

permit. We use the answer to this survey question to identify individuals as working in the formal or in the informal sector. Survey questions regarding income and demographics of the respondent household members are comparable to the U.S. CPS. We keep only observations that satisfy our selection criteria and have non-missing observations for labor income, whose variable definition we harmonize across years.

The raw microdata are publicly available for download starting from 1996 at ftp://ftp.ibge.gov.br/Trabalho_e_Rendimento/. For basic cleaning, starting with the raw data in text format, we use the standardized cleaning procedures adopted from the Data Zoom suite developed at PUC-Rio and available for replication online at <http://www.econ.puc-rio.br/datazoom/english/index.html>. From there, we apply a set of procedures to clean and recode key variables used in our analysis.

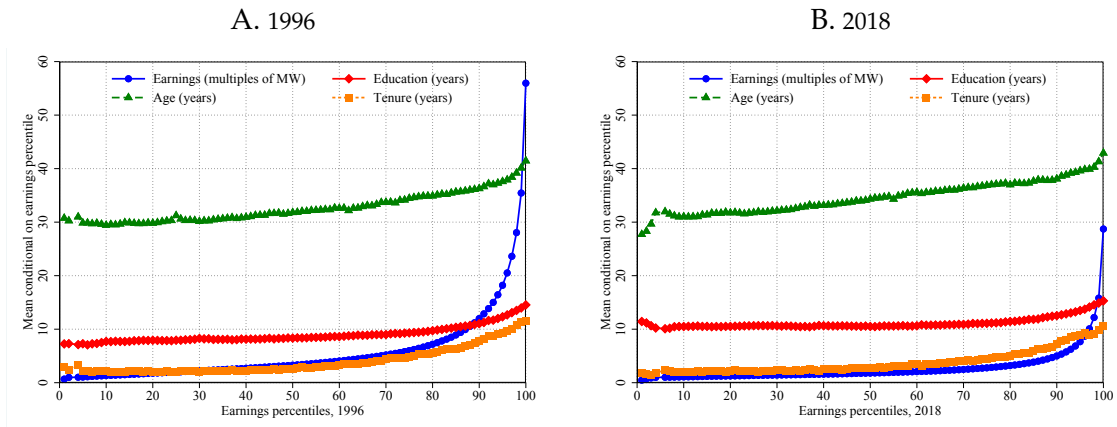
Longitudinal household survey data (PME). We also use a second household survey, the *Pesquisa Mensal de Emprego (PME)*, conducted between 2002 and 2012 in Brazil's six largest metropolitan regions: Belo Horizonte, Porto Alegre, Recife, Rio de Janeiro, Salvador, and São Paulo. The advantage of this dataset is that it features for every respondent two continuous four-month interview spells separated by an eight-month pause. Starting in 2002, this short panel component allows us to compute monthly transition rates of workers between different employment states, including formal and informal employment. For presentation purposes, we label formal sector workers as "employed," and pool informal sector workers and the unemployed under the label "nonemployed." We distinguish between the disaggregated categories in our empirical analysis of minimum wage effects later.

The raw microdata are publicly available for download starting from March 2002 at ftp://ftp.ibge.gov.br/Trabalho_e_Rendimento/. For basic cleaning, starting with the raw data in text format, we use the standardized cleaning procedures adopted from the Data Zoom suite developed at PUC-Rio and available for replication online at <http://www.econ.puc-rio.br/datazoom/english/index.html>. From there, we apply a set of procedures to clean and recode key variables used in our analysis, similar to the procedures that we applied to the PNAD data.

A.2 Summary statistics

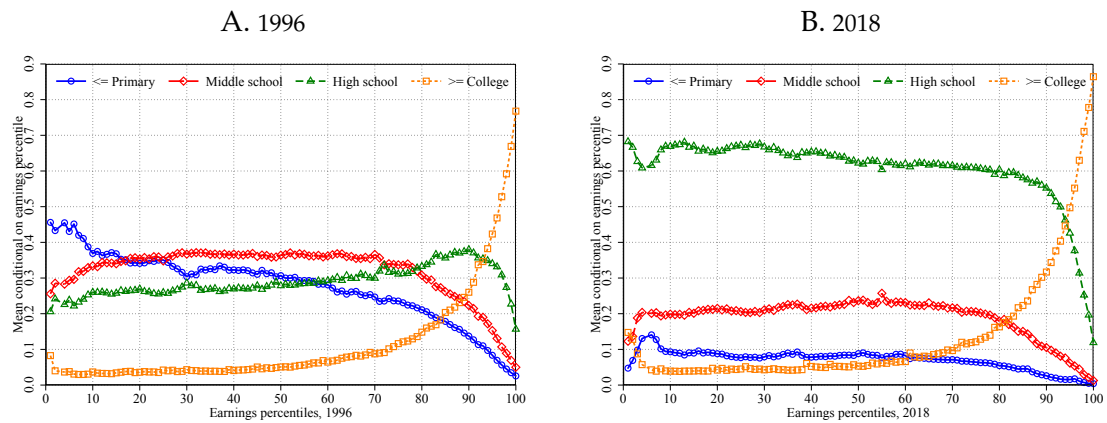
Summary statistics for administrative linked employer-employee data (RAIS). Figure A.1 shows mean values of basic descriptive variables—monthly earnings in multiples of the minimum wage, years of education, age in years, and job tenure in years—throughout the earnings distribution for 1996 in panel A and for 2018 in panel B. Zooming in on educational attainment, which increased significantly over this period, Figure A.2 shows the distribution of education degrees grouped into individuals with primary school or lower levels of education, middle school, high school, and college or higher levels of education for 1996 in panel A and for 2018 in panel B.

Figure A.1. RAIS cross-sectional summary statistics, 1996 and 2018



Notes: Figure shows mean monthly earnings (“wages”), years of education, age, and tenure across wage percentiles for 1996 in panel A and for 2018 in panel B. All statistics are for adult male workers of age 18–54. Source: RAIS, 1996 and 2018.

Figure A.2. RAIS education degree shares, 1996 and 2018



Notes: Figure shows shares of education degrees across wage percentiles for 1996 in panel A and for 2018 in panel B. All statistics are for adult male workers of age 18–54. Source: RAIS, 1996 and 2018.

Summary statistics for cross-sectional household survey data (PNAD). Table A.1 presents summary statistics on the PNAD data.

Table A.1. Summary statistics for cross-sectional household survey data (PNAD)

	# Workers	Real wage (formal)		Real wage (informal)		Employment rate	Formal share
		Mean	Std. dev.	Mean	Std. dev.		
1996	74,487	7.01	0.81	6.26	0.81	0.95	0.68
1997	78,731	7.02	0.79	6.26	0.82	0.94	0.68
1998	79,060	7.03	0.78	6.26	0.81	0.93	0.67
1999	81,230	6.97	0.77	6.21	0.79	0.93	0.66
2000							
2001	89,102	6.93	0.74	6.20	0.81	0.93	0.66
2002	90,855	6.90	0.73	6.19	0.81	0.93	0.66
2003	91,490	6.84	0.71	6.12	0.77	0.92	0.67
2004	94,526	6.85	0.69	6.15	0.77	0.94	0.68
2005	97,348	6.89	0.67	6.19	0.77	0.93	0.68
2006	97,757	6.94	0.66	6.25	0.76	0.94	0.69
2007	95,598	6.97	0.65	6.30	0.78	0.94	0.71
2008	93,677	7.00	0.65	6.35	0.76	0.95	0.72
2009	95,170	7.02	0.63	6.36	0.76	0.94	0.73
2010							
2011	84,910	7.07	0.62	6.51	0.75	0.95	0.76
2012	86,031	7.13	0.62	6.56	0.78	0.95	0.76

Notes: Table shows summary statistics on wages, employment rates, and formal employment shares between 1996 and 2012. All statistics are for adult male workers of age 18–54. Real wages are measured in 2012 BRL and in logs. Surveys are not available for census years 2000 and 2010. *Source:* PNAD, 1996–2012.

Summary statistics for longitudinal household survey data (PME). We present summary statistics on the PME data in Table A.2.

Table A.2. Summary statistics for longitudinal household survey (PME)

	# Workers	Transition rate employed-nonemployed	Transition rate employed-nonemployed
2002	94,280	0.08	0.05
2003	140,734	0.09	0.06
2004	146,847	0.08	0.05
2005	154,159	0.08	0.05
2006	153,646	0.08	0.04
2007	154,338	0.09	0.05
2008	150,104	0.10	0.05
2009	149,762	0.10	0.04
2010	150,443	0.10	0.04
2011	145,012	0.11	0.04
2012	121,211	0.10	0.04

Notes: Table shows number of workers and monthly transition rates between employment (i.e., formal employment) and nonemployment (i.e., informal employment + unemployment). All statistics are for adult male workers of age 18–54. *Source:* PME, 2002–2012.

A.3 Details of sample selection and sample size

Table A.3 shows official labor force statistics (panel A) and different sample sizes computed in the RAIS administrative data (panel B). Comparing the numbers of formal sector workers, we find that the two data sources are compatible. In 1996, official statistics state that—depending on the definition of formality—there are around 29,015,225 formal sector workers in Brazil and 29,600,720 unique workers recorded in RAIS. In 2018, official statistics state that there are around 54,611,555 formal sector workers in Brazil and 55,740,072 unique workers recorded in RAIS. That RAIS captures a somewhat larger number of workers is not surprising given that official statistics are based on survey data with respect to a reference week or month, while RAIS covers any employment spells during the entire calendar year. Cumulatively applying our selection criteria based on gender (only males), age (18–54), and nonmissing key information (earnings, worker and employer identifiers, and employment dates), our RAIS sample comprises 17,201,101 workers in 1996 and 27,602,584 workers in 2018.⁵³

Table A.3. Official labor force statistics and sample sizes in RAIS administrative data

	1996	2018
<i>Panel A. Official labor force statistics</i>		
Labor force	69,626,959	105,542,221
Unemployment rate	0.076	0.117
Informality rate	0.578	0.414
Total formal employment	29,015,225	54,611,555
<i>Panel B. Sample sizes in RAIS administrative data</i>		
Total number of jobs	34,260,198	66,214,692
Number of unique workers	29,600,720	55,740,072
Number of unique + male workers	18,940,516	31,439,096
Number of unique + male + prime-age workers	17,377,682	28,007,974
Number of workers satisfying additional selection criteria	17,201,101	27,602,584

Notes: Table shows official labor force statistics (panel A) and sample sizes calculated based on the RAIS administrative data for 1996 and 2018 (panel B). Official labor force statistics are made available by World Bank (indicator ID: SL.TLF.TOTL.IN) and are derived using data from the International Labour Organization, ILOSTAT database. Unemployment rate is from IBGE and is derived using data from the PNAD-Contínua household surveys for October–December 2018. Informality rate for 1996 is from IPEA and is derived from the PNAD household survey data for 2018, while that for 2018 is from IBGE and is derived from the PNAD-Contínua household survey data for July–September 2018. Additional selection criteria in the last line of the table include a requirement of nonmissing values for earnings, worker identifiers, employer identifiers, and employment dates. *Source:* World Bank, IBGE, IPEA, and RAIS, 1996 and 2018.

The main difference between the number of workers reported in the official labor force statistics and our final sample in RAIS is due to our selection based on gender (only males) and age (18–54). The minimum wage is significantly more binding for men outside of this age range as well as for women. Thus, our analysis focuses on a population subgroup that is relatively less affected by the minimum wage. In this sense, our results may understate the effects of the minimum wage on Brazil’s full population.

⁵³In a previous version of the paper, we also excluded workers with earnings below the minimum wage and those at firms below a minimum employment threshold, which led to a slightly smaller sample size than that reported here.

A.4 The importance of unobserved worker heterogeneity in wages

Let i index workers, t index years, and let $edu(i) \in \{e_1, e_2, \dots, e_N\}$ be the educational attainment group of individual i , which in our data is a permanent worker characteristic. The log wage of individual i in year t is denoted y_{it} . Then we can decompose the total variance of log wages as

$$Var(y_{it}) = \underbrace{Var(\mathbb{E}[y_{it}|edu(i)])}_{\text{Between-education-group variance}} + \underbrace{Var(y_{it} - \mathbb{E}_i[y_{it}|edu(i)])}_{\text{Within-education-group variance}}, \quad (\text{A.1})$$

The first term on the right-hand side of equation (A.1) is the variance of education-mean log wages, which we call the between-education-group variance. The second term is the variance of worker-year level deviations from the education-mean log wages, which we call the within-education-group variance. For education to be a meaningful skill proxy, we require the between-education-group variance to make up a significant share of the total variance of log wages. Implementing the decomposition in equation (A.1) on the RAIS data from 1994–1998, we find that out of a total variance of wages of 75.0 log points, around 14.1 log points (19 percent) are due to the between-education-group variance component, while 60.9 log points (81 percent) are due to the within-education-group variance component. From this, we conclude that, while education is a significant predictor of wages in the data, the vast majority of wage dispersion is within education groups.

We can extend our analysis to other worker and job attributes as observable skill proxies. To this end, we estimate a sequence of Mincerian wage equations with cumulatively added controls for observable worker characteristics, unobservable time-invariant worker characteristics, and unobservable time-invariant firm characteristics. Observable worker characteristics include education-specific age dummies, education-specific year dummies, hours dummies, and occupation dummies. Table A.4 shows the results from four different specifications estimated on the RAIS data. With rich controls for observable worker characteristics (column 1), the coefficient of determination (R^2) is 48.6 percent, while the root mean squared error (RMSE) is 0.623. This suggests that the largest share of wage heterogeneity and significant dispersion in absolute terms is not explained by observables. Adding firm dummies to the first specification (column 2) leads to an R^2 of 76.4 percent, suggesting that firms are an important in wage determination. However, as AKM have argued, some of this explained variance may itself be attributable to unobserved worker heterogeneity. When we add worker dummies instead of firm dummies to the first specification (column 3), we find an R^2 of 88.3 percent and an RMSE of 0.347, meaning that the explanatory power is almost twice as high when controlling worker observable and unobservable characteristics relative to when controlling only for observables. Together, the estimation results from this sequence of wage equations suggest that unobservable worker characteristics constitute an important share of overall wage dispersion, more important than education and a number of other observable characteristics.⁵⁴

⁵⁴All wage equations here are estimated on the largest available set of workers, whereas Section 2.2 of the main text reports estimates based on the leave-one-out connected set of workers and firms. Note also that all numbers reported here are with respect to the plug-in estimators of the R^2 and the RMSE. However, Section 2.2 presented leave-one-out corrected estimates of variance components, which leads to small changes relative to the plug-in estimates.

Table A.4. Explained wage dispersion when (not) controlling for observable and unobservable heterogeneity

	(1)	(2)	(3)
Coefficient of determination (R^2)	0.486	0.764	0.883
Root mean square error (RMSE)	0.623	0.427	0.347
Observations (mm)	83.2	82.9	78.2
Education-specific age dummies	✓	✓	✓
Education-specific year dummies	✓	✓	✓
Hours dummies	✓	✓	✓
Occupation dummies	✓	✓	✓
Firm dummies	✗	✓	✗
Worker dummies	✗	✗	✓

Notes: This table shows the coefficient of determination (R^2) and root mean square error (RMSE) for different specifications that project log wages on various controls: observable worker characteristics (column 1), observable worker characteristics and firm dummies (column 2), and observable worker characteristics and worker dummies (column 3). Observable worker characteristics include education-specific age dummies, education-specific year dummies, hours dummies, and occupation dummies. Note that the number of observations vary across specifications because we drop singletons based on combinations of the controls included in each specification. *Source:* RAIS, 1994–1998.

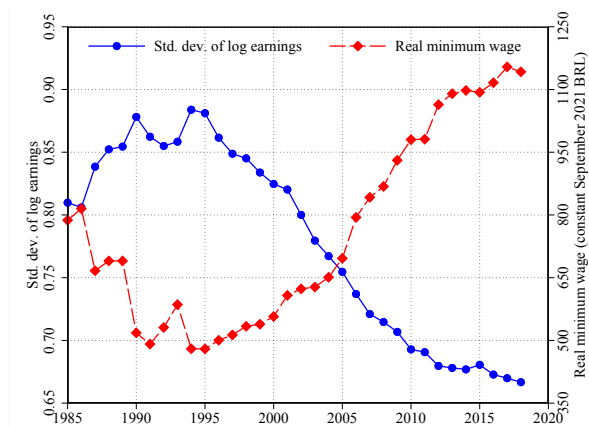
B Empirical Appendix

This appendix provides further details on the empirical exercises conducted in Section 4, including subsections on the evolution of earnings inequality and the minimum wage over time (Appendix B.1), the minimum wage spike (Appendix B.2), the incidence of minimum wage jobs (Appendix B.3), the evolution of the effective bindingness of the minimum wage (Appendix B.4), additional details on the effects of the minimum wage on wage inequality (Appendix B.5), additional regression results using alternative specifications (Appendix B.6), additional regression results using alternative controls (Appendix B.7), additional regression results using alternative time periods (Appendix B.8), additional regression results using alternative polynomial orders for region-specific time trends (Appendix B.9), additional regression results that cluster standard errors at the state level or at the mesoregion level (Appendix B.10), a comparison between our findings and subsequent work by [Haanwinckel \(2020\)](#) (Appendix B.11), a comparison of the relative bindingness of the minimum wage between Brazil and the U.S. (Appendix B.12), a comparison between the distributions of (changes in) log wages in current BRL and in multiples of the current minimum wage (Appendix B.13), and hours worked in relation to the bindingness of the minimum wage (Appendix B.14).

B.1 The evolution of earnings inequality and the minimum wage

Figure B.1 shows a strong negative comovement between the minimum wage and the standard deviation of log wages between 1985 and 2018, with a time series correlation of -0.947 .

Figure B.1. Evolution of wage inequality and the real minimum wage, 1985–2018



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 -0.947 . Source: RAIS and IPEA, 1985–2018.

B.2 The (relatively small) spike at the minimum wage

Much of the previous empirical literature has interpreted the mass of workers employed at the minimum wage as a measure of the bindingness of the wage floor (Flinn, 2006, 2010). However, theoretical labor market models in the spirit of Burdett and Mortensen (1998) predict that frictional wage dispersion for identical workers can be sustained absent any mass points in the wage distribution, including at the minimum wage. This suggests that any spike of workers at the minimum wage may be thought of independently from, or maybe in addition to, the effect of the minimum wage on the rest of the wage distribution. Although there is substantial heterogeneity in the empirical bindingness of the minimum wage across population subgroups in our administrative data from Brazil, we robustly find a relatively small spike at the wage floor for male workers of age 18–54. The remainder of this subsection is dedicated to studying the (relatively small) spike at the minimum wage in Brazil, both in the cross section and over time.

Share of workers earning exactly, below, or around the minimum wage. Panel A of Figure B.2 plots the state-level distribution of the share of workers earning exactly the minimum wage against the relative bindingness of the minimum wage measured by the P50-Kaitz index, defined as the log minimum-to-median wage, in 1996 and 2018. The average share of workers earning exactly the minimum wage is stable around two percent throughout this period.⁵⁵ We find a weak positive correlation between the P50-Kaitz index and the share of workers earning the minimum wage, but the share remains mostly below six percent even in states where the minimum wage is most binding.

We can broaden our definition of a “mass point” to three alternative measures, the evolution of which from 1996 to 2018 is depicted in panel B of Figure B.2. The share of workers earning exactly the minimum wage, shown by the blue line with circles, remains approximately flat at two percent between 1996 and 2018. A little under 3.5 percent of workers in 1996 and around 5.5 percent of workers in 2018 report earning exactly or less than the minimum wage, shown by the red line with diamonds.⁵⁶ Our most generous definition includes workers within a 5 percent band around the minimum wage, shown in green. This most generous measure evolves from 3.5 to 5.5 percent over this period, far from the roughly 30 percent of workers between the old and the new minimum wage.

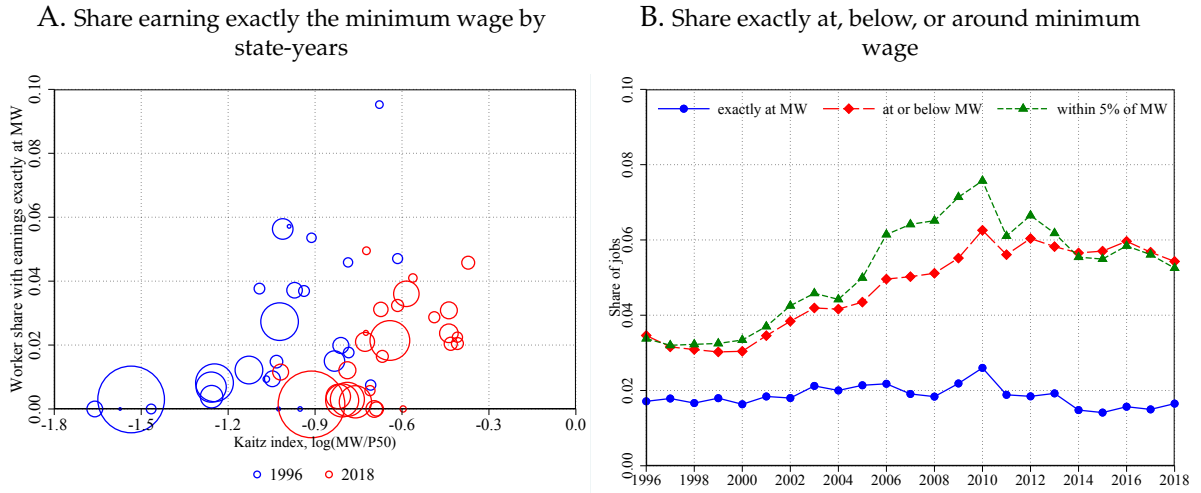
Figure B.3 shows that there is substantial heterogeneity in the share of workers earning exactly the minimum wage across states (panel A) and mesoregions (panel B). At the same time, only a small fraction of regions have a share of workers earning exactly the minimum wage above seven percent.

Histograms of wages around the minimum wage. Figure B.4 shows a histogram of wages in multiples of the minimum wage in 1996 and 2018. Figure B.5 shows a similar histogram for wages in logarithms.

⁵⁵For comparison, 3.3 percent of hourly paid workers in the U.S. earned the prevailing federal minimum wage or less in 2015 (U.S. Bureau of Labor Statistics, 2017).

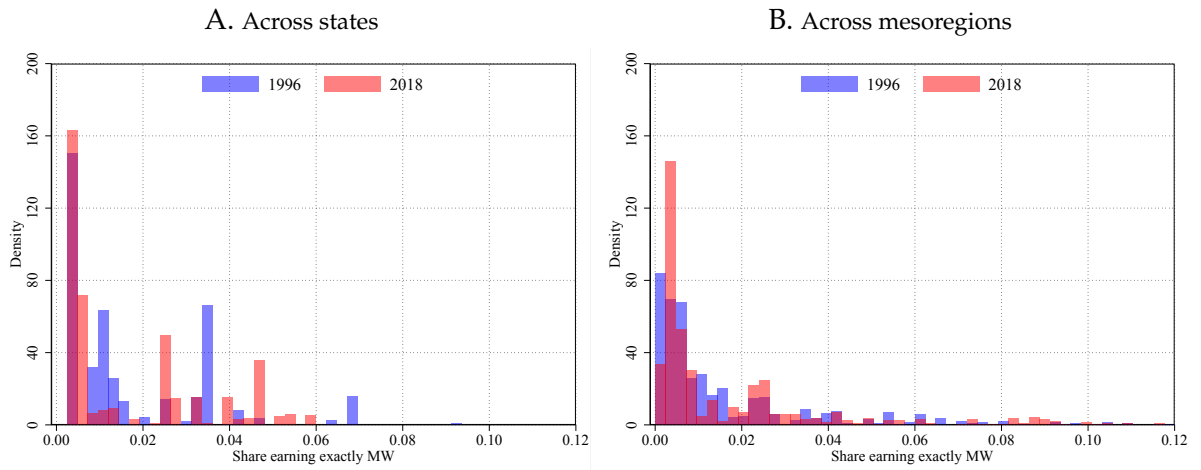
⁵⁶Observations with earnings strictly below the minimum wage are likely due to a mix of legal exceptions, misreporting, and illegal employment.

Figure B.2. Share of workers at and around the minimum wage, 1996–2018



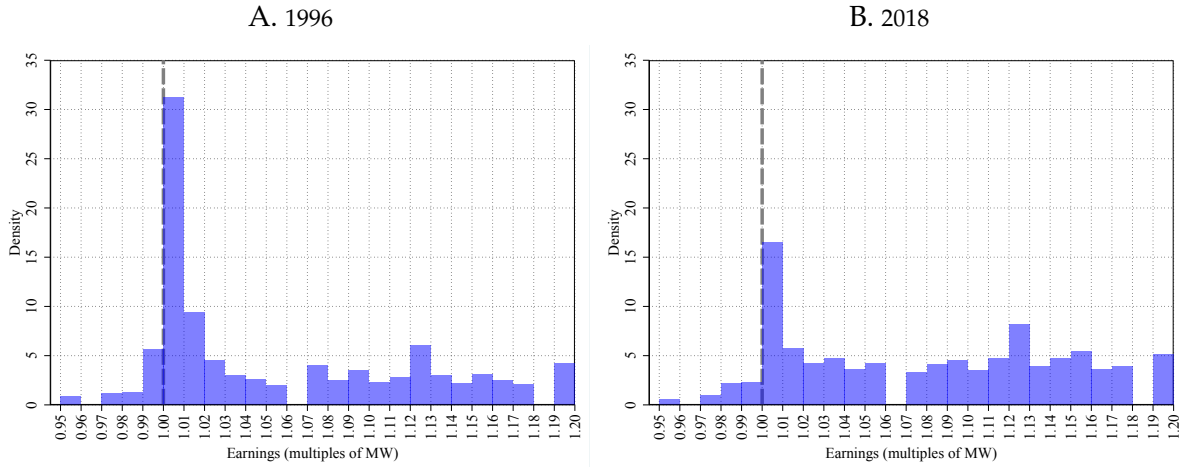
Notes: This figure shows the share of workers with earnings exactly at, below, or around the minimum wage. Panel A shows share of male workers of age 18–54 earning exactly the minimum wage against the P50-Kaitz index, $g_{kaitz_{st}}(50) \equiv \log w_t^{min} - \log w_{st}^{P50}$, across states in 1996 and 2018. Area of circles is proportional to population size. In panel B, the blue line shows share of workers earning exactly the minimum wage, the red line shows share at or below the minimum wage, and the green line plots share within 5 percent of the minimum wage. Source: RAIS, 1996–2018.

Figure B.3. Histogram of share of workers earning exactly the minimum wage, 1996 and 2018



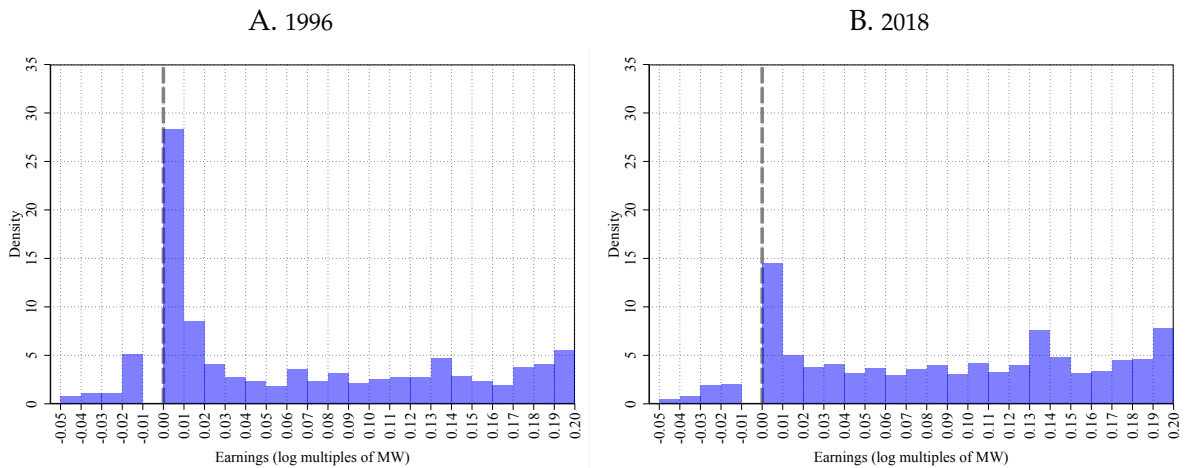
Notes: This figure shows histograms of the share of workers earning exactly the minimum wage across different population subgroups by state (Panel A) and by mesoregion (Panel B). Blue bars show the distribution in 1996, while red bars show the distribution in 2018. Source: RAIS, 1996 and 2018.

Figure B.4. Histogram of wages around the minimum wage, 1996 and 2018



Notes: This figure shows histograms of the wage distribution, measured in multiples of the minimum wage, zoomed in around the minimum wage (dashed vertical line) for 1996 (Panel A) and 2018 (Panel B). Bar width is set to 0.01, i.e., one centavo (subdivision of Brazilian Reais). Source: RAIS, 1996 and 2018.

Figure B.5. Histogram of log wages around the minimum wage, 1996 and 2018

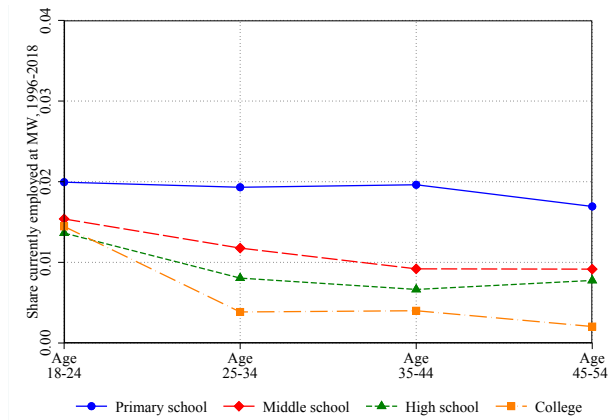


Notes: This figure shows histograms of the log wage distribution, measured in log multiples of the minimum wage, zoomed in around the minimum wage (dashed vertical line) for 1996 (Panel A) and 2018 (Panel B). Bar width is set for 0.01, i.e., approximately one percent. Source: RAIS, 1996 and 2018.

B.3 Who earns the minimum wage in Brazil?

Figure B.6 shows the share of workers currently earning the minimum wage by education group. The share of minimum wage earners is higher at younger ages and lower educational attainments. Yet the maximum share of minimum wage earners, namely that of workers of age 18–24 with at most a primary school degree, is around four percent.

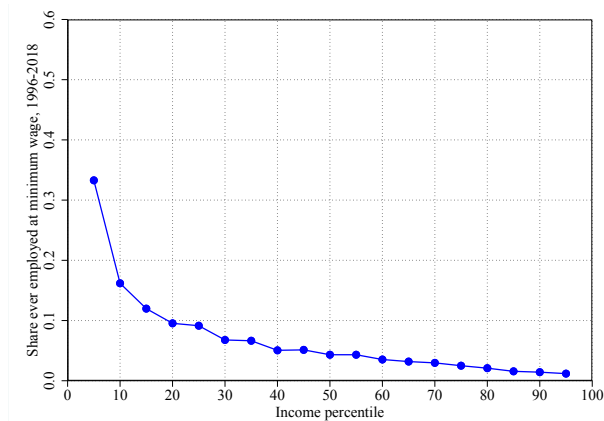
Figure B.6. Share of workers currently earning the minimum wage, by education group



Notes: Figure shows share of workers earning exactly the minimum wage by education groups (colored lines) and age groups (x-axis values) during the period from 1996 to 2018. Source: RAIS, 1996–2018.

A striking feature of the Brazilian labor market is that, in spite of a relatively small share of workers earning the minimum wage at any point in time, a surprisingly large share of workers ever—currently, in the past, or in the future—earn the minimum wage. Figure B.7 plots the share of workers who have ever earned the minimum wage during our sample period of 1996–2018.

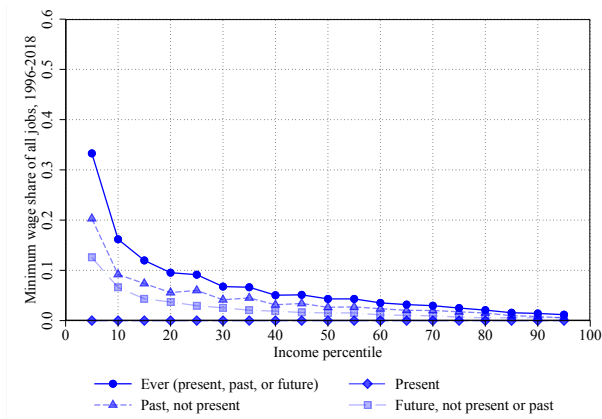
Figure B.7. Share of workers who ever earned the minimum wage from 1996–2018



Notes: Figure shows the share of workers who have ever (currently, in the past, or in the future) earned exactly the minimum wage by current income percentile. Current income percentiles are created by ranking workers within a given year according to their current wage for each year between 1996 and 2018. Source: RAIS, 1996–2018.

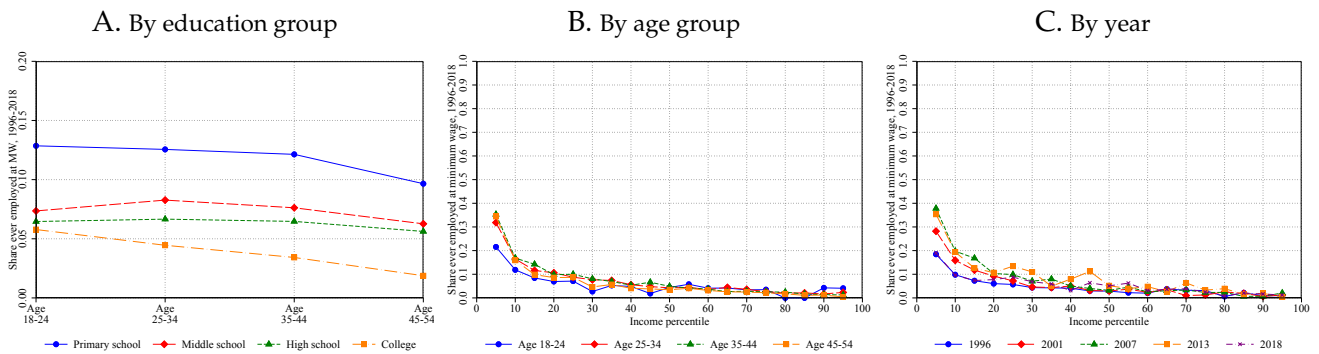
Figure B.8 decomposes the share of workers who ever earned the minimum wage into those who earn the minimum wage currently, in the past, or in the future between 1996 and 2018.

Figure B.8. Decomposition of share of workers who ever earned the MW, 1996–2018



Notes: Figure shows the share of workers who have ever (currently, in the past, or in the future) earned exactly the minimum wage. The different colored lines show the share of workers who ever, currently, in the past, and in the future earn the minimum wage across current income percentiles. Current income percentiles are created by ranking workers within a given year according to their current wage for each year between 1996 and 2018. Source: RAIS, 1996–2018.

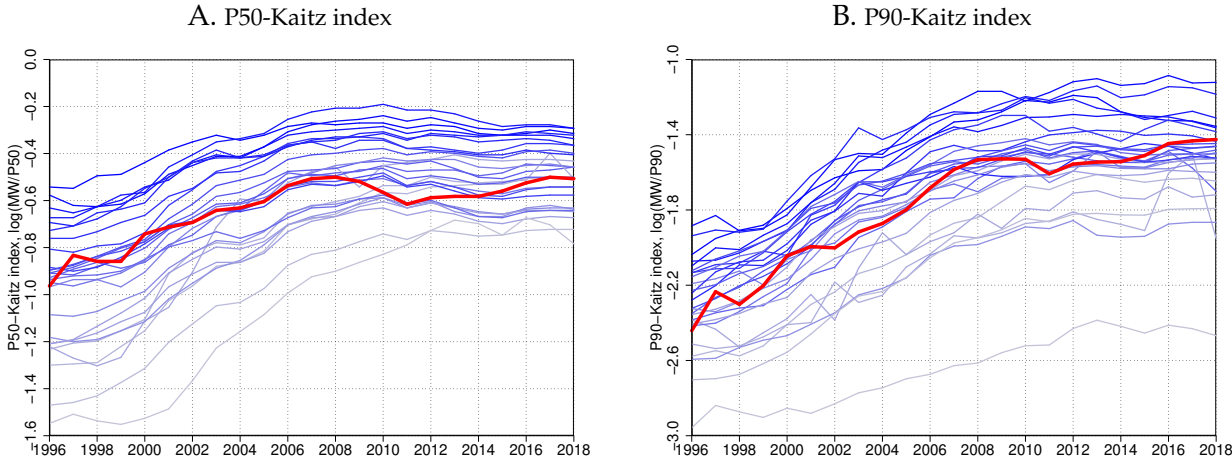
Figure B.9. Share ever employed at minimum wage, by subgroups



Notes: Figure shows the share of workers who have ever (currently, in the past, or in the future) earned exactly the minimum wage by current income percentile, separately by education group (Panel A), by age group (Panel B), and by year (Panel C). Current income percentiles are created by ranking workers within a given year according to their current wage for each year between 1996 and 2018. Source: RAIS, 1996–2018.

B.4 Evolution of generalized Kaitz indices by state

Figure B.10. Data: Evolution of generalized Kaitz indices by state, 1996–2018



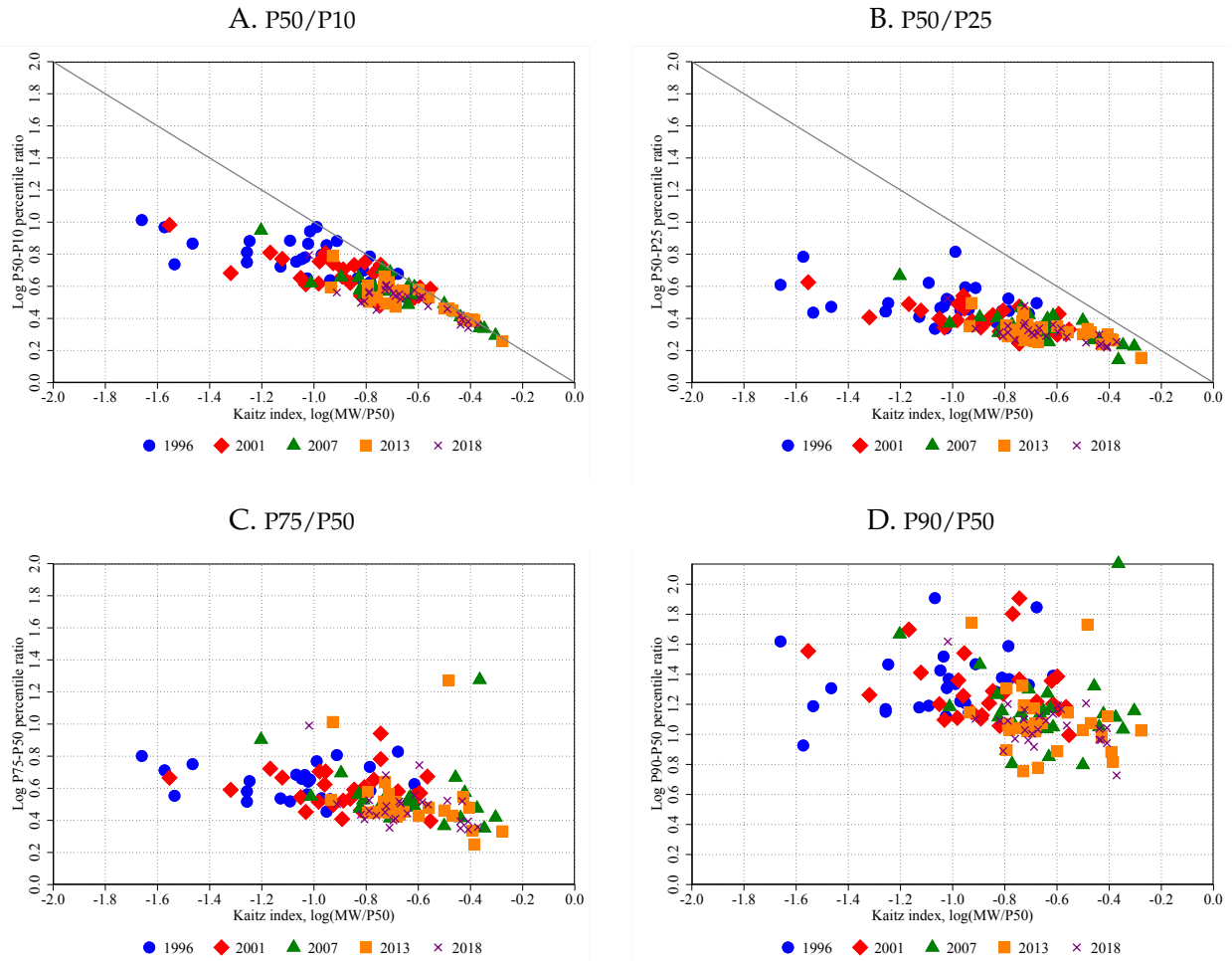
Notes: The generalized Pp -Kaitz index for state s in year t is defined as $gkatz_{st}(p) = \log(\text{federal minimum wage}_t) - \log(w^{Pp})$ for earnings percentiles $p \in \{50, 90\}$. Each blue line markets one of Brazil’s 27 states. The red line represents the weighted mean across states. Source: RAIS, 1996–2018.

B.5 Additional results on the effects of the minimum wage on wage inequality

We now show that the inverse relationship between state-year level bindingness of the minimum wage and wage inequality generalizes to the full set of states over time. To see this, we define the *generalized P50-Kaitz index* as $gk_{st}(50) \equiv \log w_t^{min} - \log w_{st}(50)$, that is, the log difference between the minimum wage prevailing at time t , w_t^{min} , and the median wage of subgroup s at time t , $w_{st}(50)$.⁵⁷ Figure B.11 plots the relation between different log wage percentile ratios and the P50-Kaitz index. Panel A plots empirical lower-tail inequality, measured by the P50/P10, against the P50-Kaitz index across Brazilian states over time. The negative 45 degree line marks states where the minimum wage is binding at the tenth percentile of the wage distribution. Panel B repeats the same exercise for the P50/P25 ratio. Both plots show a negative relationship lower-tail inequality and the P50-Kaitz index that grows more pronounced for more binding states in the cross section and over time. For comparison, the remaining two panels show a weaker relationship between top inequality, measured by the P75/P50 in panel C and by the P90/P50 in panel D, and the P50-Kaitz index.

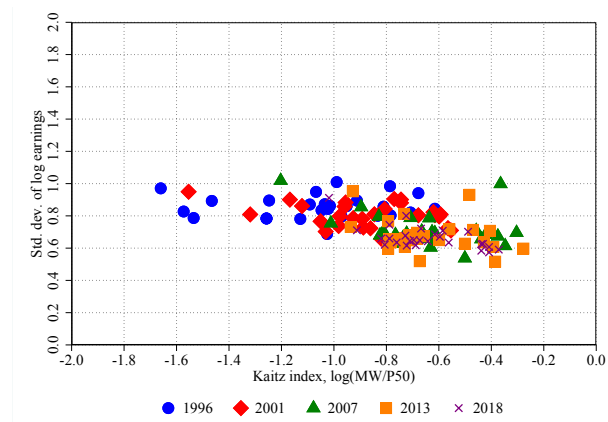
⁵⁷Recall that Figure B.10 in Appendix B.4 shows that variation in the P50-Kaitz index and the P90-Kaitz index across Brazilian states is large initially and decreases as the minimum wage increases, while approximately preserving the ranking of states over time.

Figure B.11. Log wage percentile ratios across Brazilian states over time, 1996–2018



Notes: Figure plots various log wage percentile ratios against the P50-Kaitz index, defined as $gkatz_{st}(50) \equiv \log w_t^{min} - \log w_{st}^{P50}$, where w_t^{min} is the minimum wage prevailing at time t and $w_{st}(50)$ is the median wage in subgroup s at time t . Each marker represents a combination of a state s and year t for each of Brazil's 27 states between 1996 and 2018. Source: RAIS, 1996–2018.

Figure B.12. Data: Standard deviation of log wages across states over time, 1996–2018



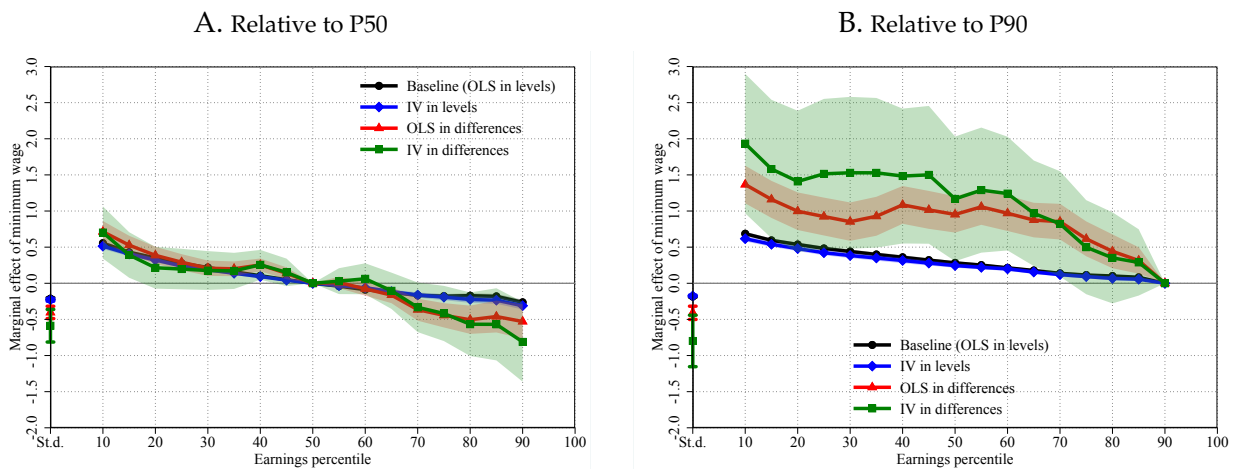
Notes: Figure plots the standard deviation of log wages against the P50-Kaitz index, $gkatz_{st}(50) \equiv \log w_t^{min} - \log w_{st}^{P50}$, with each marker representing one state-year combination for each of Brazil's 27 states between 1996 and 2018. Source: RAIS.

B.6 Additional regression results: Alternative specifications

Figure B.13 compares our baseline results (black line with circles) with three alternative specifications that consist of an IV specification in levels (blue line with diamonds), an OLS specification in differences (red line with triangles), and an IV specification in differences (green line with squares). For all specifications, relative to P50, percentiles above the median and reaching up as high as the 90th percentile remain statistically significant. Relative to P90, spillover effects are present up to at least the 70th wage percentile. Notably, the IV specification in levels closely matches our baseline results, which were estimated via OLS in levels.

Therefore, our main conclusions regarding the reach of spillovers remain unchanged under alternative specifications.

Figure B.13. Alternative specifications



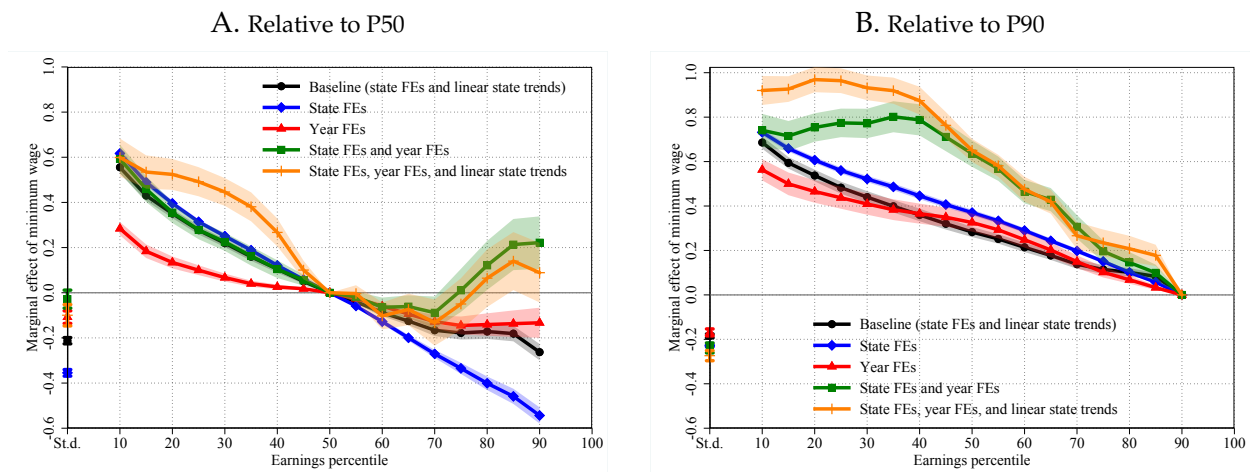
Notes: Figure plots estimates of the marginal effects from equation (3) based on the regression framework in equation (2). Each panel shows the results from four different specifications (colored markers and lines, plus error bars or shaded areas). The black circles and line correspond to the baseline specification from the main text, which is estimated via OLS in levels. The blue diamonds and line correspond to the same specification estimated via IV in levels. The red triangles and line correspond to the same specification estimated via OLS in differences. The green squares and line correspond to the same specification estimated via IV in differences. The IV strategy instruments the generalized Pp -Kaitz index and its square using 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 median wage for the region over the full sample period. 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.

B.7 Additional regression results: Alternative controls

Figure B.13 compares our baseline results (black line with circles) with four specifications using alternative sets of controls, namely only state fixed effects (blue line with diamonds), only year fixed effects (red line with triangles), state fixed effects and year fixed effects (green line with squares), and a final specification with state fixed effects, year fixed effects, and state-specific linear time trends (orange line with plus signs). For all specifications, relative to P50, percentiles above the median and reaching up as high as the 90th percentile remain statistically significant. Relative to P90, spillover effects are consistently present up to the 90th wage percentile.

Therefore, our main conclusions regarding the reach of spillovers remain unchanged under alternative sets of controls.

Figure B.14. Alternative controls



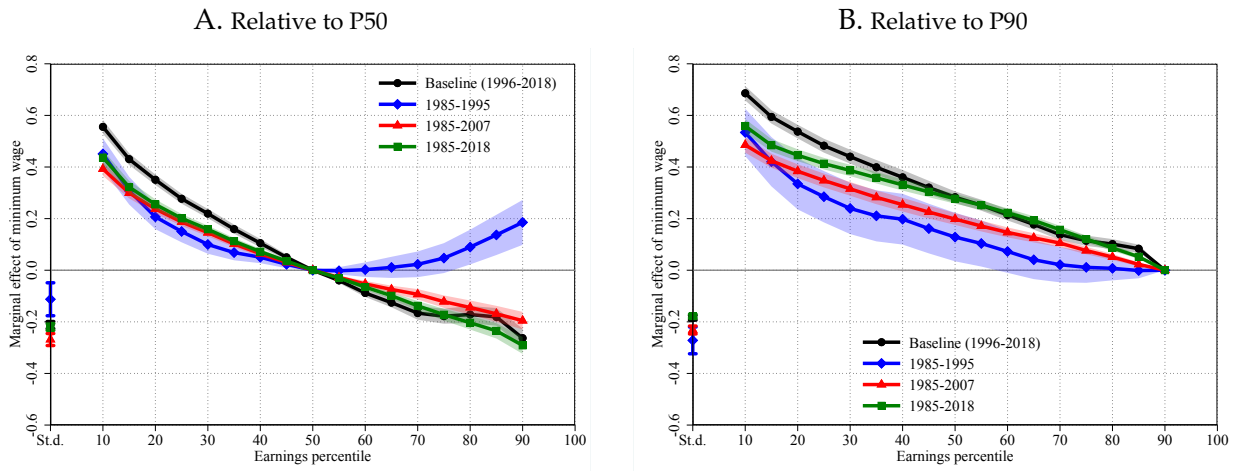
Notes: Figure plots estimates of the marginal effects from equation (3) based on the regression framework in equation (2). Source: RAIS, 1996–2018.

B.8 Additional regression results: Alternative time periods

Figure B.13 compares our baseline results (black line with circles) with three specifications using alternative time periods, namely the high-inflation period of 1985–1995 (blue line with diamonds), a period from 1985–12007 that is equally long as but earlier than our baseline period (red line with triangles), and the period of all available years from 1985–2018 (green line with squares). For all specifications, relative to P50, percentiles above the median and reaching up as high as the 90th percentile remain statistically significant. Relative to P90, all but the early high-inflation period from 1985–1995 show spillover effects that are consistently present up to the 90th wage percentile. Results for the early high-inflation period are measured more noisily and are significant only below the 60th percentile of wages.

Therefore, our main conclusions regarding the reach of spillovers remain unchanged under alternative time periods and, furthermore, Brazil early high-inflation period does not exhibit significantly stronger spillovers than the later period we study.

Figure B.15. Alternative time periods



Notes: Figure plots estimates of the marginal effects from equation (3) based on the regression framework in equation (2). Source: RAIS, 1996–2018.

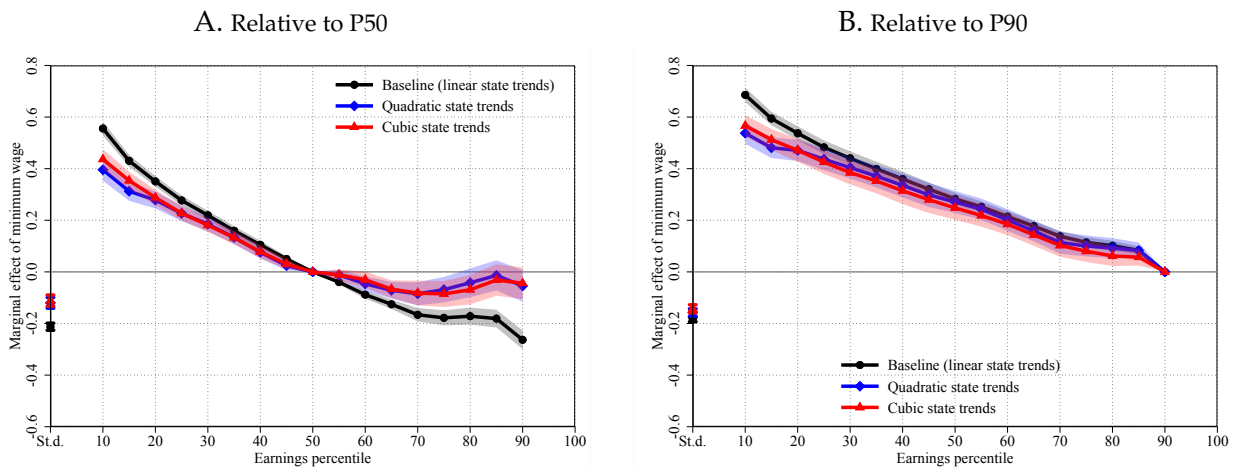
B.9 Additional regression results: Polynomial orders for state-specific trends

There has been a fruitful debate concerning the potential benefits and harms from including region-specific time trends in econometric studies of the minimum wage—see for example [Neumark et al. \(2014\)](#), [Allegretto et al. \(2017\)](#), and [Neumark and Wascher \(2017\)](#). To demonstrate the robustness of our findings to the concerns raised by this debate, Figure B.16 shows additional specifications based on the econometric methodology in Section 4.1. Specifically, we vary the polynomial degree order for state-specific time trends between one and three (with the degree-zero specification being that with only state fixed effects presented in Appendix B.14). Figure B.16 presents the results from these alternative specifications.

Starting with a description of Figure B.16, we note that specifications with either a quadratic or cubic trend show similar patterns to one another in terms of estimated marginal effects, particularly in the lower tail of the wage distribution. The estimated patterns are also similar to our baseline specification with state-specific linear time trends. All three specifications deliver significant effects of the minimum wage above the median, when measured relative to P50, and up to the 90th percentile of wages, when measured relative to P90.⁵⁸

Therefore, our main conclusions regarding the reach of spillovers remain unchanged under alternative polynomial orders for state-specific time trends.

Figure B.16. Alternative trends



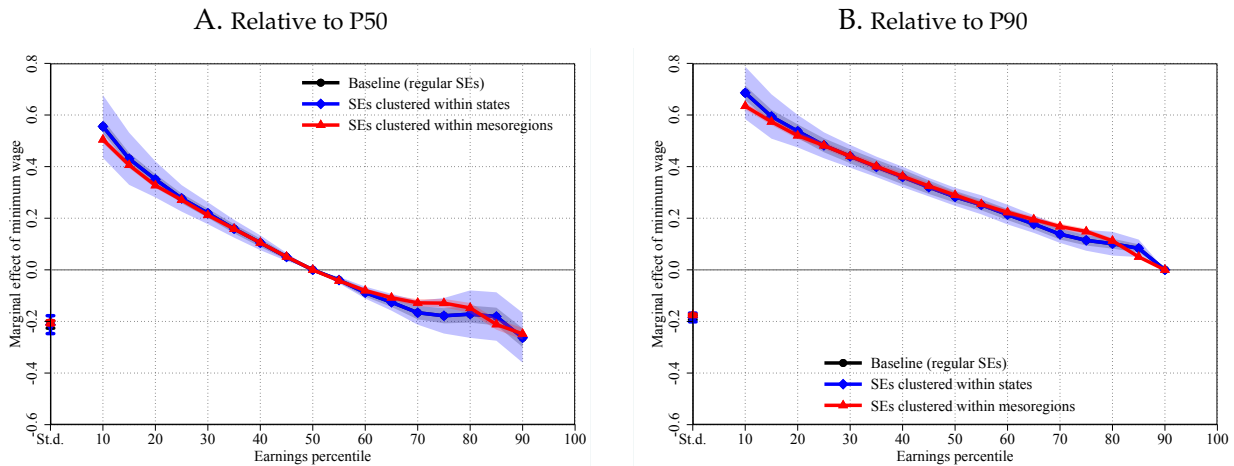
Notes: Figure plots estimates of the marginal effects from equation (3) based on the regression framework in equation (2). Each panel shows the results from three different specifications (colored lines and error bars or shaded areas) with different polynomial degrees of the region-specific time trends: linear (black circles and line), quadratic (blue diamonds and line), and cubic (red triangles and line) polynomials in the calendar year—all estimated using OLS in levels. 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 three error bars and three shaded areas represent 99 percent confidence intervals based on regular (i.e., not clustered) standard errors. Source: RAIS, 1996–2018.

⁵⁸While our finding of far-reaching spillover effects of the minimum wage are robust to the choice of state-specific time trends, we note that including state-specific higher-order time trends in this specification may possibly be asking for too much from our comparably short state-year panel of 23 years. For this reason, we prefer the specification with state fixed effects and only state-specific linear time trends as our baseline.

B.10 Additional regression results: Clustering standard errors

Figure B.17 shows additional specifications based on the econometric methodology in Section 4.1 of the main text. Specifically, although the number of clusters at the state level falls below common thresholds for clustering (Cameron and Miller, 2015), we here cluster standard errors at the state level. In contrast, in Section 4.1 we presented results based on unadjusted standard errors. The main take-away from Figure B.17 is that standard errors become somewhat larger under clustering of standard errors at the state level, though they become smaller again when estimating our specification and clustering standard errors at the mesoregion level. Therefore, our main conclusions regarding the reach of spillovers remain unchanged under alternative ways of clustering standard errors.

Figure B.17. Alternative standard errors



Notes: Figure plots estimates of the marginal effects from equation (3) based on the regression framework in equation (2). Each panel shows the results from three different specifications (colored lines and error bars or shaded areas) with different ways of constructing standard errors: estimating equation (2) at the state level with regular (i.e., not clustered) standard errors (black circles and line), estimating equation (2) at the state level with standard errors clustered at the state level (blue diamonds and line), and estimating equation (2) at the mesoregion level with standard errors clustered at the mesoregion level (red triangles and line). 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 error bars and shaded areas represent 99 percent confidence intervals based on standard errors that are clustered either at the state level (black and blue markers and lines) or at the mesoregion level (red markers and line). Source: RAIS, 1996–2018.

B.11 Comparison with Haanwinckel (2020)

In complementary work, Haanwinckel (2020) follows our approach of estimating spillover effects of the minimum wage in Brazil using a methodology based on the seminal framework by Lee (1999) and the more recent contribution by Autor et al. (2016). Using a subset of 14 years of the RAIS data from 1996–2001, 2005–2009, and 2011–2013, Haanwinckel (2020) reports significant spillover effects of the minimum wage up to the 40th wage percentile with a 95 percent confidence interval, and up to the 30th wage percentile with a 99 percent confidence interval. The standard error bands estimated by Haanwinckel (2020) are relatively large above the median, rendering the point estimates indistinguishable from zero. In contrast, our baseline results using the 1996–2018 data indicates spillovers that are significant up to at least the 75th percentile of the wage distribution.

There are several notable differences between our empirical approach and that in Haanwinckel (2020). We discuss two key differences here. One difference is the exact econometric specification, which in the case of Haanwinckel (2020) includes a national quadratic time trend in addition to the state fixed effects and state-specific linear trends that we include in our baseline specification. We show below, by including a national quadratic trend, that this difference in specifications does not systematically change our insights, though some error bands increase significantly. A second difference is the set of years on which these specifications are estimated. We show below, by estimating our specification as well as those including a national quadratic trend, that this difference does explain some of the discrepancy in findings between our work and that by Haanwinckel (2020). Furthermore, estimating our baseline specification and those with national quadratic trends on the full sample of 34 years of the RAIS data from 1985–2018, we robustly find significant spillovers up to at least the 75th wage percentile with comparably narrow standard error bands.

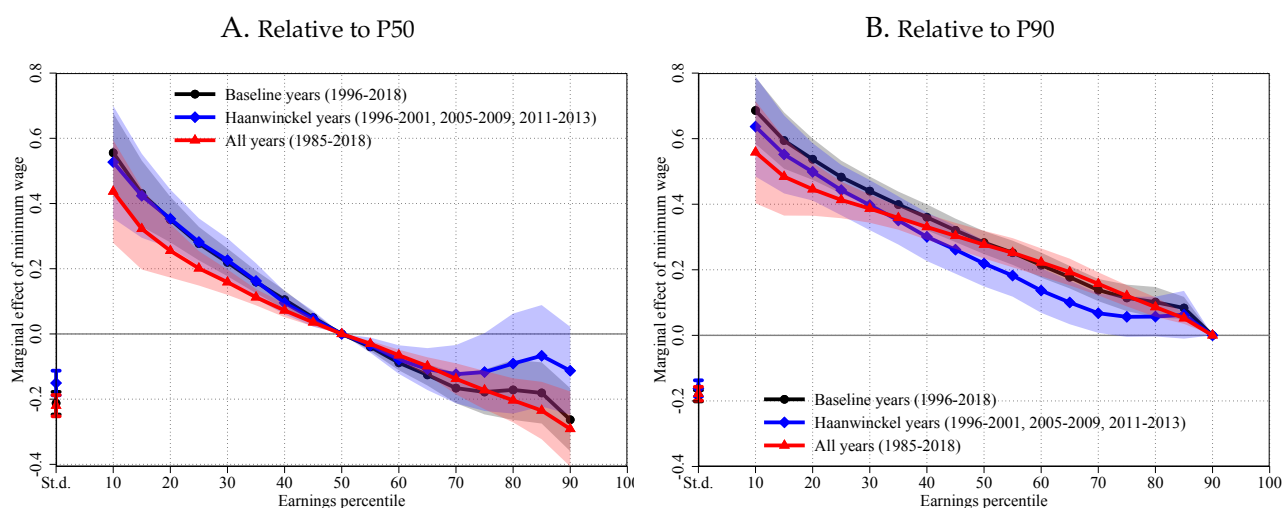
To establish these results, we proceed in two steps. First, we re-estimate our baseline specification for different sets of years to investigate their sensitivity to the choice of time period. Second, we implement the specifications from Haanwinckel (2020) on our baseline period (1996–2018) and compare the results to those from the same specification using either the restricted set of years used in Haanwinckel (2020) (1996–2001, 2005–2009, and 2011–2013), or the full set of years in the RAIS data (1985–2018).

Alternative results using baseline specification estimated on different time periods. We re-estimate our baseline specification with state fixed effects and state-specific linear trends on three sets of years of the RAIS data, namely our baseline period comprising 1996–2018 (black line with circles), the years used in Haanwinckel (2020) comprising 1996–2001, 2005–2009, and 2011–2013 (blue line with diamonds), and the full period comprising 1985–2018 (red line with triangles). To remain conservative and also to match the choice in Haanwinckel (2020), we cluster standard errors at the state level.

Figure B.18 shows the resulting estimates of these three specifications. Several points are worth noting. First, our baseline estimates remain significant up to the 90th percentile, both relative to P50 and also relative to P90. Second, the point estimates based on the subset of years used in Haanwinckel (2020) are close to ours in the lower tail, and slightly less pronounced in the upper tail, relative to P50. They are uniformly below ours, relative to P90. Third, at the same time, standard errors are significantly higher when using a subset of years, particularly in the upper tail. This results in point estimates above the 70th percentile being insignificant based on the years used in Haanwinckel (2020), while they remain significant in our baseline. Fourth, using additional years going back to 1985 leads to similar point estimates and standard error bands compared to our baseline estimates.

From this, we conclude that—starting from our baseline specification—the choice of years matters somewhat for the estimated reach of spillovers, though the estimated effects remain significant up to the 70th percentile of wages.

Figure B.18. Comparison with Haanwinckel (2020): State FEs and linear state time trends, OLS in levels

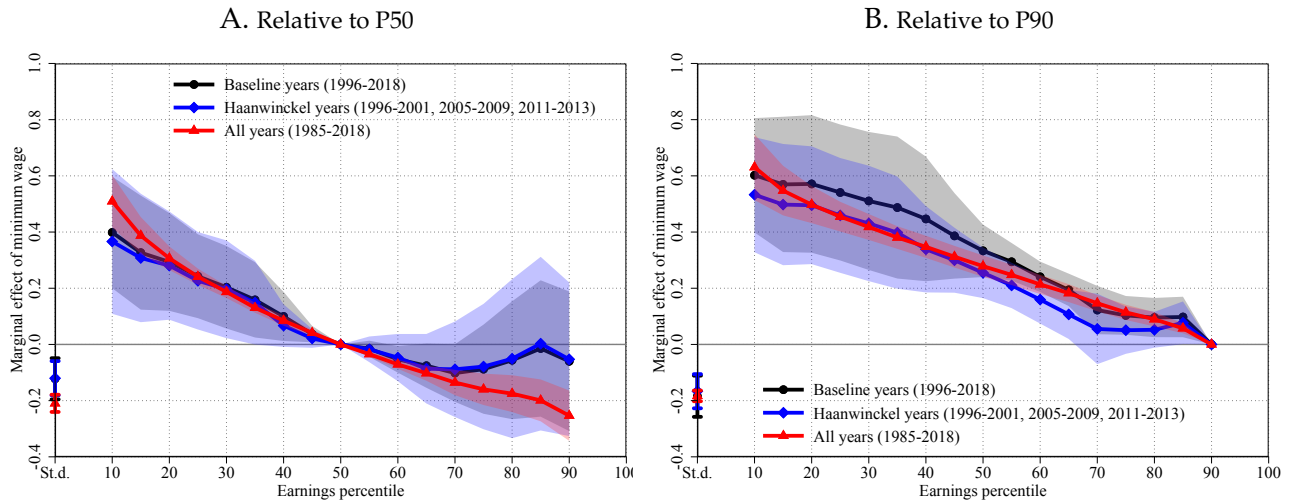


Notes: Figure plots estimates of the marginal effects from equation (3) based on the regression framework in equation (2). Each panel shows three sets of estimation results (colored lines and error bars or shaded areas) based on different time periods: our baseline period from 1996–2018 (black circles and line), the subset years used in Haanwinckel (2020), comprising 1996–2001, 2005–2009, and 2011–2013 (blue diamonds and line), and all available years from 1985–2018 (red triangles and line). The included controls comprise a set of state fixed effects and state-specific linear time trends, which corresponds to the baseline specification in the main text. The specification is estimated via OLS in levels. 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 error bars and shaded areas represent 99 percent confidence intervals based on standard errors that are clustered at the state level. Source: RAIS, 1985–2018.

Alternative results using specifications from Haanwinckel (2020) estimated on different time periods. Next, we estimate specifications that include the same set of controls as in Haanwinckel (2020): state fixed effects, state-specific linear trends, and a national quadratic trend. We first estimate these specifications via OLS in levels. As above, we estimate the specification on three different time periods, namely our baseline period comprising 1996–2018 (black line with circles), the years used in Haanwinckel (2020) comprising 1996–2001, 2005–2009, and 2011–2013 (blue line with diamonds), and the full period comprising 1985–2018 (red line with triangles). As above, we cluster standard errors at the state level.

The results are presented in Figure B.19. There are a couple of take-aways. First, the inclusion of a national quadratic trends slightly attenuates the point estimates and significantly increases the standard error bands. Second, using our baseline years continues to yield significant effects of the minimum wage up to the median and again at the 60th wage percentile, relative to P50. All estimated effects remain significant up to the 90th wage percentile, relative to P90. Third, the subset of years used in Haanwinckel (2020) yield point estimates that are substantially similar to our baseline but not statistically significant above the 35th wage percentile, relative to P50. Point estimates are somewhat attenuated and remain significant up to the 65th wage percentile, relative to P90. Finally, using the full set of years yields point estimates that lie within the standard error bands of the other two sets of estimates but themselves have significantly tighter error bands.

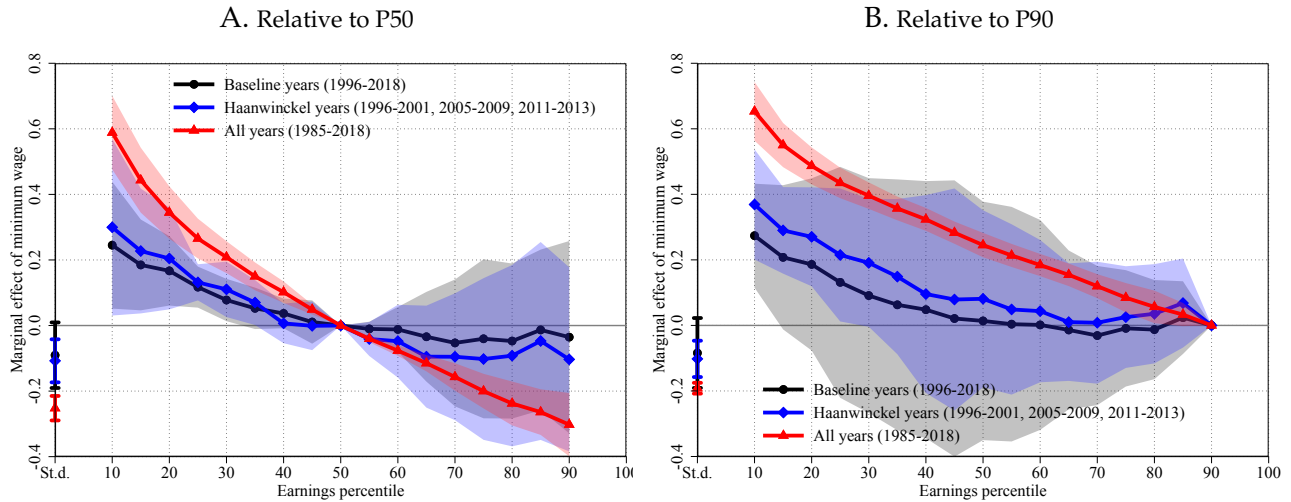
Figure B.19. Comparison with Haanwinckel (2020): State FEs, linear state time trends, and quadratic national trend, OLS in levels



Notes: Figure plots estimates of the marginal effects from equation (3) based on the regression framework in equation (2). Each panel shows three sets of estimation results (colored lines and error bars or shaded areas) based on different time periods: our baseline period from 1996–2018 (black circles and line), the subset years used in Haanwinckel (2020), comprising 1996–2001, 2005–2009, and 2011–2013 (blue diamonds and line), and all available years from 1985–2018 (red triangles and line). The included controls comprise a set of state fixed effects, state-specific linear time trends, and a national quadratic time trend, which corresponds to the specification in Haanwinckel (2020). The specification is estimated via OLS in levels. 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 error bars and shaded areas represent 99 percent confidence intervals based on standard errors that are clustered at the state level. Source: RAIS, 1985–2018.

Next, we estimate specifications that include state fixed effects, state-specific linear trends, and a national quadratic trend via IV in levels. Figure B.20 shows the results. Both the estimates for our baseline set of years and that used in Haanwinckel (2020) yield estimates that are significant up to the 30th wage percentile but not above, due to very wide standard error bands, relative to P50. Relative to P90, the error bands are even wider. Both of these results suggest that the inclusion of a quadratic national trend is leaving little variation over and above that induced by the instrumented generalized Kaitz indices over the period from 1996 to 2018. In contrast, the specification based on the full set of years continues to show significant effects of the minimum wage up to the 90th percentile.

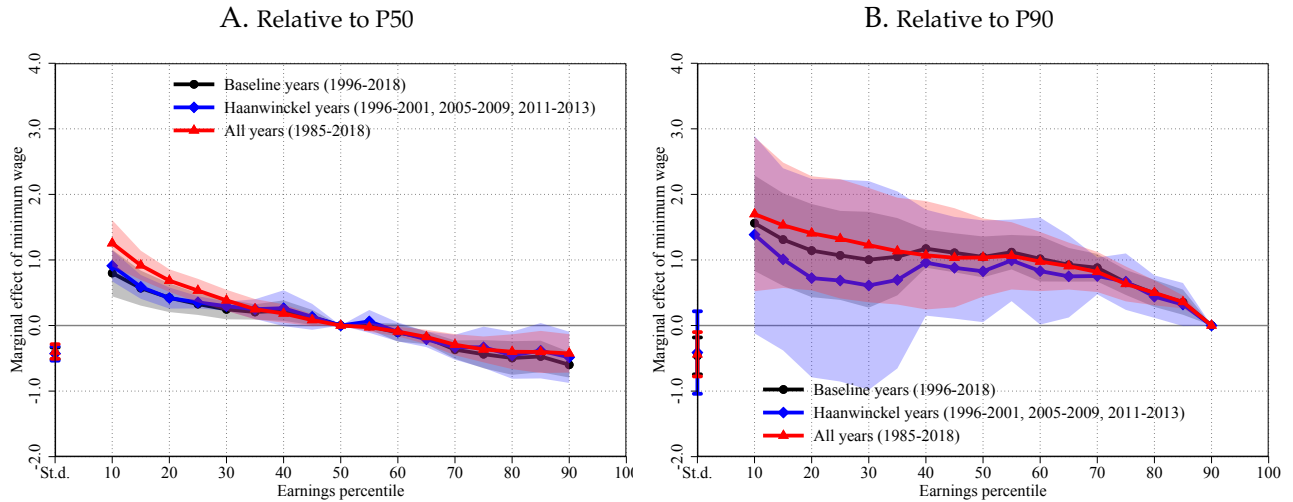
Figure B.20. Comparison with Haanwinckel (2020): State FEs, linear state time trends, and quadratic national trend, IV in levels



Notes: Figure plots estimates of the marginal effects from equation (3) based on the regression framework in equation (2). Each panel shows three sets of estimation results (colored lines and error bars or shaded areas) based on different time periods: our baseline period from 1996–2018 (black circles and line), the subset years used in Haanwinckel (2020), comprising 1996–2001, 2005–2009, and 2011–2013 (blue diamonds and line), and all available years from 1985–2018 (red triangles and line). The included controls comprise a set of state fixed effects, state-specific linear time trends, and a national quadratic time trend, which corresponds to the specification in Haanwinckel (2020). The specification is estimated via IV in levels. The IV strategy instruments the generalized Pp -Kaitz index and its square using 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 median wage for the region over the full sample period. 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 error bars and shaded areas represent 99 percent confidence intervals based on standard errors that are clustered at the state level. Source: RAIS, 1985–2018.

Next, we estimate specifications that include state fixed effects, state-specific linear trends, and a national quadratic trend via OLS in differences. Figure B.21 shows the results. Qualitatively, the results are similar to the OLS specification in levels above. All specifications show some significant effects above the median and up to the 85th percentile, relative to P50. At the same time, the standard error bands are relatively wider for the specification using only the subset of years in Haanwinckel (2020). This becomes particularly evident when looking at the results relative to P90, which have error bands large enough to render some of the lower—but not the higher—wage percentiles insignificant. As above, the specification estimated on the full set of years remains significant throughout most of the wage distribution.

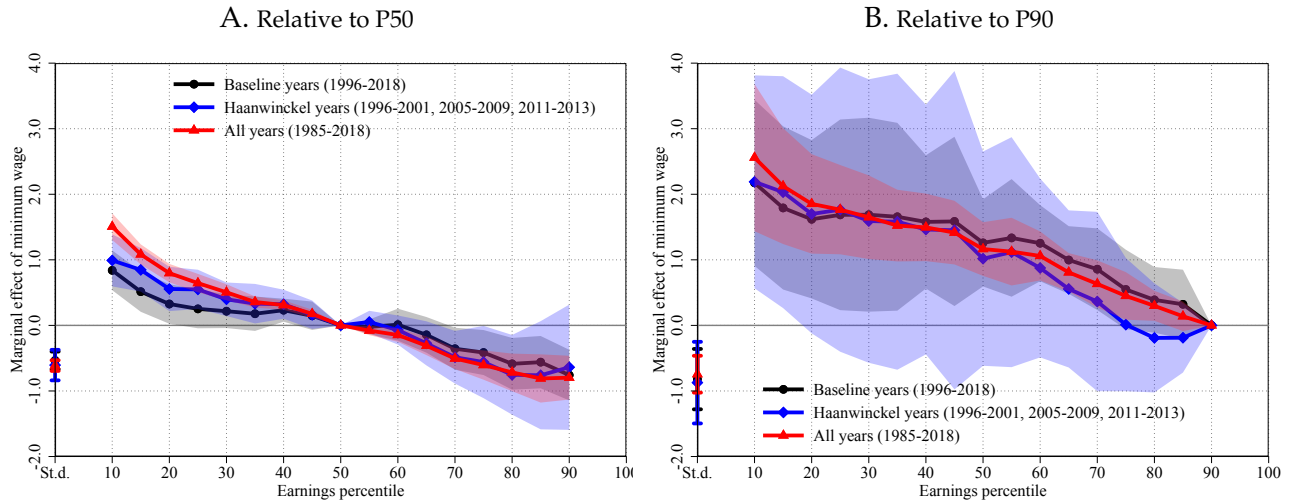
Figure B.21. Comparison with Haanwinckel (2020): State FEs, linear national trend, OLS in differences



Notes: Figure plots estimates of the marginal effects from equation (3) based on the regression framework in equation (2). Each panel shows three sets of estimation results (colored lines and error bars or shaded areas) based on different time periods: our baseline period from 1996–2018 (black circles and line), the subset years used in Haanwinckel (2020), comprising 1996–2001, 2005–2009, and 2011–2013 (blue diamonds and line), and all available years from 1985–2018 (red triangles and line). The included controls comprise a set of state fixed effects and a national linear time trend, which corresponds to the specification in Haanwinckel (2020). The specification is estimated via OLS in differences. 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 error bars and shaded areas represent 99 percent confidence intervals based on standard errors that are clustered at the state level. Source: RAIS, 1985–2018.

Finally, we estimate specifications that include state fixed effects, state-specific linear trends, and a national quadratic trend via IV in differences. Figure B.22 shows the results. Qualitatively, the results are similar to the previous specification using OLS in differences. One notable difference is that, while our baseline estimates remain significant throughout most of the wage distribution, both relative to P50 and relative to P90, the estimates using the years in Haanwinckel (2020) are all significant up to the 85th wage percentile using our baseline set of years, but significant only up to the 15th wage percentile using the subset of years in Haanwinckel (2020).

Figure B.22. Comparison with Haanwinckel (2020): State FEs, linear national trend, IV in differences



Notes: Figure plots estimates of the marginal effects from equation (3) based on the regression framework in equation (2). Each panel shows three sets of estimation results (colored lines and error bars or shaded areas) based on different time periods: our baseline period from 1996–2018 (black circles and line), the subset years used in Haanwinckel (2020), comprising 1996–2001, 2005–2009, and 2011–2013 (blue diamonds and line), and all available years from 1985–2018 (red triangles and line). The included controls comprise a set of state fixed effects and a national linear time trend, which corresponds to the specification in Haanwinckel (2020). The specification is estimated via IV in differences. The IV strategy instruments the generalized Pp -Kaitz index and its square using 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 median wage for the region over the full sample period. 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 error bars and shaded areas represent 99 percent confidence intervals based on standard errors that are clustered at the state level. Source: RAIS, 1985–2018.

From this, we conclude that our results are largely robust to the set of specifications used in Haanwinckel (2020), although for some specifications the standard error bands associated with the inclusion of quadratic national trends for the time period starting in 1996 leads to strikingly wide error bands. It is worth noting that our results are similarly pronounced and tightly estimated when using the full set of years from 1985 to 2018. In contrast, the results using the subset of years from Haanwinckel (2020) tend to deliver more noisy estimates, leading point estimates to turn insignificant lower in the wage distribution than would otherwise be the case.

Summary. From the above analysis, we conclude that the results presented in the main text are robust to alternative specifications, including those presented in Haanwinckel (2020).

Considering additional years of data between 1996 and 2018 (and, separately, between 1985 and 2018)

allows us to exploit significantly more variation in the effective bindingness of the federal minimum wage—see Appendix B.12—which leads us to find minimum wage spillovers that robustly reach up to at least the 75th wage percentile. This finding is reassuring given that our structural model, as well as the alternative structural model developed by [Haanwinckel \(2020\)](#), predict spillover effects throughout most of the wage distribution.

To conclude, we note that there are other important differences between our work and the complementary analysis contained in [Haanwinckel \(2020\)](#), over and above the exact specification and choice of years. For example, [Haanwinckel \(2020\)](#) uses the population of men and women between the ages of 18 and 54, while the analysis of the current paper and that in [Engbom and Moser \(2018\)](#) is restricted to only men. These differences might explain some of the remaining divergence between our results and those presented in subsequent work by [Haanwinckel \(2020\)](#).

B.12 Comparison of relative bindingness of the minimum wage, Brazil versus U.S.

Table B.1 compares the relative bindingness of the minimum wage, as proxied by lower-tail wage inequality, between Brazil and the U.S.

Table B.1. Lower-tail wage inequality in Brazil and in the U.S.

Year	Brazil		U.S.
	Baseline (1996–2018)	All years (1985–2018)	
1979			–0.64
1980			–0.65
1981			–0.68
1982			–0.71
1983			–0.73
1984			–0.73
1985		–0.68	–0.74
1986		–0.73	–0.74
1987		–0.81	–0.73
1988		–0.76	–0.72
1989		–0.80	–0.72
1990		–0.90	–0.72
1991		–0.85	–0.71
1992		–0.81	–0.72
1993		–0.76	–0.73
1994		–0.82	–0.71
1995		–0.84	–0.71
1996	–0.79	–0.79	–0.71
1997	–0.77	–0.77	–0.69
1998	–0.74	–0.74	–0.69
1999	–0.72	–0.72	–0.69
2000	–0.68	–0.68	–0.68
2001	–0.67	–0.67	–0.68
2002	–0.65	–0.65	–0.69
2003	–0.58	–0.58	–0.69
2004	–0.58	–0.58	–0.70
2005	–0.59	–0.59	–0.71
2006	–0.55	–0.55	–0.70
2007	–0.54	–0.54	–0.70
2008	–0.53	–0.53	–0.71
2009	–0.52	–0.52	–0.74
2010	–0.52	–0.52	–0.73
2011	–0.53	–0.53	–0.72
2012	–0.51	–0.51	–0.74
2013	–0.52	–0.52	
2014	–0.54	–0.54	
2015	–0.55	–0.55	
2016	–0.52	–0.52	
2017	–0.51	–0.51	
2018	–0.51	–0.51	
Minimum	–0.79	–0.90	–0.74
Maximum	–0.51	–0.51	–0.64
Range	0.28	0.39	0.10
Standard deviation	0.09	0.13	0.02

Notes: This table shows the relative bindingness of the minimum wage, as proxied by lower-tail wage inequality, for Brazil between 1996 and 2018 (column 1), Brazil from 1985 to 2018 (column 2), and the U.S. from 1979 to 2012. Lower-tail inequality is measured using the mean log wage percentile ratio P10/P50 computed across states in a given year. “Minimum” denotes the minimum of the mean log wage percentile ratio taken across all years in a given country. “Maximum” denotes the maximum of the mean log wage percentile ratio taken across all years in a given country. “Range” denotes the range (i.e., the maximum minus the minimum) of the mean log wage percentile ratio taken across all years in a given country. “Standard deviation” denotes the standard deviation of the mean log wage percentile ratio taken across all years in a given country. The data for Brazil are the same as used in the analysis presented in the main text and cover 1985 to 2018. The data for the U.S. are from Autor et al. (2016), who report these statistics between 1979 and 2012. *Source:* RAIS, 1985–2018, and Autor et al. (2016).

B.13 Comparison of wages in nominal terms and in multiples of the minimum wage

In this subsection, we compare the distributions of (changes in) wages across two numeraires: current BRL and the current minimum wage. We demonstrate that while the minimum wage does share certain attributes of a numeraire (Neri and Moura, 2006), it does so imperfectly. Consequently, it is not purely mechanical that wages throughout the wage distribution are affected by the minimum wage, as we document in Section 4.1.

To see why the distinction between the two numeraires matters, consider the following example. Suppose worker A gets paid 2.0 times the minimum wage throughout their employment spell that lasts from January to June of a given calendar year. Suppose worker B also gets paid 2.0 times the minimum wage but their employment spell lasts from January to December. Now suppose that the statutory minimum wage stands at BRL 400 from January to June, then increases to BRL 500 from July to December. Then the two workers' wages are the same in multiples of the current minimum wage (i.e., both receive constant pay equal to 2.0 times the current minimum wage) but differ in terms of nominal BRL (i.e., worker A has a mean wage of BRL 400 that consists of a constant stream, while worker B has a mean wage of BRL 450 that changes levels over time). Therefore, the numeraire matters for our measure of wage dispersion within and across individuals.

We begin our analysis with the variable in RAIS that contains each job's mean wage in multiples of the current minimum wage in each year, which is the one underlying our entire analysis in the main text. To obtain a wage measure in nominal BRL, we multiply the mean wage in multiples of the current minimum wage by the months-of-employment-weighted mean of the minimum wage prevailing during that year, using each job's start and end months. Our measurement likely contains some noise because both wages and the minimum wage itself can change over time within a job spell.

Comparing log wages in current BRL and multiples of the current minimum wage, we note that only 2.4 percent of all workers have a constant wage in terms of multiples of the current minimum wage between two consecutive years. For comparison, that number is 0.2 percent in nominal terms. That the latter number is smaller than the former suggests that the minimum wage does serve some numeraire function. At the same time, both shares are small, highlighting the importance of idiosyncratic wage changes.

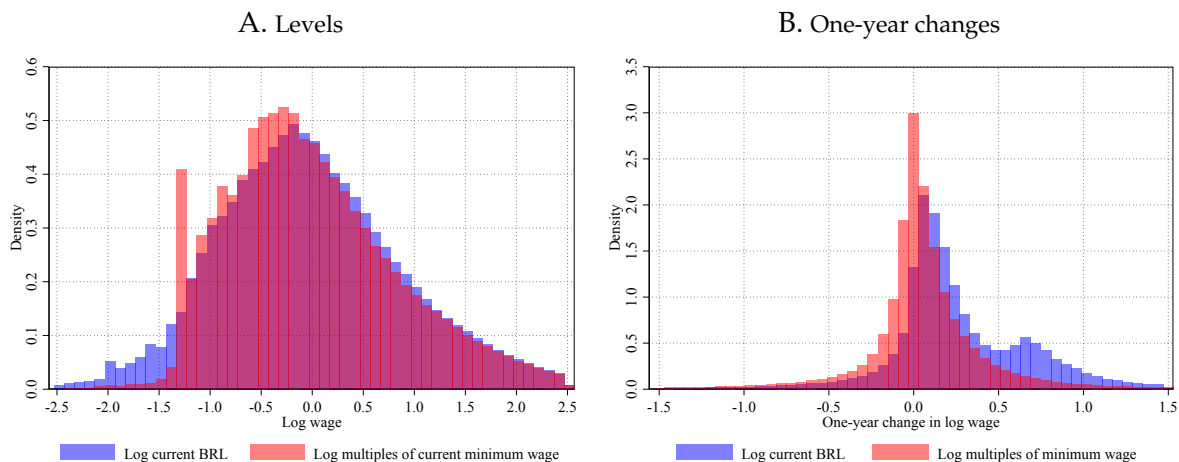
Figure B.23 shows histograms of (changes in) wages in each of the two numeraires. Panel A shows that the distribution of log wages has a relatively more pronounced spike in multiples of the current minimum wage, which is our baseline wage measure. The distribution of one-year changes in log wages in panel B shows less dispersion in multiples of the minimum wage, particularly in the right tail. However, both distributions are significantly dispersed, indicating that by both wage measures are far from fixed at a constant multiple of the numeraire.

Another way to assess the minimum wage's numeraire function is a simple variance decomposition, where we write the variance of some outcome variable of interest, y_{it} , across individuals i and years t as

$$\text{Var}(y_{it}) = \underbrace{\text{Var}(\mathbb{E}[y_{it}|i])}_{\text{Variance of individual-level means}} + \underbrace{\text{Var}(y_{it} - \mathbb{E}[y_{it}|i])}_{\text{Variance of dispersion around individual-level means}}. \quad (\text{B.1})$$

Here, the outcome variable y_{it} can be either log wages or the one-year changes in log wages. Table B.2 shows the results from the variance decomposition in equation (B.1) for different population subgroups (all workers, only stayers in the same occupation, only stayers at the same employer), for log wages versus one-year changes in log wages, and for the two numeraires: current BRL and the current minimum wage. Starting with wage levels in panel A, the total variance of log wages is slightly higher in current BRL than in multiples of the current minimum wage, 88.8 log points compared to 75.0 log points.

Figure B.23. Histograms of (changes in) log wages, nominal versus multiples of minimum wage



Notes: Figure shows levels of (panel A) and one-year changes in (panel B) log wages in terms of two numeraire: current BRL and the current minimum wage. That is, each panel shows the distribution of earnings in log current BRL (blue bars), calculated as the logarithm of the mean multiples of the current minimum wage recorded during each calendar year multiplied by the mean minimum wage prevailing during the months of employment during that year, and the log mean multiples of the current minimum wage (red bars). For panel A, log wages in each numeraire are normalized to be mean zero. Source: RAIS, 1994–1998.

Around 25 percent of the total variance is attributable to the variance of dispersion around individual-level means when measured in current BRL, compared to 12 percent when measured in multiples of the current minimum wage. This suggests that the minimum wage partially serves as a numeraire for wages in the economy. Turning now to one-year changes in log wages, we see that, at the same time, there is substantial dispersion in wages from one year to the next, regardless of the numeraire, with variances of 25.1 log points in current BRL and 17.9 log points in multiples of the current minimum wage. A similar share of the total variance of one-year changes in log wages is due to the variance of dispersion around individual-level means, around 73 percent in current BRL compared to 70 percent in multiples of the current minimum wage. This tells us that earnings are not fixed, not even in terms of multiples of the current minimum wage. Finally, Panels B and C show the same variance decompositions for workers who remain in the same occupation (panel B) or at the same employer (panel C) between years, leading us to draw broadly similar conclusions.

We conclude that, while the minimum wage does share certain attributes of a numeraire (Neri and Moura, 2006), it does so imperfectly and thus our empirical results in Section 4.1 are unlikely to be driven by this phenomenon.

Table B.2. Comparison of wages in nominal terms and in multiples of the minimum wage

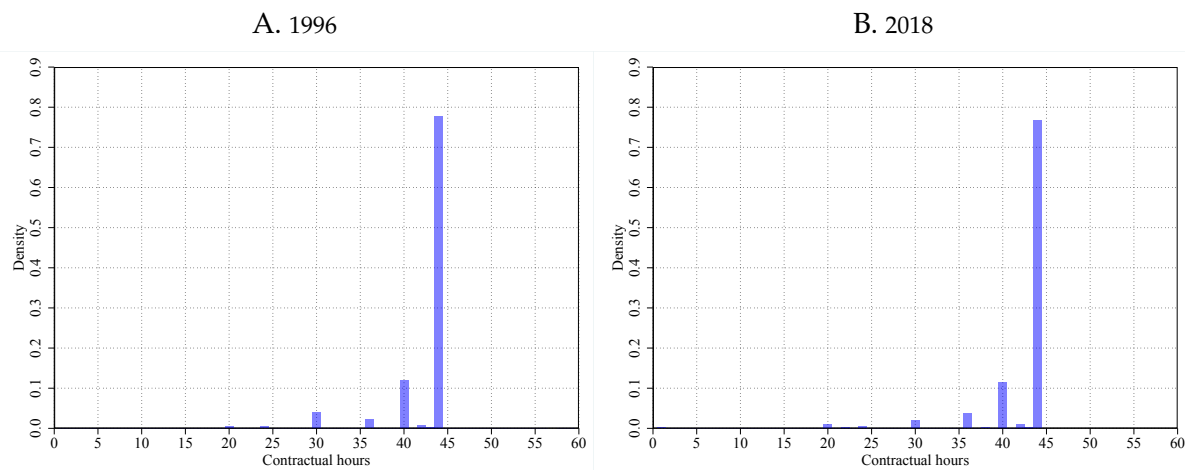
	Log wages		One-year changes in log wages	
	Current BRL	Current MW	Current BRL	Current MW
<i>Panel A. All workers</i>				
Total variance	0.888	0.750	0.251	0.179
Variance of individual-level means	0.667 (75%)	0.661 (88%)	0.069 (27%)	0.054 (30%)
Variance of dispersion around individual-level means	0.221 (25%)	0.088 (12%)	0.182 (73%)	0.125 (70%)
<i>Panel B. Only stayers in same occupation</i>				
Total variance	0.791	0.768	0.174	0.115
Variance of individual-level means	0.727 (92%)	0.728 (95%)	0.071 (41%)	0.055 (48%)
Variance of dispersion around individual-level means	0.064 (8%)	0.040 (5%)	0.103 (59%)	0.060 (52%)
<i>Panel C. Only stayers at same employer</i>				
Total variance	0.791	0.778	0.157	0.101
Variance of individual-level means	0.739 (93%)	0.741 (95%)	0.065 (41%)	0.052 (51%)
Variance of dispersion around individual-level means	0.052 (7%)	0.036 (5%)	0.091 (58%)	0.049 (49%)

Notes: This table shows the total variance of log wages and of one-year changes in log wages based on equation (B.1). Panel A shows the results for the whole population, while panel B shows those for workers who stay in the same occupation between consecutive years and panel C shows those for workers who stay at the same employer between years. Source: RAIS, 1994–1998.

B.14 Hours distribution and its relation to the bindingness of the minimum wage

Most adult males in Brazil’s formal sector work in a full-time contract, defined as either 40 work hours (spread across 5 days) or 44 work hours (spread across 6 days) per week. Figure B.24 shows the raw distribution of hours for this population for 1996 in panel A, and for 2018 in panel B. In the initial period, around 74 percent of all workers work 44 hours per week and another 15 percent work 40 hours per week, constituting around 89 percent of workers in full-time employment. Only around five percent of all employees are in employment arrangements with less than 35 contractual work hours per week.⁵⁹ Furthermore, the comparison between panels A and B show that there is no evidence over time—as the minimum wage increases—of a shift towards shorter work weeks in the aggregate. In contrast, there was a small reduction in the share of workers with 30 hour contracts that in the aggregate shifted toward 44 hour contracts.

Figure B.24. Histogram of contractual hours, 1996 and 2018

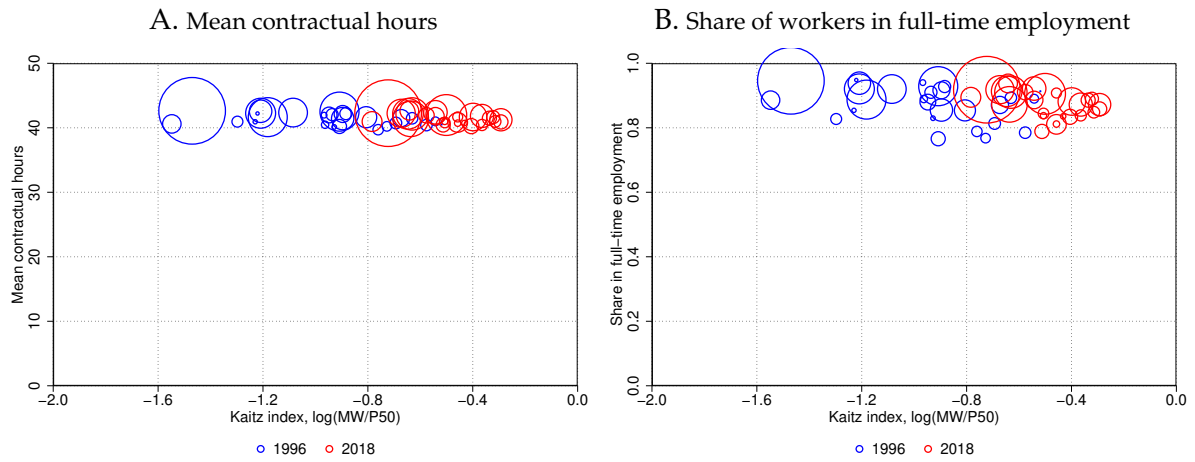


Notes: Figure shows density of contractual work hours for period 1996–2000 in panel A and for 2018 in panel B. A small number of observations reporting more than 60 hours are omitted from the graphs. Source: RAIS, 1996 and 2018.

Going beyond the aggregate statistics, there is also little systematic covariation between the relative bindingness of the minimum wage and work hours across Brazilian states. Figure B.25 shows that both the share of full-time employment in panel A and the mean number of hours in panel B stay constant as the minimum wage increases between 1996 and 2018. While in 1996 there is a weak systematic negative relationship between the full-time worker share and the bindingness of the minimum wage, measured by the P50-Kaitz index, this appears almost entirely driven by transitory fluctuations and permanent state-specific heterogeneity, rather than a correlation with the rising minimum wage over time within states.

⁵⁹According to the Bureau of Labor Statistics a higher share, around 12 percent of employees, works part-time (less than 35 hours) in the US in 2017.

Figure B.25. Relation between contractual hours and bindingness of the minimum wage



Notes: Figure shows for male workers of age 18–49 the share in full-time employment, defined as working 40 hours or more (panel A), and the mean number of contractual work hours (panel B), against the P50-Kaitz index, $gk_{aitz_{st}}(50) \equiv \log w_t^{min} - \log w_{st}^{P50}$, across states in 1996 and 2018. Area of circles is proportional to population size. Source: RAIS, 1996 and 2018.

C Model Appendix

This appendix provides further details on the equilibrium model presented in Section 5, including subsections on the model-implied employment distribution (Appendix C.1), the steady-state firm size mapping (Appendix C.2), the equilibrium definition (Appendix C.3), and the numerical solution algorithm (Appendix C.4).

C.1 The employment distribution

The employment distribution, $G(z|a, s)$, is given by the Kolmogorov Forward Equation (KFE),

$$0 = -\left(\delta(a, s) + sp(a, s)(1 - F(z|a, s))\right)G(z|a, s)e(a, s) + p(a, s)u(a, s)F(z|a, s)$$

The first term reflects the number $G(z|a, s)e(a, s)$ of workers employed at firms with productivity at most z . These workers flow into unemployment at rate $\delta(a, s)$. They receive outside offers at rate $sp(a, s)$, which in equilibrium they accept if they come from more productive firms, $1 - F(z|a, s)$. The last term reflects inflows into firms with productivity at most z . Since no employed worker accepts a job offer from a less productive firm, the only inflows are from unemployment. In particular, the unemployed receive job offers at rate $p(a, s)$. Rearranging, we get the expression in the paper,

$$G(z|a, s) = \frac{p(a, s)F(z|a, s)}{\delta(a, s) + sp(a, s)(1 - F(z|a, s))} \frac{u(a, s)}{e(a, s)}$$

C.2 The steady-state firm size mapping

The size $l(w, v|a, s)$ of a firm posting vacancies v with wage w in market (a, s) is given by the KFE

$$0 = -\left(\delta(a, s) + sp(a, s)(1 - F(z|a, s))\right)l(w, v|a, s) + vq(a, s) \left(\frac{u(a, s)}{S(a, s)} + \frac{se(a, s)}{S(a, s)}G(z|a, s)\right)$$

The firm loses workers to unemployment and up the job ladder. Each vacancy contacts a potential hire at rate $q(a, s)$, who is unemployed with probability $u(a, s)/S(a, s)$ and employed with complementary probability. Employed workers are hired iff they are at a less productive firm. Noting that $q(a, s) = p(a, s)S(a, s)/V(a, s)$, substituting and rearranging,

$$l(w, v|a, s) = \frac{v}{V(a, s)}p(a, s)\frac{u(a, s) + se(a, s)G(z|a, s)}{\delta(a, s) + sp(a, s)(1 - F(z|a, s))}$$

Using equation (6) to substitute for the employment distribution $G(\cdot)$,

$$\begin{aligned} l(w, v|a, s) &= \frac{v}{V(a, s)}p(a, s)\frac{u(a, s)\frac{(\delta(a, s) + sp(a, s)(1 - F(w|a, s)))}{(\delta(a, s) + sp(a, s)(1 - F(w|a, s)))} + s\frac{p(a, s)F(w|a, s)}{\delta(a, s) + sp(a, s)(1 - F(w|a, s))}u(a, s)}{\delta(a, s) + sp(a, s)(1 - F(w|a, s))} \\ &= \frac{vu(a, s)p(a, s)}{V(a, s)}\frac{\delta(a, s) + sp(a, s)(1 - F(w|a, s)) + sp(a, s)F(w|a, s)}{(\delta(a, s) + sp(a, s)(1 - F(w|a, s)))^2} \\ &= \frac{vu(a, s)p(a, s)}{V(a, s)}\frac{\delta(a, s) + sp(a, s)}{(\delta(a, s) + sp(a, s)(1 - F(w|a, s)))^2} \end{aligned}$$

C.3 Equilibrium definition

We here define a equilibrium of the model economy presented in Section 5.

Definition 1. *An equilibrium of our economy consists of*

- a set of wage and vacancy posting policies $\{w(z|a, s), v(z|a, s)\}$ that solve firms' problem;
- a reservation wage $r(a, s)$ that solves workers' problem; and
- aggregate states $\{G(z|a, s), e(a, s), u(a, s), V(a, s), p(a, s), q(a, s)\}$ that are consistent with their laws of motion in steady-state as well as the matching technology.

To characterize the equilibrium, we start by substituting our assumed iso-elastic cost function into firms' problem (7) and taking first-order conditions,

$$c(a, s)v(z|a, s)^\eta = (z - w) \frac{\partial l(w, v|a, s)}{\partial v} \quad (\text{C.1})$$

$$l(w, v|a, s) = (z - w) \frac{\partial l(w, v|a, s)}{\partial w} \quad (\text{C.2})$$

Differentiating the equilibrium size (8) with respect to vacancies

$$\frac{\partial l(w, v|a, s)}{\partial v} = \frac{u(a, s)p(a, s)}{V(a, s)} \frac{\delta(a, s) + sp(a, s)}{(\delta(a, s) + sp(a, s)(1 - F(w|a, s)))^2}$$

Substituting this into the first-order condition for vacancies (C.1),

$$c(a, s)v(z|a, s)^\eta = (z - w(z|a, s)) \frac{u(a, s)p(a, s)}{V(a, s)} \frac{\delta(a, s) + sp(a, s)}{(\delta(a, s) + sp(a, s)(1 - F(w(z|a, s)|a, s)))^2} \quad (\text{C.3})$$

Differentiating the equilibrium size (8) with respect to wages

$$\frac{\partial l(w, v|a, s)}{\partial w} = 2sp(a, s)f(w|a, s) \frac{vu(a, s)p(a, s)}{V(a, s)} \frac{\delta(a, s) + sp(a, s)}{(\delta(a, s) + sp(a, s)(1 - F(w|a, s)))^3}$$

Substituting this into the first-order condition for wages (C.2) and cancelling terms

$$\delta(a, s) + sp(a, s)(1 - F(w(z|a, s)|a, s)) = (z - w(z|a, s)) 2sp(a, s)f(w(z|a, s)|a, s) \quad (\text{C.4})$$

As in [Burdett and Mortensen \(1998\)](#), more productive firms post higher wages. Consequently,

$$F(w(z|a, s)|a, s) = \frac{M}{V} \int_{\underline{z}}^z v(\tilde{z}|a, s) d\Gamma(\tilde{z}), \quad f(w(z|a, s)|a, s)w'(z|a, s) = \frac{M}{V} v(z|a, s)\gamma(z)$$

Define $h(z|a, s) = F(w(z|a, s)|a, s)$ so that $f(w(z|a, s)|a, s) = h'(z|a, s)/w'(z|a, s)$. Substituting in (C.4),

$$w'(z|a, s) = (z - w(z|a, s)) \frac{2sp(a, s)h'(z|a, s)}{\delta(a, s) + sp(a, s)(1 - h(z|a, s))} \quad (\text{C.5})$$

We also have that $h'(z|a, s) = \frac{M}{V(a, s)}v(z|a, s)\gamma(z)$ so that $v(z|a, s) = \frac{V(a, s)}{M} \frac{h'(z|a, s)}{\gamma(z)}$. Substituting in (C.3),

$$h'(z|a, s) = \frac{M}{V(a, s)}\gamma(z) \left(\frac{1}{c(a, s)} (z - w(z|a, s)) \frac{u(a, s)p(a, s)}{V(a, s)} \frac{\delta(a, s) + sp(a, s)}{(\delta(a, s) + sp(a, s)(1 - h(z|a, s)))^2} \right)^{\frac{1}{\eta}} \quad \text{C.6}$$

Equations (C.5)–(C.6) constitute a system of differential equations in the two functions $w(z|a, s)$ and $h(z|a, s)$. The first boundary condition is that wages of the least productive firm must equal the lowest possible pay in the market, $\lim_{z \rightarrow \underline{z}(a, s)} w(z|a, s) = \max \left\{ r(a, s), \frac{w^{\min}}{a} \right\}$. The second boundary condition is that the CDF of the offer distribution is zero for the least productive firm, $\lim_{z \rightarrow \underline{z}(a, s)} h(z|a, s) = 0$, where $\underline{z}(a, s)$ is the least productive firm active in market (a, s) : $\underline{z}(a, s) = \max \left\{ \underline{z}, \max \left\{ r(a, s), \frac{w^{\min}}{a} \right\} \right\}$. Finally, the key equilibrium consistency condition is that the total number of vacancies, $V(a, s)$, is such that the CDF of offered wages integrates to one, $\lim_{z \rightarrow \bar{z}} h(z|a, s) = 1$.

C.4 Numerical solution algorithm

Recall that the parameter vector \mathbf{p} includes the reduced form job finding rate λ . Hence given a parameter vector, we know all worker flows since \mathbf{p} also includes $\{\delta_0, \delta_1, \phi_0, \phi_1, \pi\}$. We use the flows to get the implied stock of workers, $\{u(a, s), e(a, s)\}$, and based on that we recover the required aggregate number of vacancies $V(a, s)$ consistent with the job finding rate $p(a, s) = \lambda$. Recall that the parameter vector \mathbf{p} also includes the reduced form parameters fully characterizing the reservation wage, $r(a, s)$. Hence, we also know the boundary conditions.

To solve for the equilibrium, we start by solving the system of differential equations (9) for a low cost $c_0(a, s)$ and a high cost, $c_1(a, s)$. Recall that the key consistency condition is $\lim_{z \rightarrow \bar{z}} h(z|a, s) = 1$. We require that under the low cost, firms create too many jobs, $\lim_{z \rightarrow \bar{z}} h_0(z|a, s) > 1$, while under the high cost, firms create too few jobs, $\lim_{z \rightarrow \bar{z}} h_1(z|a, s) < 1$. If this is not true under $c_0(a, s)$ ($c_1(a, s)$), we adjust $c_0(a, s)$ ($c_1(a, s)$) down (up) until it is true. After we have found $c_0(a, s)$ and $c_1(a, s)$ such that both of these conditions hold, we apply a bisection to find the cost $c(a, s)$ such that $\lim_{z \rightarrow \bar{z}} h(z|a, s) = 1$.

We subsequently simulate a monthly approximation to the model, starting workers off from the steady-state distribution. We follow exactly our empirical procedure to construct both a monthly and an annual data set based on the simulated data, including how to select a main employment spell and compute all outcome variables of interest. In particular, we estimate an AKM regression based on the simulated annual data set restricted to the largest connected set, which as in the data covers the vast majority of employment spells.

The steps above are sufficient to estimate the model. Having obtained an estimated parameter vector \mathbf{p}^* , we compute the implied flow value of leisure, $b(a)$, such that the reservation wage is consistent with our reduced form parameter or alternatively makes workers indifferent between working at the minimum wage and unemployment.

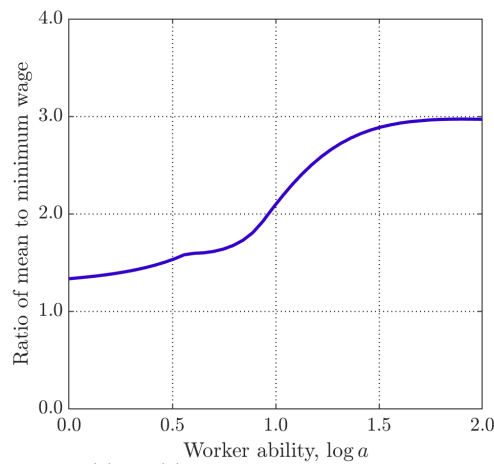
To subsequently solve the model for alternative levels of the minimum wage, we instead hold the cost $c(a, s)$ fixed at its estimated value, as well as the flow value $b(a)$. Applying a similar bisection as above, we instead guess a low job finding rate $p_0(a, s)$ and a high job finding rate $p_1(a, s)$, solve for the equilibrium number of vacancies $V(a, s)$ consistent with these job finding rates, and solve the system of differential equations (9). Since the job finding rate $p(a, s)$ is inversely related to the worker finding rate $q(a, s)$, we require that firms want to create too many jobs under the low job finding rate $p_0(a, s)$ (i.e. high worker finding rate $q_0(a, s)$), and vice versa. If not, we adjust the initial guesses $\{p_0(a, s), p_1(a, s)\}$ until this holds. After that, we apply a bisection for the job finding rate $p(a, s)$ until the key equilibrium consistency condition $\lim_{z \rightarrow \bar{z}} h(z|a, s) = 1$ holds.

D Estimation Appendix

This section provides additional details on the model estimation that build on the material presented in Section 6, including subsections on the mean-to-min wage ratio in the estimated model (Appendix D.1), the implied parameter estimates and additional model fit (Appendix D.2), details of the identification (Appendix D.3), additional model validation (Appendix D.4), and a discussion of the structure of the unbalanced panel (Appendix D.5).

D.1 Mean-to-min wage ratio in the estimated model

Figure D.1. Mean-to-min wage ratio in the estimated model



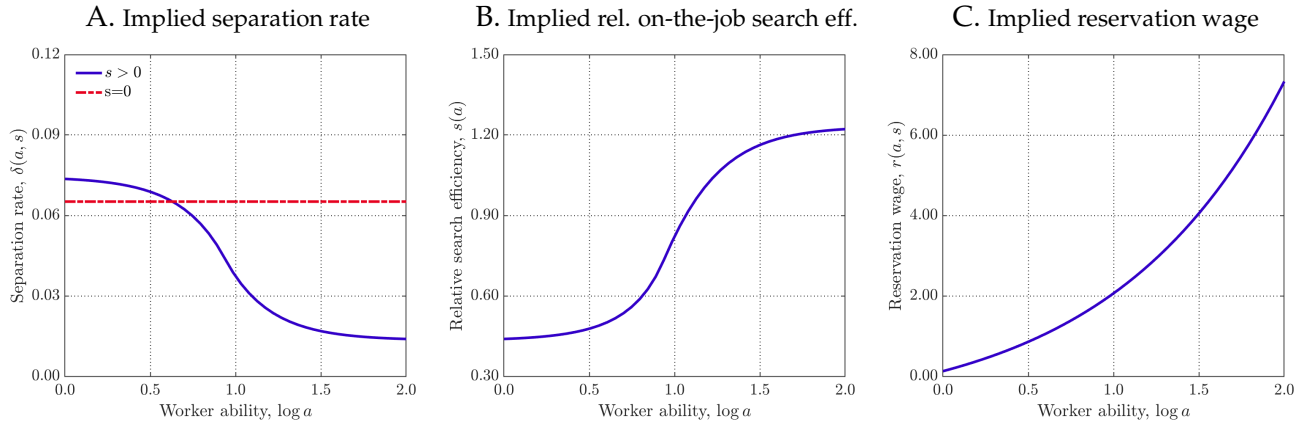
Notes: Figure shows the mean-to-min wage ratio $\bar{w}(a)/w^*(a)$, as defined in [Hornstein et al. \(2011\)](#), from our estimated model. All statistics are computed from model solution before applying the estimated measurement error. The mean wage $\bar{w}(a)$ is defined as the arithmetic mean over the realized distribution of wages in levels for a given ability type a . The min wage $w^*(a)$ is defined as the lowest accepted wage in levels by workers of ability a , which might be either the statutory minimum wage w^{min} or the workers' reservation wage if the latter exceeds the statutory minimum wage. Source: Model and RAIS, 1994–1998.

D.2 Implied parameter estimates and additional model fit

This section discusses additional details regarding the implied parameter estimates and model fit. This follows up on the results presented in Section 6.2, specifically Table 4 and Figure 4, of the main text.

Figure D.2 shows the implied parameter values for the separation rates, $\delta(a, s > 0)$ and $\delta(a, s = 0)$, relative on-the-job search efficiency, $s(a)$, and reservation piece rate, $r(a)$, across the distribution of worker ability, a , based on the estimates presented in Table 4 of the main text.

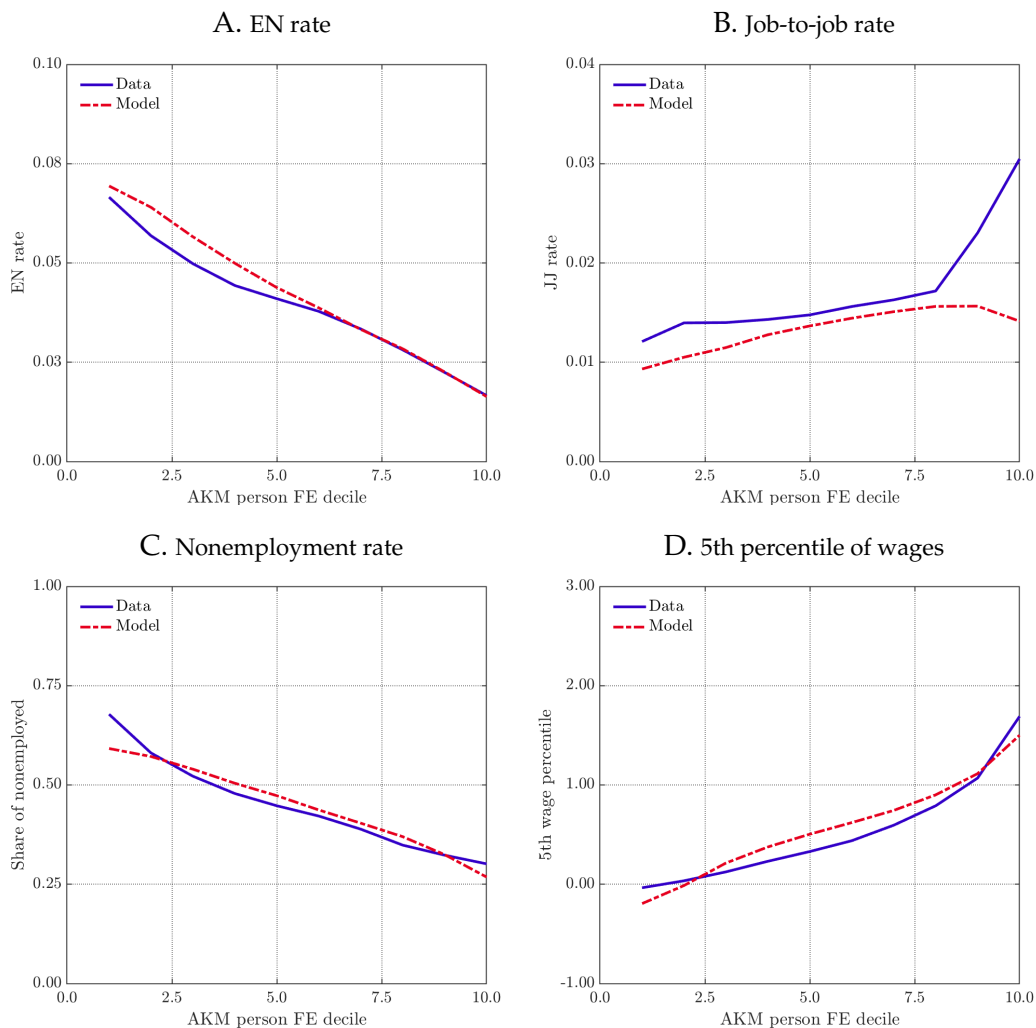
Figure D.2. Implied parameter estimates



Notes: This figure shows the implied parameter values of the separation rates, $\delta(a, s > 0)$ and $\delta(a, s = 0)$, relative on-the-job search efficiency, $s(a)$, and reservation piece rate, $r(a)$, across the distribution of worker ability, a , based on the estimates in Table 4. Source: Model.

Figure D.3 illustrates the model's ability to replicate labor market stocks and flows by AKM worker fixed effects. Panel A shows that the model matches well the lower EN rate among higher paid workers, as a result of the decline in the separation rate, $\delta(a, s)$, with worker ability. Panel B highlights that we understate somewhat the level of job-to-job mobility as well as its gradient with AKM worker fixed effect. Although underlying search efficiency $s(a)$ rises monotonically with worker ability and higher ability workers are less likely to be minimum wage workers, the resulting job-to-job rate is not monotone in AKM worker fixed effects. The reason is that the separation rate $\delta(a, s)$ declines in ability, such that higher ability workers are higher up the job ladder. Since workers higher up the job ladder are less likely to accept an outside offer, the realized job-to-job rate is non-monotone in ability. Panel C shows that the model matches well the nonemployment rate by AKM worker fixed effect decile. Although we do not target this in estimation—in fact we impose the same job finding rate λ across worker types—the model matches well the empirical pattern, because the separation rate, $\delta(a, s)$, declines with worker ability. Panel D shows that the model matches well the fifth percentile of wages by AKM worker fixed effect decile.

Figure D.3. Worker outcomes by AKM person FE, model vs. data



Notes: Panel A shows the share of employed workers who are nonemployed in the subsequent month. Employment refers to formal sector employment in the data; nonemployment is everything else (unemployment, not in the labor force and informal sector employment). Panel B shows the share of employed workers who are employed at a different main employer in the subsequent month. Panel C shows the share of population that is not working in the formal sector. Panel D shows the 5th percentile of log wages. All panels are by decile of AKM person fixed effects based on a regression of log monthly earnings on person fixed effects and firm fixed effects. Model and data sample selection and variable construction are identical—see text for details. Source: Model and RAIS, 1994–1998.

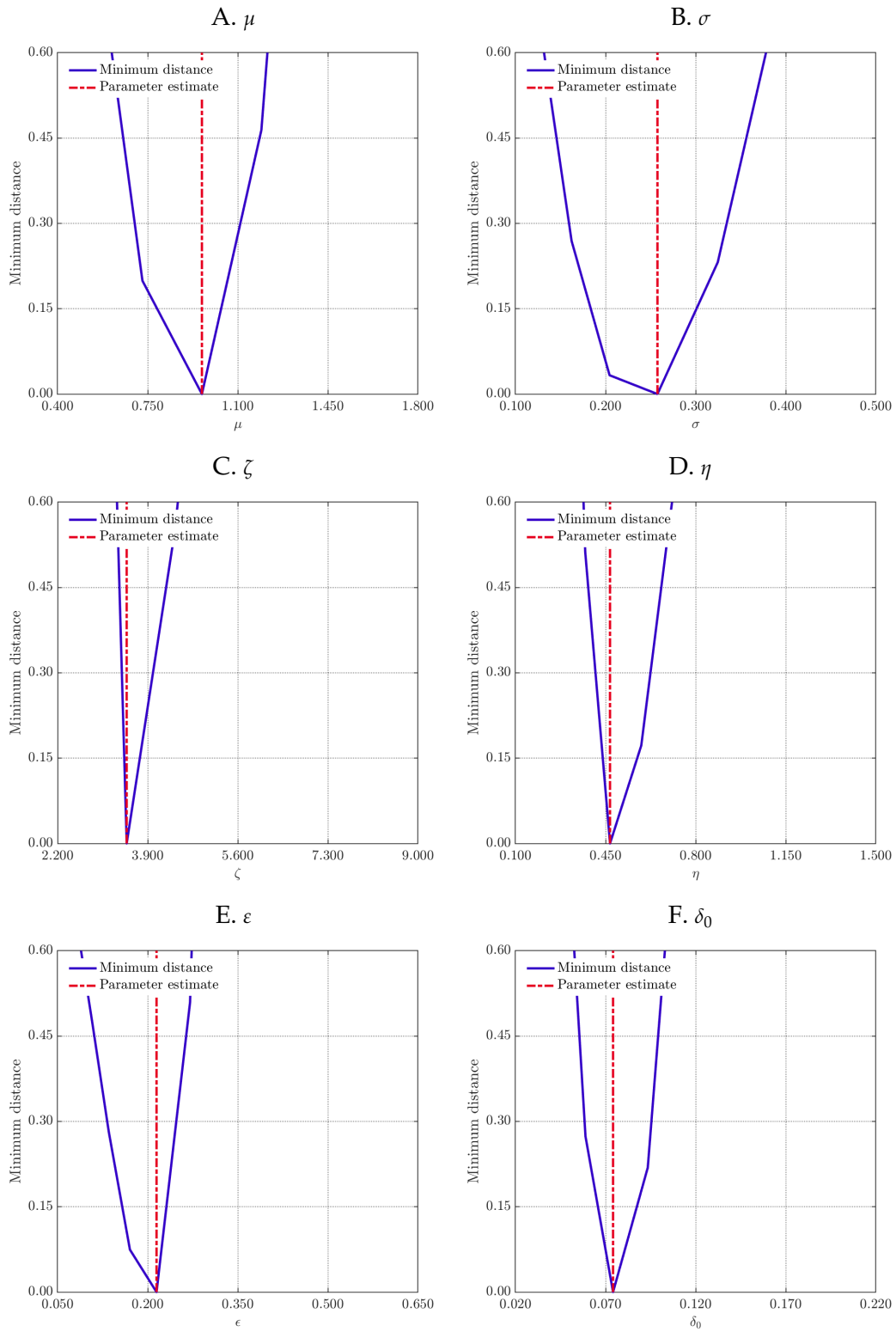
D.3 Details of the identification

This subsection provides a further discussion of identification of the 12 internally estimated parameters of our model. We consider two exercises. The first plots how the minimum distance objective function changes as each parameter varies around its estimated value, holding all other parameters fixed at their estimated values. This exercise is local in nature in the sense that an envelope condition ensures that the other parameters remain optimal as one parameter varies around its optimum.

Figure D.5 provides the results. Evidently, 11 of the 12 internally estimated parameters are well informed by the joint information contained in the targeted moments. The exception is the intercept in the reservation wage, r_0 , for which the minimum distance is relatively flatter compared to other parameters. For the main objective of this paper, we believe that this is a somewhat minor issue. The reason is that the impact of the minimum wage on both inequality and employment is essentially invariant to the particular value of this parameter, as we highlight further in Appendix E.5.

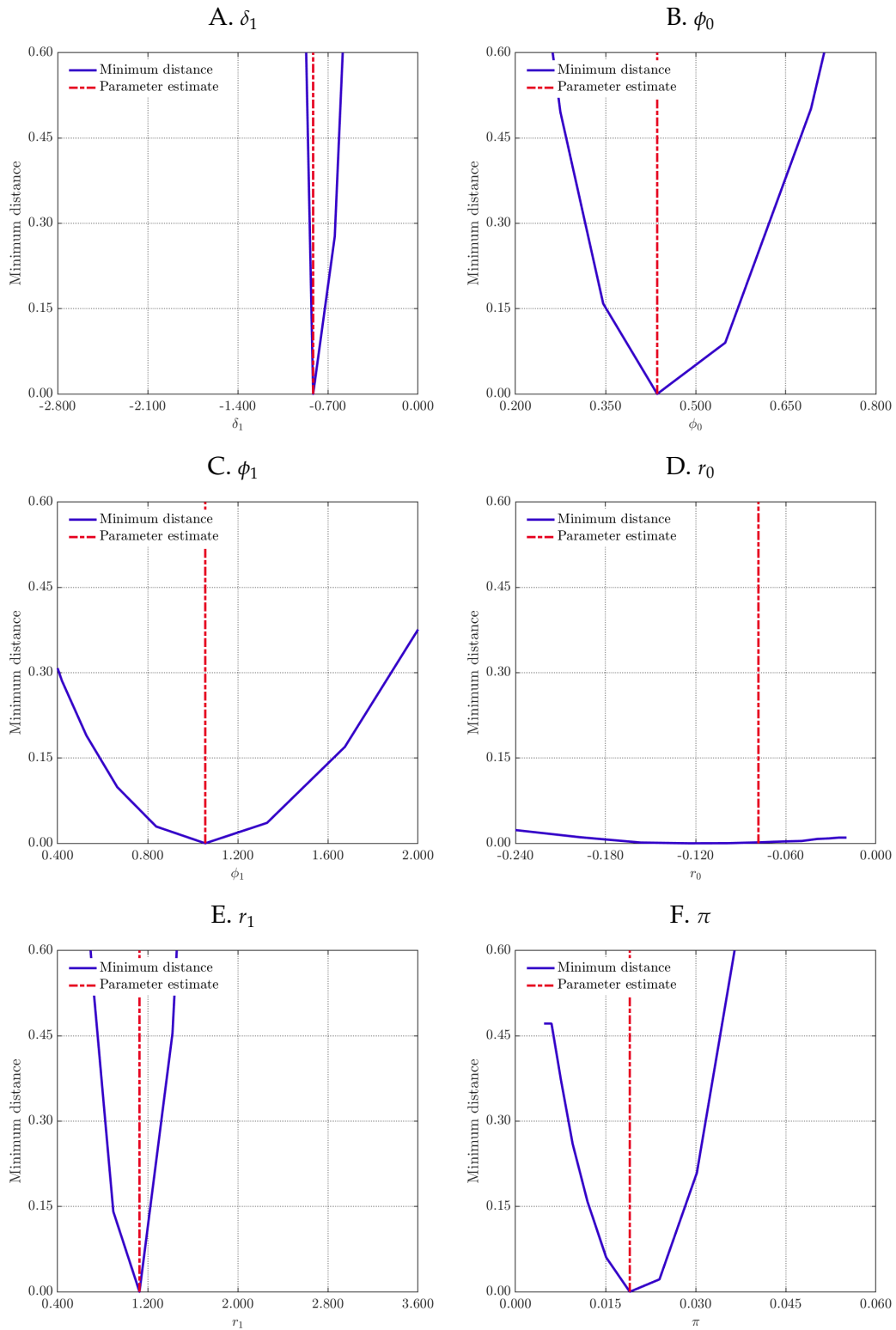
The second exercise plots how an individual parameter moves its particularly informative moment. Figure D.6 plots those parameters that are particularly informed by a single moment against its chosen moment as the parameter varies around its estimated value (between 25 and 300 percent of the estimated value), holding the other parameters fixed at their estimated values. Reassuringly, each parameter distinctly moves its particularly informative moment, suggesting that these parameters are well informed by our choice of targets. In the interest of space, we focus this exercise primarily on those parameters that are particularly informed by a single moment. Nevertheless, for reference we also show in Figure D.7 how the overall EN and EE rates move as we change the intercept in the separation rate, δ_0 , and the intercept in relative search efficiency, ϕ_0 , respectively. Note, though, that these two moments are not targeted in estimation, as we target the EN (EE) rate *by decile* of AKM worker fixed effect deciles for δ_0 (ϕ_0) and δ_1 (ϕ_1) jointly. These two parameters move the overall mobility rates in the expected direction.

Figure D.4. Minimum distance, model



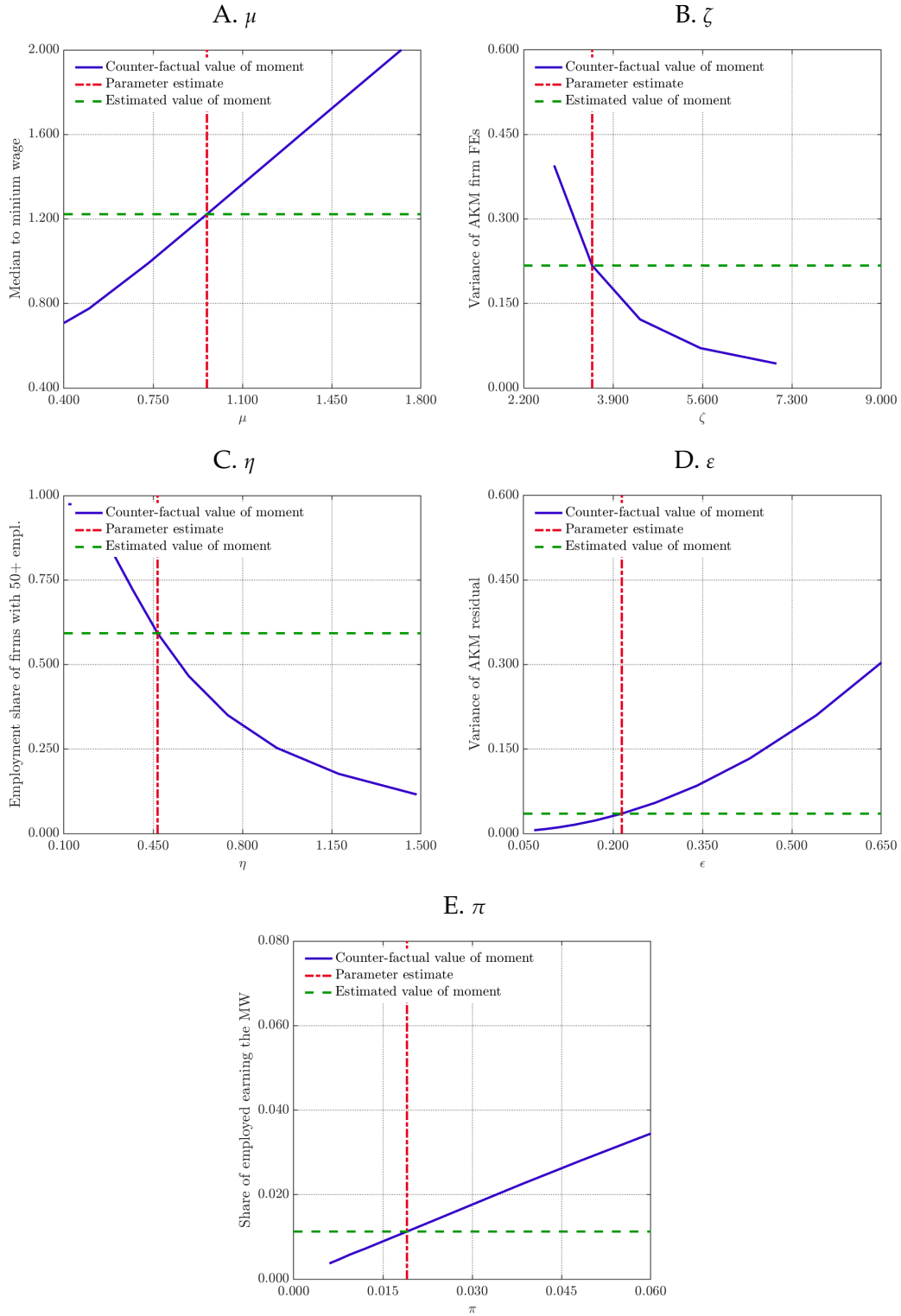
Notes: Impact on minimum distance objective function of varying one parameter at a time, holding all other parameters fixed at their estimated values. Source: Model.

Figure D.5. Minimum distance, model (cont'd)



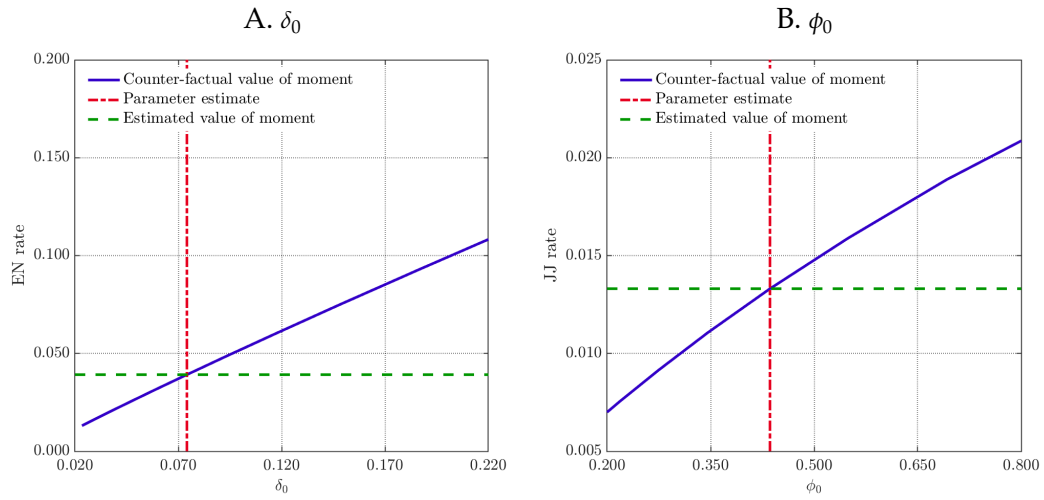
Notes: Impact on minimum distance objective function of varying one parameter at a time, holding all other parameters fixed at their estimated values. Source: Model.

Figure D.6. Targeted moments versus parameters, model



Notes: Impact on an associated target moment of varying one parameter at a time, holding all other parameters fixed at their estimated values.
 Source: Model.

Figure D.7. Additional moments versus parameters, model

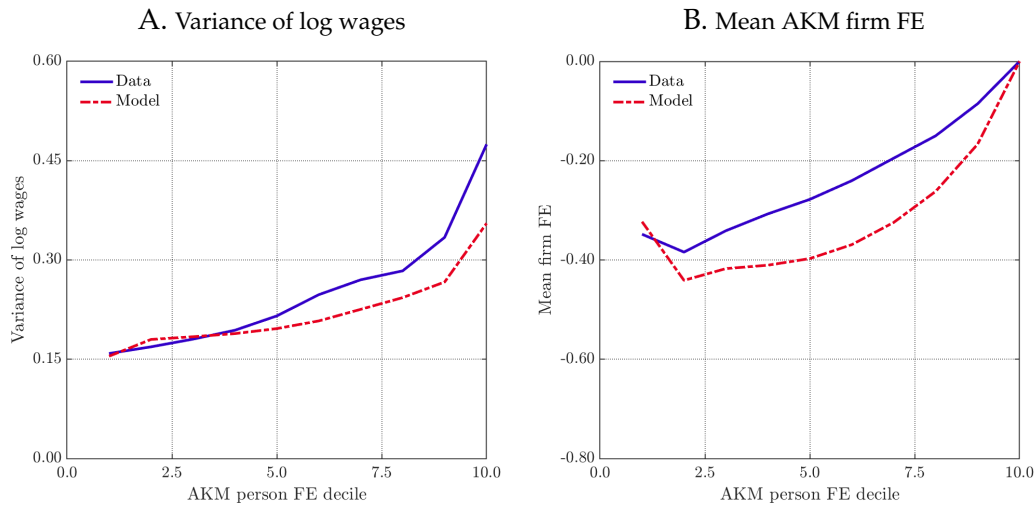


Notes: Impact on an associated target moment of varying one parameter at a time, holding all other parameters fixed at their estimated values.
 Source: Model.

D.4 Additional model validation

Figure D.8 contrasts some additional predictions of the model that were not explicitly targeted with the data. Panel A shows that dispersion in (log) pay is larger among high paid workers, in both the model and data. This pattern is driven by the top deciles having greater dispersion in underlying worker ability, a , as well as greater dispersion in pay conditional on ability among high skilled workers. The latter is, in turn, due to the fact that the minimum wage does not constrain pay at the top of the ability distribution. Panel B plots the average AKM firm fixed effect by decile of AKM worker fixed effects. Higher paid workers work for higher paying firms, in both the model and data. The reason is that more skilled workers climb the job ladder faster and fall off it less frequently. At the bottom of the worker pay distribution, however, the pattern is reversed, because the minimum wage makes matches between the lowest skilled workers and the lowest productivity firms unviable.

Figure D.8. Model validation across AKM person FE deciles, model versus data



Notes: Figure shows the estimated impact of a 57.7 log point increase in the productivity adjusted real minimum wage. Workers are binned by decile of AKM worker fixed effect. Firms are binned by (employment-unweighted) AKM firm fixed effect decile. AKM regression is estimated on model-simulated monthly data aggregated to the annual level following an identical sample selection and variable construction methodology as in the data. Panel A shows the impact on the variance of log wages. Panel B shows the impact on the mean of AKM firm fixed effects. Source: Model and RAIS, 1994–2018.

D.5 Structure of the unbalanced panel

A salient feature of the formal-sector RAIS data is that both workers and firms do not appear in a balanced panel. Our estimated model rationalizes this through stochastic worker separation rates into nonemployment and stochastic job findings rates from nonemployment. Our estimation procedure relies on an indirect inference logic and the AKM wage equation, which we use as an auxiliary model, is estimated on finite samples—both in the data and on the model-simulated data. Therefore, it is interesting to know to what extent panel structure in the data is replicated by simulations from our estimated model.

Table D.1 compares worker and firm survival rates in the data for two periods, the estimation period 1994–1998 (panel A) and the final period 2010–2014 (panel B), as well as in the simulated data from our estimated model (panel C), which we fit to a separate set of moments from the estimation period 1994–1998. Specifically, we consider two concepts of worker or firm survival rates. First, we compute the survival rates of a cohort of workers or firms observed in the first year of the five-year time window. We report the share of that cohort of workers or firms who survive for each number of consecutive years, including the first one, during this time window in the columns labeled “Cohort”. Second, we compute the share of all workers or firms who are observed for each of one, two, three, four, or five years in the data in the columns labeled “Pooled”. The two statistics are related but distinct because—in the real world like in our simulated model—workers may be observed for the first time after the first year of our data time window.

A few points are worth noting about the results in Table D.1. Cohort survival rates are concentrated around five years—the complete panel—both for workers and for firms, as well as in the two data periods and in the model. In comparison, pooled survival rates are more spread out. The model matches very well the empirical worker cohort survival rates. At the same time, the model overpredicts the cohort survival rates of firms. Vis-a-vis the data, the model also underpredicts the pooled survival rates of workers but does a very good job at capturing that of firms. The model fit is not perfect, which may be not surprising given that there were no free parameters that could have been used to match these survival rate profiles jointly. At the same time, the parsimonious model does an adequate job at capturing key features of the empirical panel structure, which gives us confidence in our indirect inference procedure.

Table D.1. Cohort survival rates and pooled survival shares, data and model

<i>Panel A. Data, 1994–1998</i>				
Number of years	Workers		Firms	
	Cohort	Pooled	Cohort	Pooled
1	2.0%	4.5%	3.0%	2.8%
2	3.6%	8.6%	5.2%	5.7%
3	5.1%	12.4%	6.6%	7.4%
4	8.8%	20.2%	8.4%	11.5%
5	80.4%	54.3%	76.7%	72.7%

<i>Panel B. Data, 2010–2014</i>				
Number of years	Workers		Firms	
	Cohort	Pooled	Cohort	Pooled
1	1.6%	3.2%	2.6%	1.8%
2	1.9%	6.2%	4.4%	4.2%
3	3.6%	9.2%	5.3%	6.0%
4	5.9%	16.3%	7.0%	8.6%
5	87.0%	65.1%	80.7%	79.5%

<i>Panel C. Model</i>				
Number of years	Workers		Firms	
	Cohort	Pooled	Cohort	Pooled
1	1.0%	7.8%	0.0%	1.3%
2	2.7%	14.2%	0.3%	4.7%
3	5.6%	20.0%	1.4%	9.4%
4	11.2%	23.9%	4.7%	15.3%
5	79.4%	34.2%	93.7%	69.4%

Notes: Table compares worker and firm survival rates in the data for two periods, the estimation period 1994–1998 (panel A) and the final period 2010–2014 (panel B), as well as in the simulated data from our estimated model (panel C), which was fit to data from 1994–1998. Two concepts of worker or firm survival rates are presented: the share of the starting year’s cohort of workers or firms who survive for each number of consecutive years (columns “Cohort”) and the share of all workers or firms who are observed for each number of years in the data (columns “Pooled”). *Source:* RAIS, 1994–1998 and 2010–2014, and model.

E Results Appendix

This section provides additional details on the simulated impact of the minimum wage, building on the material presented in Section 7, including subsections on a model-based AKM wage decomposition (Appendix E.1), the impact of the minimum wage on sorting (Appendix E.2), further results on heterogeneity in effects on disemployment and firm size (Appendix E.3), and the dependence of minimum wage effects on model parameters (Appendix E.5).

E.1 AKM decomposition

Table E.1 summarizes the impact of the minimum wage on earnings inequality as viewed through the lens of the AKM decomposition. The increase in the minimum wage accounts for about a third of the fall in the overall variance of earnings over this period in Brazil. It accounts for roughly half of the compression in the variance in AKM person fixed effects and 10 percent of the fall in the variance of the AKM firm effects. We caution, however, that *all* of the fall in inequality in the model is due to changes in firms' wage and vacancy policies.

Table E.1. Impact of minimum wage on AKM decomposition, model versus data

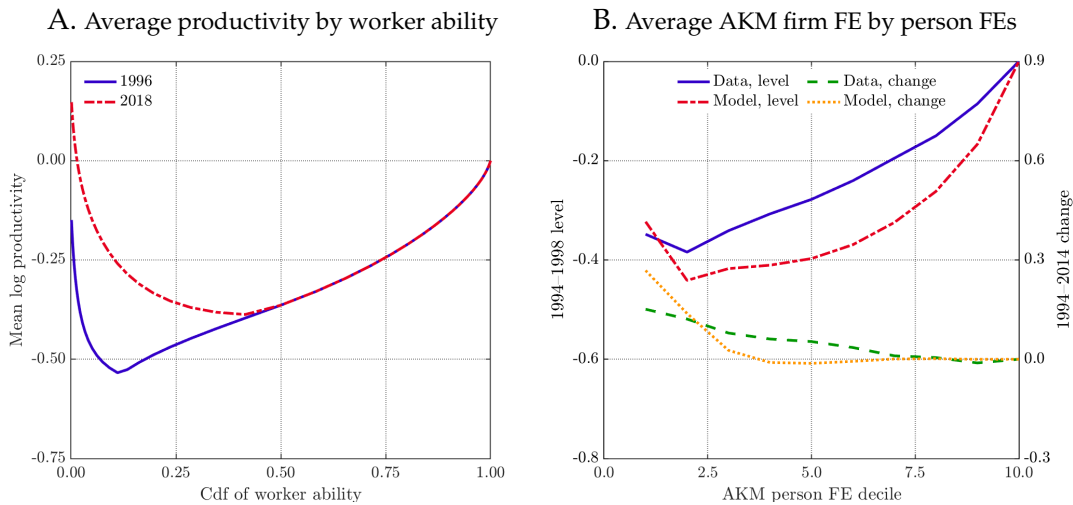
	1994–1998		2014–2018		Change		
	Data	Model	Data	Model	Data	Model	Due to MW
Variance of log wages	0.704	0.600	0.436	0.478	-0.268	-0.121	45.3%
Variance of AKM person FEs	0.333	0.259	0.262	0.208	-0.070	-0.051	72.7%
Variance of AKM firm FEs	0.217	0.195	0.085	0.176	-0.131	-0.018	14.1%
Variance of AKM residual	0.032	0.035	0.016	0.036	-0.016	0.001	-8.1%
2×covariance AKM person-firm FEs	0.123	0.111	0.072	0.058	-0.051	-0.053	104.3%

Notes: Men aged 18–54. Estimated impact of a 57.7 log point increase in the minimum wage in the model as well as the raw data. Model and data sample selection and variable construction is identical. Source: Model and RAIS 1994–2018.

E.2 Empirical support for the impact of the minimum wage on sorting

Figure E.1 illustrates this change in sorting in the model and provides empirical support for it. Panel A plots average firm productivity by worker ability, highlighting that average productivity rises, particularly among the lowest-ability workers. The reason is that matches between low-ability workers and low-productivity firms become unviable when the minimum wage is raised. Panel B of the figure provides reduced-form support consistent with this prediction. Specifically, it plots average AKM firm fixed effect by decile of AKM worker fixed effects in the model and data. For completeness, we replicate the level in the initial period from Figure D.8. As the minimum wage is increased, the average AKM firm fixed effect rises disproportionately among the lowest AKM worker fixed effects workers.

Figure E.1. Reallocation of lower-ability workers toward higher-productivity firms, model versus data

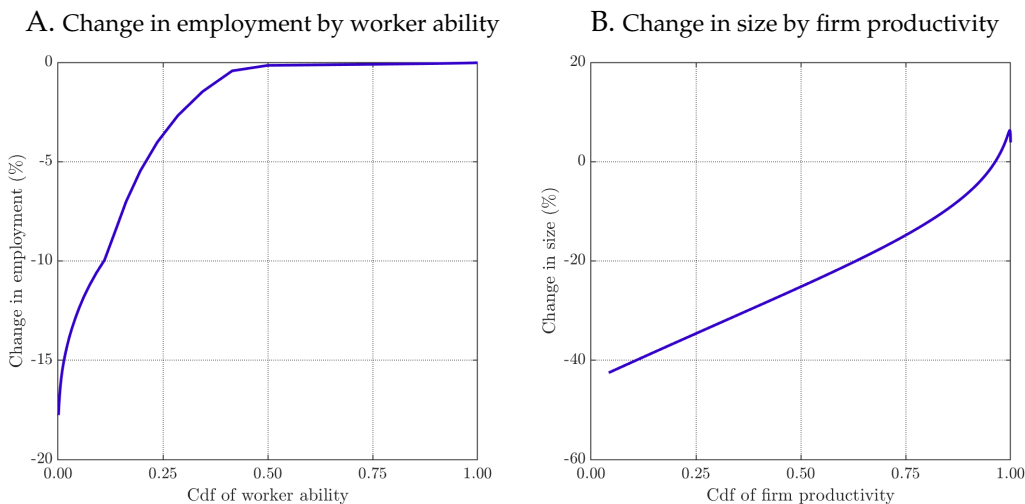


Notes: Men aged 18–54. Estimated impact of a 57.7 log point increase in the productivity adjusted real minimum wage. Panel A shows average log firm productivity by worker ability, $\int_{\frac{z}{2}}^{\infty} \log zdG(z|a, s)$, in market for workers with $s(a) > 0$ (the vast majority of workers). Panel B shows average AKM firm fixed effect by decile of AKM worker fixed effects. AKM regression is estimated on model-simulated monthly data aggregated to the annual level following an identical sample selection and variable construction methodology as in the data. Source: Model and RAIS 1994–2018.

E.3 Further results on heterogeneity in effects on disemployment and firm size

Figure E.2 sheds light on the heterogeneous effects of the minimum wage on employment and firm sizes. Panel A shows that, among the lowest-ability workers, employment falls by over 13 percent, while employment is essentially unaffected among workers above the bottom third of the ability distribution. Panel B focuses again on a group of workers most affected by the minimum wage—specifically, the first percentile of worker ability. Firms near the bottom of the firm productivity distribution shrink by almost 30 percent, while firms in the top five percent of the productivity distribution in fact expand in response to an increase in the minimum wage, for reasons that we analyze further below.

Figure E.2. Impact of minimum wage on aggregate outcomes, model



Notes: Impact of a 57.7 log point increase in the minimum wage in the estimated model. Panel A shows the log change in employment rate by worker ability in market with positive search efficiency, $s(a) > 0$ (the vast majority of workers). Panel B shows the log change in employment by firms ranked by employment-unweighted productivity in the first percentile of the worker ability distribution among workers with $s(a) > 0$. Source: Model.

E.4 Robustness of the small employment response

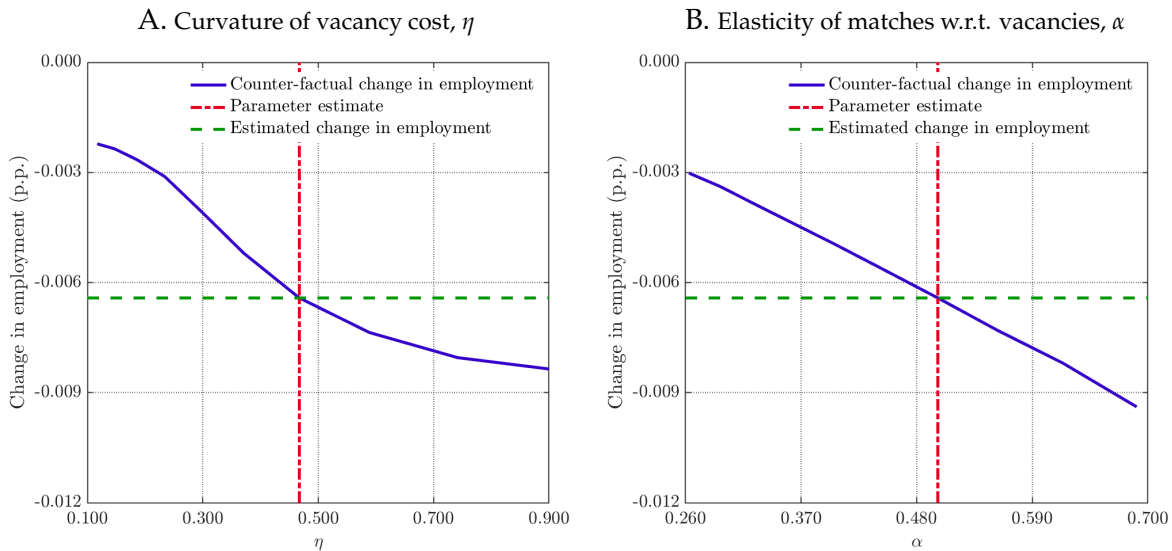
In light of our finding of modest aggregate disemployment effects of the minimum wage, we now investigate the robustness of our conclusions. In order for us to find a larger aggregate employment response, one or more of the channels in our decomposition based on equation (12) would need to be larger in magnitude. Their magnitude in turn relates to a set of estimated parameters and equilibrium objects, including the job finding rate, $p(a, s)$, the separation rate $\delta(a, s)$, the on-the-job search efficiency, $s(a)$, the elasticity of the vacancy cost function, η , and the elasticity of the matching function, α . We start by discussing the parameters that most clearly stand out based on (12), and subsequently present the sensitivity analysis with respect to the other model parameters.

Compared to common values for the U.S., we estimate a relatively low job finding rate, $p(a, s)$, and a comparable separation rate $\delta(a, s)$ for Brazil. All else equal, this would lead to a smaller job finding channel in the U.S. than what we find in Brazil. Compared to the U.S., we estimate a relatively high on-the-job search efficiency, $s(a)$. To see that this high value has limited effects on our results, consider the opposite extreme with $s(a) \approx 0$. Then the congestion channel approximately equals $\alpha / (1 - 0.4\alpha) = 0.6$. Hence, even in this extreme case, the congestion channel is a significant moderation force.

The sensitivity of the aggregate employment response with respect to the elasticity of the vacancy cost function, η , and the elasticity of the matching function, α , are shown in Figure E.3. Panel A shows that, perhaps surprisingly, a higher value of η actually amplifies the disemployment effects of the minimum wage. This is due to the equilibrium reallocation effects. Under a higher value of η , the minimum wage leads to smaller employment cuts among unproductive firms but also reduces the scaling up of more productive firms. Quantitatively, the latter force outweighs the former.

Panel B shows that higher values of λ are associated with greater disemployment effects. But our preset value of $\alpha = 0.50$ is relatively high compared to other values in the literature. For example, Meghir et al. (2015) estimate $\alpha = 0.34$ using the Brazil’s PME data, Shimer (2005) estimates $\alpha = 0.28$ for the U.S., and Mortensen and Nagypal (2007) argue that a reasonable value is $\alpha = 0.40$. Therefore, our results likely represent an upper bound on the aggregate disemployment effects of the minimum wage.

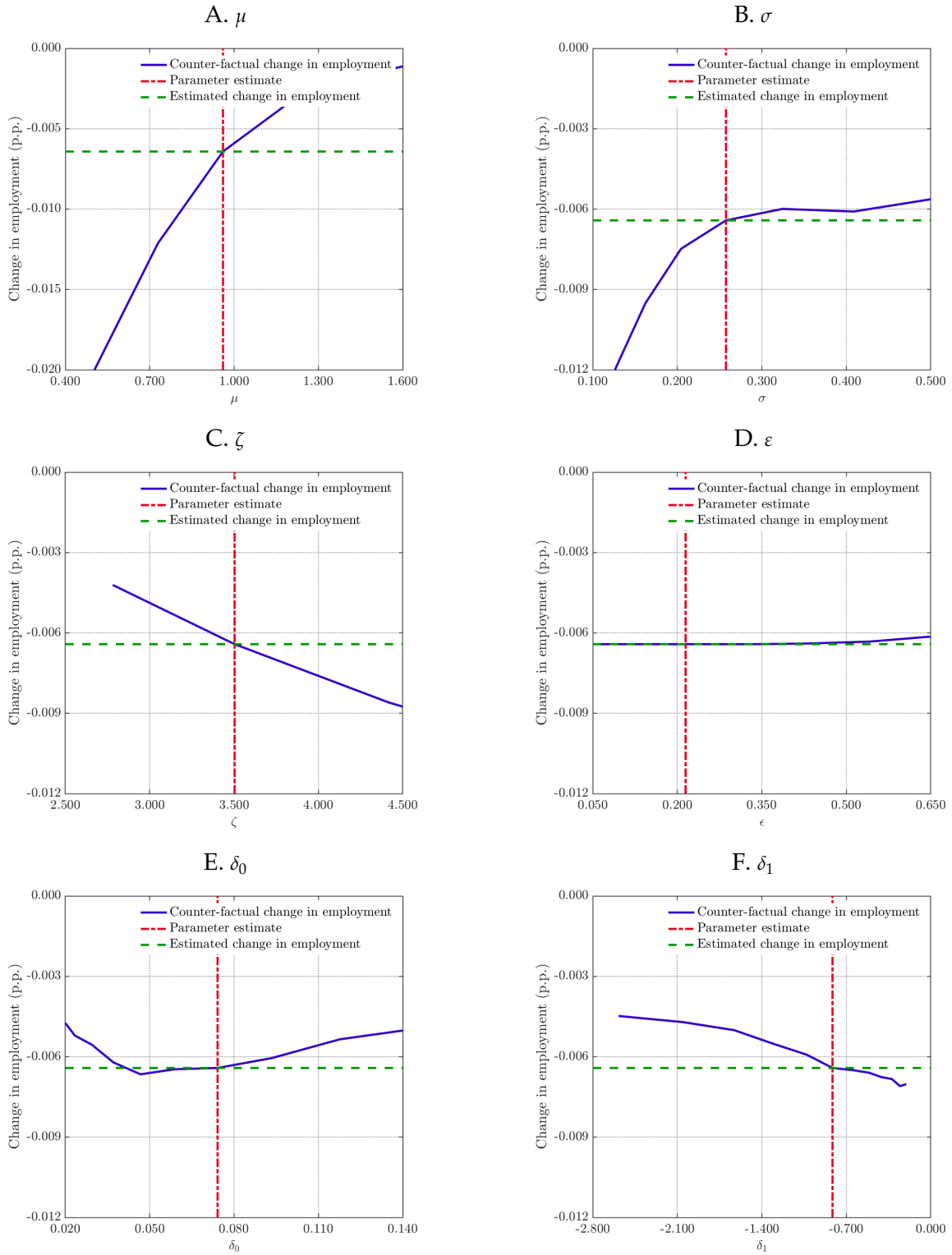
Figure E.3. Sensitivity of the employment effect of the minimum wage to parameter values



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.

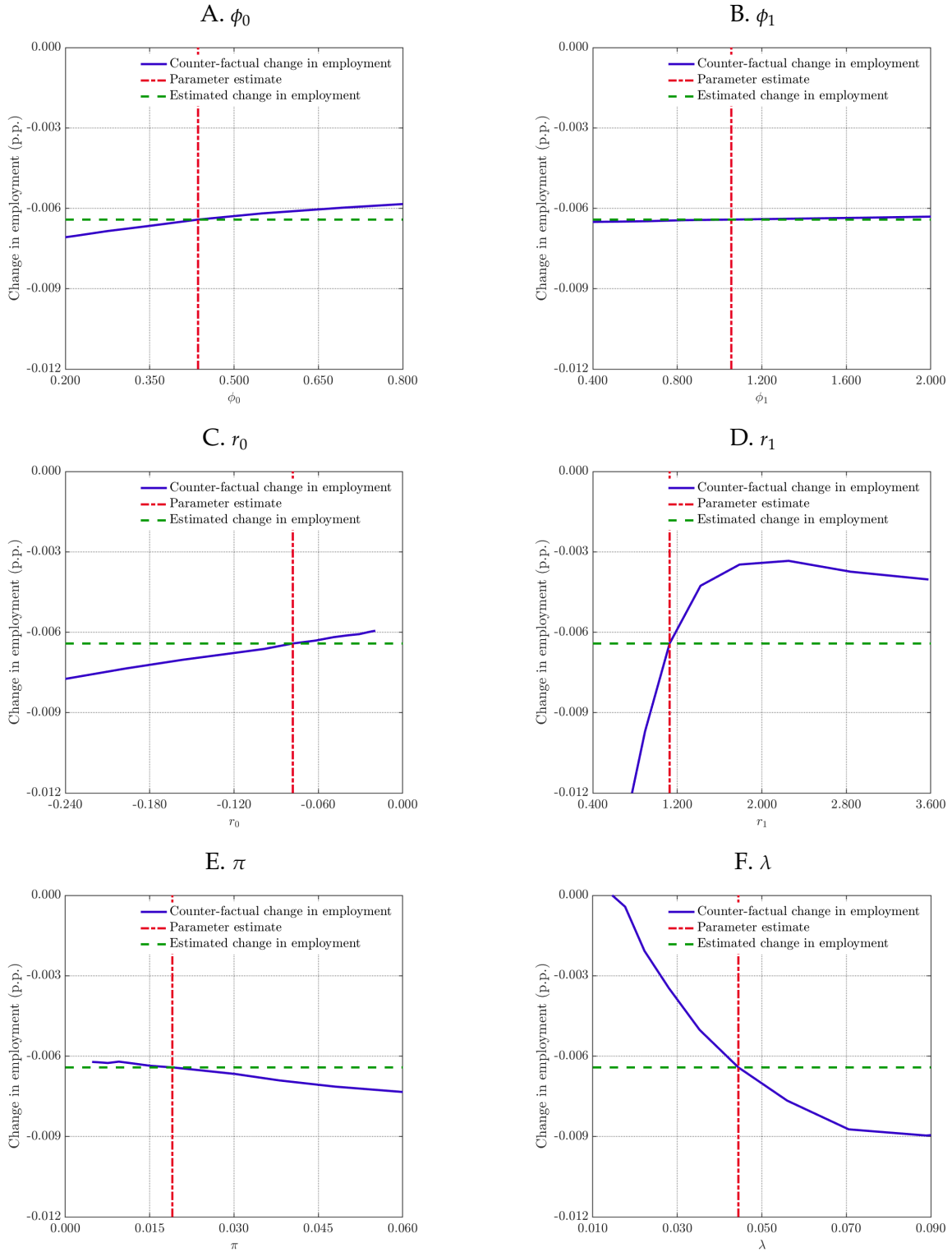
Figures E.4–E.6 conduct the same exercise as above across the remaining 11 internally estimated structural parameters of the model, as well as for the calibrated job finding rate λ and separation rate of minimum wage workers, δ_{MW} . As for the impact of the minimum wage on inequality, the key parameters determining the employment effect of the minimum wage are the mean of worker ability (μ), the tail index of the firm productivity distribution (ζ), the slope of the reservation wage (r_1), and to a lesser extent the job finding rate (λ). The larger is μ , the less binding is the minimum wage initially and the smaller is the effect of an increase in the minimum wage on employment (as well as inequality—recall Figure 11). A larger ζ (i.e. a thinner tail of the firm productivity distribution) raises the disemployment effect of the minimum wage, as there is a larger number of low productive firms that are heavily exposed to the minimum wage and fewer high productive firms to pick up the employment slack. The faster the reservation wage rises in ability—the larger is r_1 —the less the minimum wage binds and hence the smaller is the disemployment effect of a rise in the minimum wage. A lower λ is associated with a smaller disemployment effect of the minimum wage. The remaining parameters have at most a modest effect on the impact of a rise in the minimum wage on employment.

Figure E.4. Change in the employment rate across model parameters



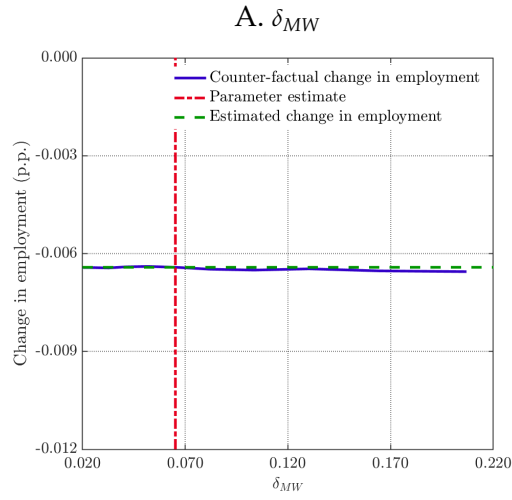
Notes: Estimated impact of a 57.7 log point increase in the minimum wage across different parameter values, varying one parameter at a time and holding fixed all other parameters at their estimated values. Source: Model.

Figure E.5. Change in the employment rate across model parameters, continued



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.

Figure E.6. Change in the employment rate across model parameters, continued

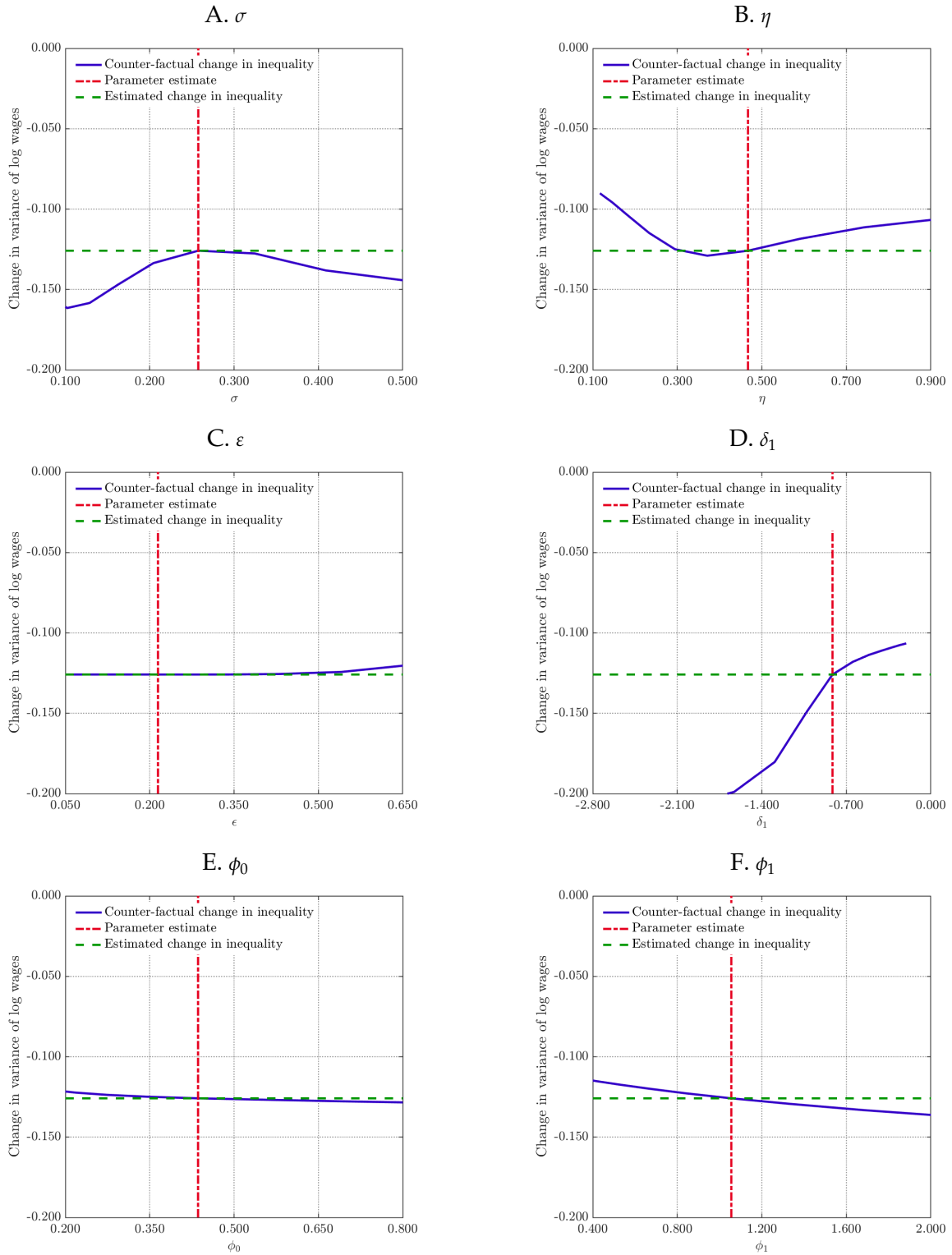


Notes: Estimated impact of a 57.7 log point increase in the minimum wage across different parameter values, varying one parameter at a time and holding fixed all other parameters at their estimated values. Source: Model.

E.5 Dependence of estimated inequality effect on model parameters

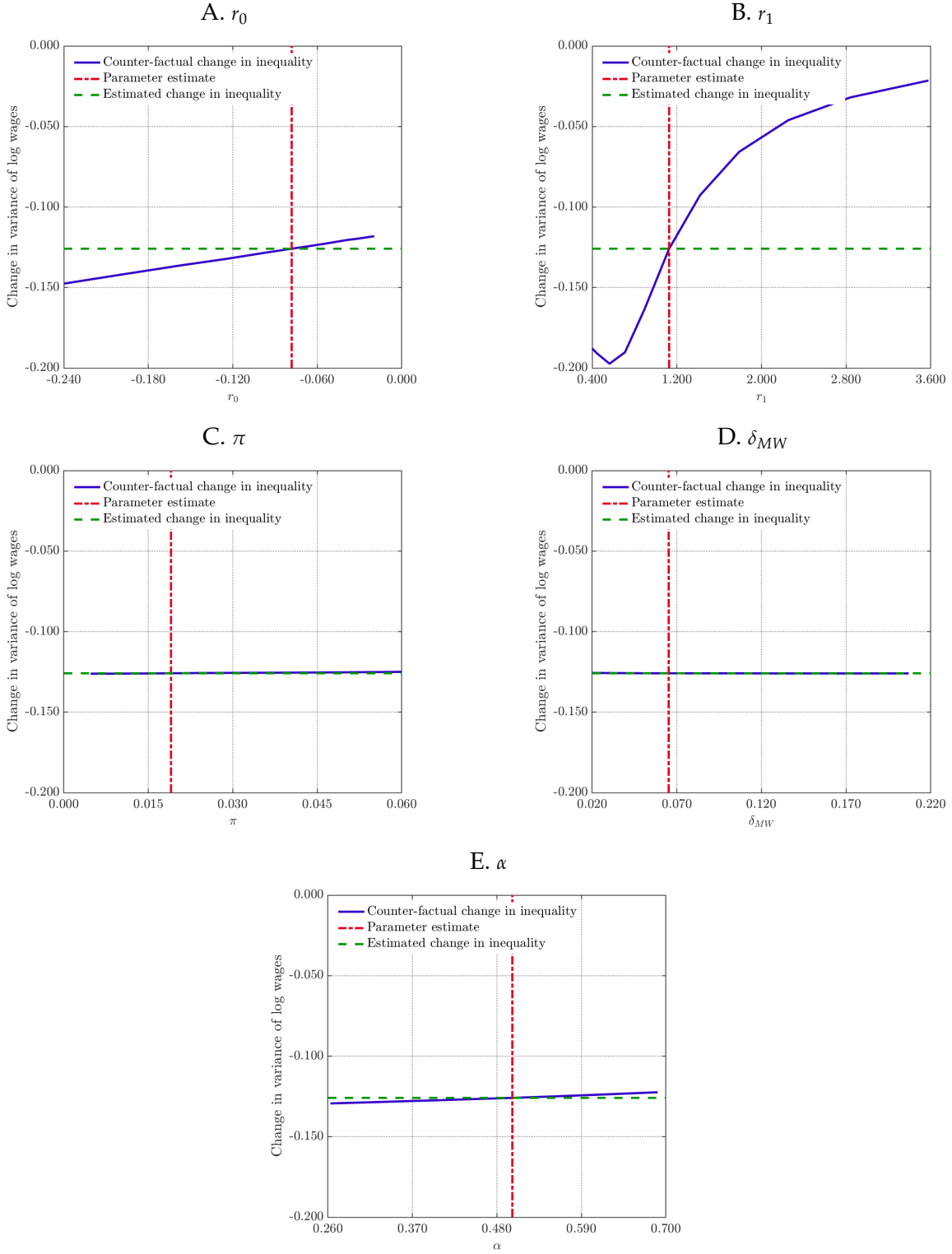
Figures E.7–E.8 conduct the same exercise as in Section 7.4 across the remaining nine internally estimated structural parameters of the model, the calibrated separation rate of minimum wage workers (δ_{MW}) and the preset elasticity of the matching function (α). Most of these parameters have at most a modest effect on the impact of a rise in the minimum wage on inequality. The main exception is the slope of the reservation wage, r_1 . Intuitively, a higher reservation wage leaves less scope for the minimum wage to impact markets, as the reservation increasingly becomes the binding constraints across worker ability markets. Recall from Appendix D.3 that the parameter the model primarily struggles to inform well based on the available data is r_0 . This parameter, however, is not critical in terms of driving the estimated impact of the minimum wage on inequality. Finally, δ_{MW} and α have no meaningful effect on the impact of the minimum wage on inequality.

Figure E.7. Change in the variance of log wages across 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.

Figure E.8. Change in the variance of log wages across model parameters, continued



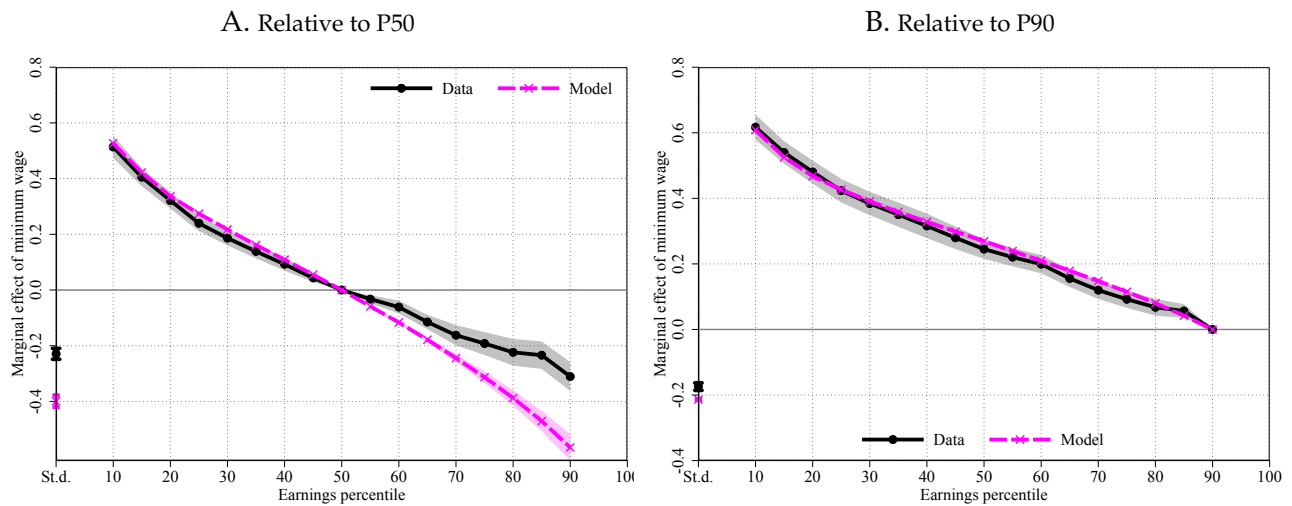
Notes: Estimated impact of a 57.7 log point increase in the minimum wage across different parameter values, varying one parameter at a time and holding fixed all other parameters at their estimated values. Source: Model.

F Model Validation Appendix

This appendix provides further details on the model validation presented in Section 8, including subsections on the comparison of spillover effects between the model and the data (Appendix F.1) comparative statics of the distributional effects of the minimum wage with respect to local economic conditions (Appendix F.2), and comparative statics of the employment effects of the minimum wage with respect to local economic conditions (Appendix F.3).

F.1 Comparing estimated spillover effects between model and data

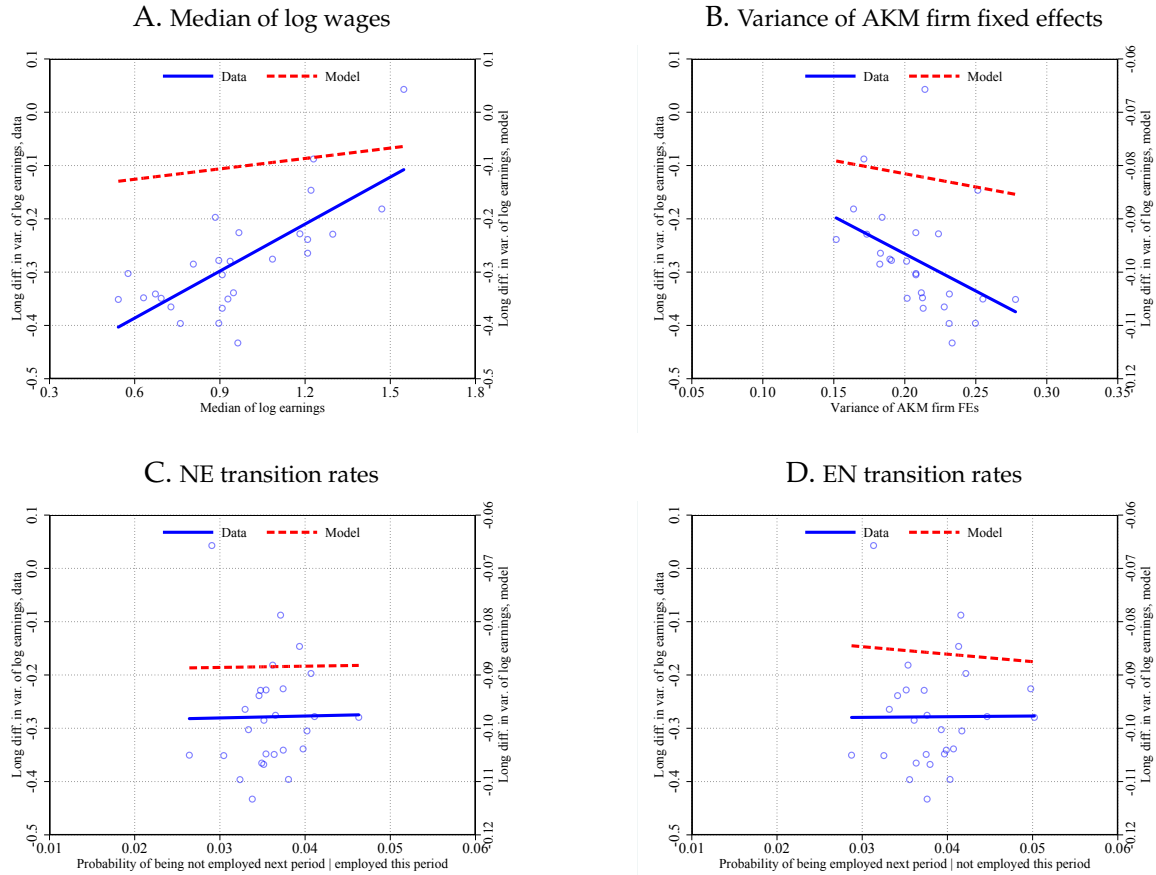
Figure F.1. Model vs. data: Estimated minimum wage effects throughout the wage distribution, IV



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 F.1B)—and two sources—the RAIS data (black circles and solid lines) and model-simulated data (magenta crosses and dashed lines). All four sets of estimates use a specification that includes state fixed effects in addition to state-specific linear time trends, estimated using an IV strategy. The IV strategy instruments the generalized Pp -Kaitz index and its square using 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 median wage for the region over the full sample period. 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.

F.2 Additional comparative statics of the distributional effects of minimum wage with respect to local economic conditions

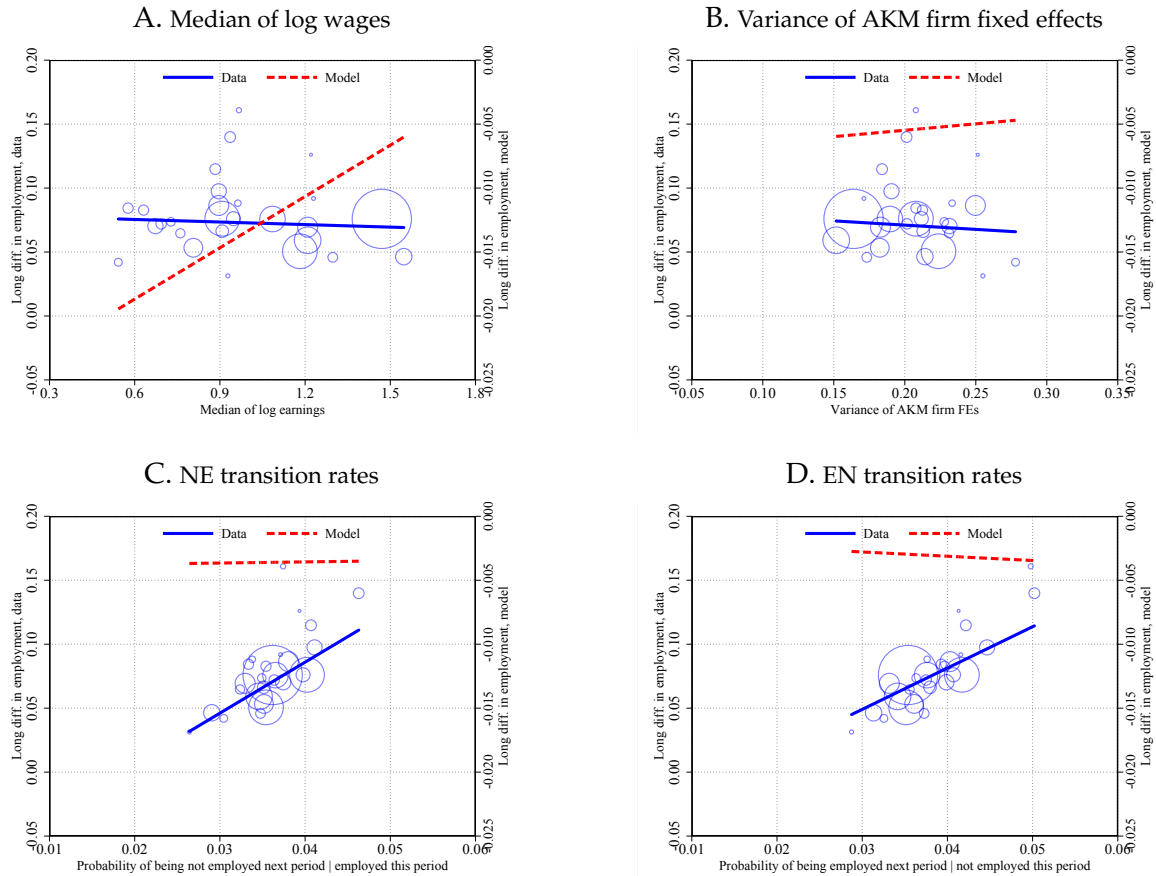
Figure F.2. Changes in inequality across observable labor market characteristics, model vs. data (unweighted)



Notes: Figure plots long differences between 1996 and 2018 in wage inequality—measured by the variance of log wages—across states in the data (blue solid line) and across simulations in the model (red dashed line). Variables on the x-axis are the median of log wages (panel A), the variance of AKM firm fixed effects (panel B) the probability of a transition from nonemployment into employment (panel C), and the probability of a transition from employment into nonemployment (panel D). The median of log wages is computed in 1996, while transition probabilities are computed in a balanced monthly panel from 1994 to 1998. States are represented as hollow circles, with their area proportional to their sample population in 1996. Linear best fit line is shown for the data (blue solid line) and the model (red dashed line), using OLS regression of inequality measures on the respective variable on the x-axis. Data points and line of best fit are equally weighted across states both in the data and in the model. *Source:* RAIS, 1994–1998 and 2018.

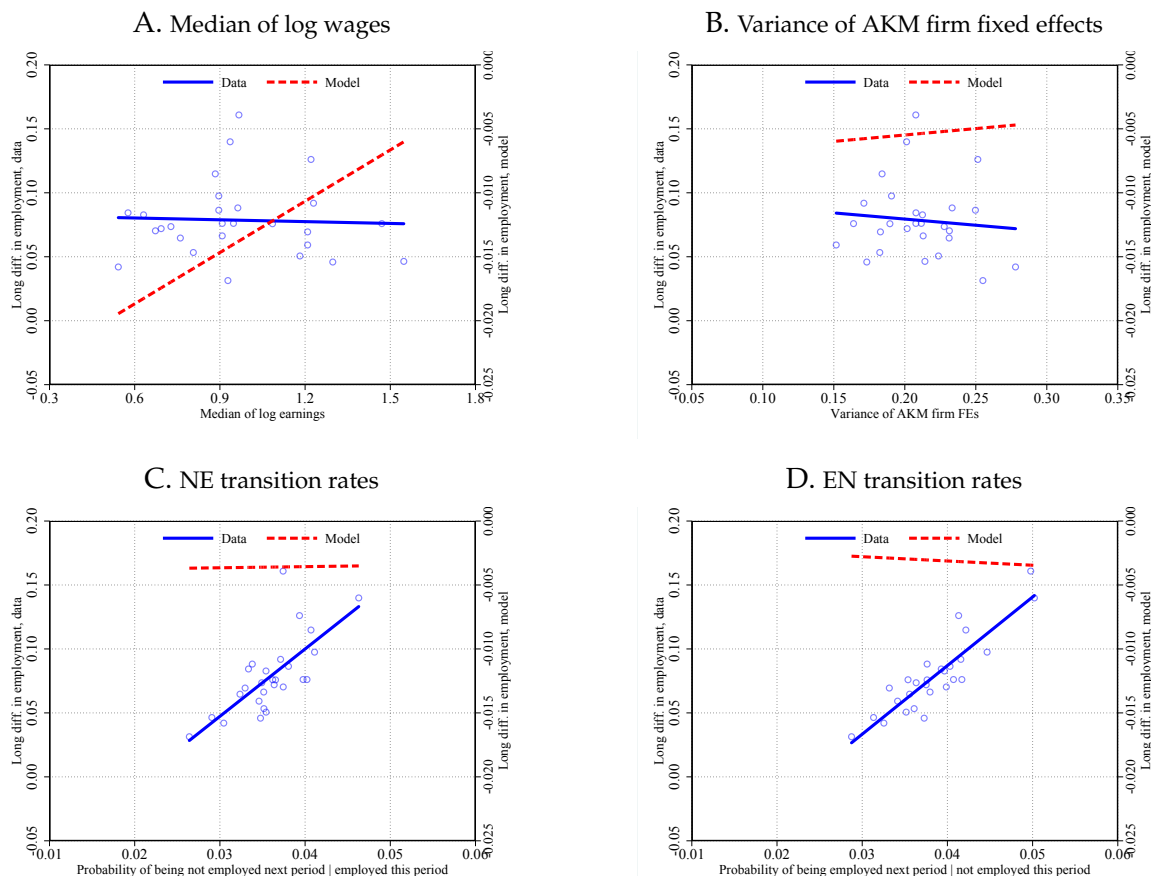
F.3 Comparative statics of the employment effects of minimum wage with respect to local economic conditions

Figure F.3. Changes in employment rates across observable labor market characteristics, model vs. data (weighted)



Notes: Figure plots long differences between 1996 and 2018 in wage inequality—measured by the share of workers that are employed at a given point in time—across states in the data (blue solid line) and across simulations in the model (red dashed line). Variables on the x-axis are the median of log wages (panel A), the variance of AKM firm fixed effects (panel B) the probability of a transition from nonemployment into employment (panel C), and the probability of a transition from employment into nonemployment (panel D). The median of log wages is computed in 1996, while transition probabilities are computed in a balanced monthly panel from 1994 to 1998. States are represented as hollow circles, with their area proportional to their sample population in 1996. Linear best fit line is shown for the data (blue solid line) and the model (red dashed line), using OLS regression of inequality measures on the respective variable on the x-axis. Data points and line of best fit are population-weighted across states in the data and unweighted in the model. *Source:* RAIS, 1994–1998 and 2018.

Figure F.4. Changes in employment rates across observable labor market characteristics, model vs. data (unweighted)



Notes: Figure plots long differences between 1996 and 2018 in wage inequality—measured by the share of workers that are employed at a given point in time—across states in the data (blue solid line) and across simulations in the model (red dashed line). Variables on the x-axis are the median of log wages (panel A), the variance of AKM firm fixed effects (panel B) the probability of a transition from nonemployment into employment (panel C), and the probability of a transition from employment into nonemployment (panel D). The median of log wages is computed in 1996, while transition probabilities are computed in a balanced monthly panel from 1994 to 1998. States are represented as hollow circles, with their area proportional to their sample population in 1996. Linear best fit line is shown for the data (blue solid line) and the model (red dashed line), using OLS regression of inequality measures on the respective variable on the x-axis. Data points and line of best fit are equally weighted across states both in the data and in the model. Source: RAIS, 1994–1998 and 2018.