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Firms and the Fragility of Inequality Reduction: Evidence from Argentina*

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October 15, 2026

Abstract

Earnings inequality in Latin America fell during the 2000s and stagnated in the 2010s, with cross-country inequality reversals associated with growth slowdowns. Using Argentine matched employer-employee data from 1995–2019, we show that firm wage premia compressed in the 2000s and dispersed again in the 2010s. Rising firm-effect dispersion drove Argentina’s inequality reversal, which was concentrated among smaller firms. Worker-effect dispersion fell in the 2000s without subsequently increasing. The reversal coincided with declining productivity and weakening negotiated wage floors and was correlated with informality. These findings suggest that macroeconomic stagnation can reverse inequality reduction by allowing low-paying firms to fall behind.

Keywords: earnings inequality, firm wage premia, macroeconomic stagnation, collective bargaining, informality, Latin America, Argentina.

JEL codes: J31, E24, O15, J38, J52, J46.

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1 Introduction

Latin America experienced a decline in earnings inequality in the 2000s (e.g., [Gasparini and Lustig 2011](#)), followed by a slowdown and, in some cases, a reversal in the 2010s amid weaker economic growth (e.g., [Gasparini et al. 2016](#), [Messina and Silva 2019](#)). Research on the decline has emphasized changes in educational attainment and the returns to education (e.g., [Manacorda et al. 2010](#), [Fernández and Messina 2018](#)), alongside a compression of pay differences across firms (e.g., [Alvarez et al. 2018](#)) and stronger labor market institutions (e.g., [Maurizio and Vazquez 2016](#), [Engbom and Moser 2022](#)). Less is known about the role of firms in subsequent trends in inequality. Even if returns to worker characteristics remain low, widening pay differences across firms could contribute to rising inequality.

Firm wage premia may be particularly sensitive to growth in developing economies. Productivity dispersion is large in these settings ([Hsieh and Klenow 2009](#), [Busso et al. 2010](#)). As more productive firms tend to pay higher premia, productivity dispersion may widen pay differences across firms ([Card et al. 2018](#)). Transitions from growth to stagnation may affect firms unevenly and disrupt resource allocation ([Oberfield 2013](#), [Gopinath and Neiman 2014](#)). Less productive firms may have less capacity to absorb adverse conditions, lowering their premia. Labor market institutions, which typically compress wage premia (e.g., [Card et al. 2013](#)), may also erode. Weak enforcement offers another margin of adjustment, as firms may evade labor regulations in response to adverse shocks ([Ponczek and Ulyssea 2021](#)).

Across Latin America, slowdowns in inequality reduction coincided with weaker GDP growth and slower earnings growth at small firms. Panel A of Figure 1 shows that, between 2003–11 and 2012–19, countries with larger growth declines saw larger increases in the annual Gini trend. Panel B shows that these increases were associated with weaker earnings growth at small firms (fewer than five employees) relative to larger firms.¹ These patterns suggest that heterogeneous firm responses to weak growth may have shaped inequality trends.

¹Panels C and D show that a one-point increase in the annual Gini trend was associated with 3.18 log points lower annual real earnings growth at small firms, versus 1.11 at larger firms.

We study firms’ contribution to earnings inequality among Argentina’s male formal workers over 1995–2019, spanning periods of growth, recession, and stagnation. A rich administrative dataset tracking worker mobility across firms allows us to quantify the contribution of firms. Sectoral productivity measures, newly digitized information on collective bargaining wage floors, and household survey data allow us to examine the forces behind changes in firm-premium dispersion. We find that firm wage premia more than account for the 2010s increase in inequality. The rise in premia dispersion is concentrated among smaller firms, with nearly half reflecting widening gaps between industries. We relate these patterns to sectoral productivity, labor market institutions, and informality across local labor markets.

We first present descriptive evidence on the evolution of earnings inequality and the role of firms. Inequality rose during the 1990s, fell sharply during the 2000s, and increased again during the 2010s.² While the 2000s decline was broad-based, the subsequent increase was concentrated at the bottom of the earnings distribution. Between-firm differences in mean earnings account for about two-thirds of the variance of log earnings. The 2010s increase in between-firm inequality occurred both within and between industries, but mostly within firm-size groups, even as employment shifted toward larger firms.

To separate firm wage premia from changes in workforce composition, we estimate fixed effects models following [Abowd et al. \(1999\)](#) (AKM) in five-year intervals. The AKM model isolates the contribution of workers, firms, and assortative matching between them to the variance of log earnings. Worker mobility identifies firm premia (firm effects). Diagnostic evidence, following [Card et al. \(2013\)](#), supports the model’s identifying assumptions. Our baseline variance estimates correct for limited mobility bias ([Kline et al. 2020](#)).

The sources of inequality fluctuations differed between the 2000s and 2010s. Firm premia account for 31% of the earlier decline, while worker effects account for 60%. In contrast, during the 2010s the variance of firm premia increased more than twice as much as the overall earnings variance, whereas the variance of worker effects declined slightly. The rise in premia

²[Blanco et al. \(2022\)](#) also document the 2000s decline in earnings inequality using the same data.

dispersion is most pronounced among small firms and at the bottom of the premia distribution, and widespread across regions. By 2015–19, firm premia accounted for 41% of the variance of log earnings, compared with 33% in 1995–99. By contrast, changes in assortative matching (or sorting) played only a minor role in the evolution of earnings inequality.

We then examine how the transition from growth to stagnation changed firms’ wage-setting conditions. Labor productivity rose during the 2000s expansion but declined in the 2010s, while sectoral gaps widened. Constructing industry wage differentials following [Card et al. \(2024\)](#), we find that widening gaps between industries account for nearly half of the increase in the variance of firm premia during the 2010s. Less productive sectors pay lower premia on average and exhibit greater within-sector dispersion. This negative association strengthened from 2005–09 to 2015–19. These patterns suggest that uneven productivity performance contributed to rising dispersion of firm premia in the 2010s.³

Rising wage floors compressed firm premia during the 2000s, but this compression weakened during the 2010s. We leverage differential exposure to the large national minimum-wage increase between 2004 and 2007 to identify the effect of negotiated wage floors on the dispersion of firm premia within industries. Identification requires that exposure affect premia dispersion only through wage floors, an assumption supported by institutional evidence, pre-trend analyses, and the absence of a detectable relationship between exposure and sectoral productivity growth. A 10 log point increase in wage floors raised the 10th percentile of firm wage premia by 4.1 log points between 1995–99 and 2005–09, with little estimated effect at the top. This compression partially reversed during the 2010s, when wage floors eroded, and weak compliance may have further limited their ability to protect pay at the bottom.

Consistent with this possibility, local labor markets with higher informality rates experienced larger increases in the dispersion of firm premia, with the divergence most pronounced during the 2010s. The widening came from lower percentiles falling behind, with little differential change at the top, and was accompanied by a relative shift toward smaller formal

³Our administrative records lack firm productivity measures. A 2010–12 manufacturing survey shows a positive association between value added per worker and firm wage premia.

firms. These patterns are consistent with firms downsizing and cutting labor costs in the 2010s, with weak enforcement providing scope for such adjustments.

Our findings suggest a hypothesis for Latin America: inequality reduction supported by economic growth may prove fragile when growth slows. In Argentina, widening productivity gaps and weakening labor market institutions coincided with low-paying firms falling behind, especially in more informal labor markets. Firm wage-setting practices may thus help explain how stagnation can reverse inequality reduction even as worker-effect compression persists.

This paper contributes to several strands of literature. First, we study the role of firms in Latin America’s slowdown in inequality reduction. Previous research links the 2000s inequality decline to compression in firm pay differences and highlights the roles of labor demand and wage-setting institutions (e.g., [Alvarez et al. 2018](#), [Messina and Silva 2019](#), [Engbom and Moser 2022](#), [Haanwinckel 2025](#)), as well as changes in skill supply and demand (e.g., [Lustig et al. 2016](#), [Fernández and Messina 2018](#), [Acosta et al. 2019](#)). [Lachowska et al. \(2023\)](#) document greater dispersion of firm premia during the Great Recession in Washington State. We build on these findings by showing that falling worker-effect dispersion accounted for most of the 2000s decline in Argentina, whereas rising premia dispersion, concentrated among smaller firms, more than accounted for the 2010s inequality increase.

Second, we provide new evidence on how wage floors negotiated in collective bargaining affect the dispersion of firm premia. Several articles show that firms partly absorb increases in wage floors by narrowing the “wage cushion,” i.e., the gap between actual pay and those floors ([Cardoso and Portugal 2005](#), [Card and Cardoso 2022](#), [Bhuller et al. 2022](#)).⁴ Recent work also examines variation in firm premia across unions ([Derenoncourt et al. 2025b](#)) and the effects of minimum wages on firm premia ([Bergolo et al. 2025](#)).⁵ We complement these studies by identifying how wage floors compress firm wage premia from below and examining

⁴For Argentina, [Hermo \(2025\)](#) studies how wage floors determine the adjustment to firm demand shocks. Other papers in the Argentine context study collective bargaining coverage and wage dispersion ([Lombardo and Martinez-Correa 2019](#)), the effects of wage floors on wages and employment ([Ramírez Leira et al. 2025](#)), and the employment effects of national minimum-wage increases ([Abbate and Jiménez 2026](#)).

⁵Minimum wages can affect wages in the informal sector as well (see, e.g., [Pérez Pérez 2020](#), [Derenoncourt et al. 2025a](#), [Machado Parente et al. 2026](#)).

whether this compression persists as macroeconomic conditions deteriorate.

Third, we study how industry wage differentials contribute to changes in the dispersion of firm premia (e.g., [Krueger and Summers 1988](#), [Katz and Autor 1999](#)). Following [Card et al. \(2024\)](#), we construct industry wage differentials—to our knowledge, the first application of their approach in a developing country—and show that widening gaps between sectors account for nearly half of the increase in the variance of firm premia during the 2010s.⁶ The standard deviation of industry premia is more than twice that in the United States (US), while their relationship with mean worker effects is substantially weaker. Additionally, we find that firm wage premia are more dispersed within less productive sectors.⁷

Finally, we contribute to a growing literature studying firms and inequality in developing economies. Studies for, e.g., South Africa ([Bassier 2023](#)), Mexico ([Pérez Pérez and Nuño-Ledesma 2024](#)), and Uruguay ([Bergolo et al. 2025](#)) document a large role for firm premia in earnings inequality, often larger than in developed countries ([Kline 2024](#)). Related research emphasizes the prevalence of microbusinesses and their low earnings in Latin America ([Eslava et al. 2025](#)). We extend this evidence by showing how changes in firm premia among smaller formal firms contributed to Argentina’s inequality reversal, and linking these changes to sectoral productivity and labor market institutions. These changes were larger in more informal local labor markets, consistent with theories linking informality to productivity heterogeneity ([Levy 2008](#), [Ulyssea 2018](#), [Haanwinckel and Soares 2021](#)).

The rest of the paper is organized as follows. Section 2 describes the context and data. Section 3 describes our empirical strategy. Section 4 presents our variance decomposition results, and Section 5 explores drivers of changes in firm premia. Section 6 concludes.

⁶In related work, [Haltiwanger et al. \(2024\)](#) and [Briskar et al. \(2024\)](#) document the role of between-sector differences in contributing to rising inequality in the US and Italy, respectively.

⁷Our findings also connect with a classical literature on productivity differences across industries and their implications for development ([Prebisch 1950](#), [Lewis 1954](#), [Furtado 1963](#)).

2 Context and Data

2.1 Macroeconomic and Institutional Context

Argentina experienced three distinct macroeconomic regimes during our study period. The market-oriented regime of the 1990s ended in the deep 2001–02 crisis. A rapid post-crisis recovery and expansion followed, before giving way to stagnation in the 2010s. Figure 2 shows that real output grew rapidly following the crisis, but fluctuated around a flat trend after 2011 while inflation accelerated. The 1990s saw trade liberalization and structural reforms, while the post-crisis expansion coincided with a depreciated exchange rate and improved terms of trade. Exchange-rate controls adopted in 2011 coincided with the beginning of the subsequent stagnation. Appendix Figure 1 shows that unemployment fell after the crisis, while the employment-to-population ratio rose during the recovery and remained stable during the 2010s. Informality remained high throughout and also peaked around the crisis.

The regimes coincided with changes in three potential determinants of earnings inequality. First, Panel A of Figure 3 shows that aggregate labor productivity rose during the post-crisis expansion and fell in the 2010s. Panel B shows that the employment-weighted standard deviation of log labor productivity across sectors fell in the 2000s and rose after 2012, from 0.588 in 2004–08 to 0.640 in 2015–19.⁸ Second, Panel C shows that the skill premium fell during the 2000s and stabilized in the 2010s.⁹ Third, Panel D shows that the real minimum wage rose during the 2000s and negotiated wage floors rose into the early 2010s, with both stagnating thereafter.¹⁰ Thus, the expansion combined productivity gains and stronger labor market institutions, whereas the 2010s brought stagnation and eroding wage floors.

⁸This widening is concentrated in the lower tail: the P50–P10 gap in log productivity rose from 0.545 to 0.729, while the P90–P50 gap fell slightly from 0.838 to 0.770. [Schteingart et al. \(2022\)](#) study industry premia in Argentina, and [Ciaschi et al. \(2021\)](#) discuss these trends in Latin America more broadly.

⁹The increase in the skill premium in the 1990s has been linked to the trade liberalization pursued in that decade (e.g., [Galiani and Sanguinetti 2003](#), [Bustos 2011](#)). For Brazil, [Dix-Carneiro and Kovak \(2015\)](#) find significant effects of the early 1990s liberalization on skill premia. [Gasparini and Cruces \(2010\)](#) discuss inequality trends and their determinants, and [Hermo \(2017\)](#) analyzes supply and demand factors behind the skill premium in Argentina. [Manacorda et al. \(2010\)](#), [Fernández and Messina \(2018\)](#), and [Acosta et al. \(2019\)](#) relate skill supply and demand to inequality trends in Latin America.

¹⁰The 2000s also saw active policies aimed at registering informal workers (e.g., [Beccaria et al. 2015](#)).

2.2 Trends in Earnings Inequality

The evolution of earnings inequality in Argentina between 1995 and 2019 mirrors the macroeconomic cycle. Panel A of Figure 4 shows that the variance of log earnings rose during the 1990s, fell sharply after the 2001–02 crisis, and increased again during the 2010s stagnation. This broad pattern is common across Latin America (e.g., Gasparini et al. 2016, Messina and Silva 2019, Alvaredo et al. 2025). Appendix Figure 2 shows that these trends are similar among formal workers in the survey data and extend to informal workers as well.¹¹

Approximately two-thirds of the variance of log earnings reflects differences between firms, and the between-firm component drives changes over time. Panel B of Figure 4 shows the between- and within-firm components of log earnings variance: the between-firm component declined during the 2000s compression and returned to 1990s levels during the 2010s.¹²

Industry differences account for nearly half of between-firm earnings variance. Panel C of Figure 4 decomposes between-firm variance into between-industry and within-industry components using 4-digit industry codes.¹³ Appendix Figure 3 illustrates this divergence: by the 2010s, average monthly pay in mining and quarrying was roughly twice its 1990s level, while pay in hotels and restaurants dropped back to its 1990s level.

Contributions to fluctuations in between-industry variance are not uniform across industries. Appendix Figure 4 displays the eight largest and smallest 4-digit industry contributions in each period.¹⁴ Oil and gas services and non-ferrous metal mining are among the leading contributors to the 2010s expansion in inequality, alongside restaurants, construction, and education. Telecommunications, banking, and pharmaceuticals made large contributions to

¹¹The survey data show stagnation rather than a clear increase in the 2010s, which may partly reflect under-reporting in the tails of the distribution (Albina et al. 2024).

¹²To derive the decomposition, let y_{it} be log earnings of worker i in year t , and write $y_{it} = \bar{y}_{j(i),t} + (y_{it} - \bar{y}_{j(i),t})$, where $j(i)$ is i 's firm and $\bar{y}_{jt}$ is mean log earnings at j . Then, $\text{Var}(y_{it}) = \text{Var}(\bar{y}_{j(i),t}) + \text{E}[\text{Var}(y_{it} | j(i))]$.

¹³Following a similar procedure as in the previous footnote, we can write $\text{Var}(\bar{y}_{j(i),t}) = \text{Var}(\bar{y}_{k(j(i)),t}) + \text{E}[\text{Var}(\bar{y}_{j(i),t} | k(j(i)))]$, where $k(j)$ is j 's industry and $\bar{y}_{kt}$ is mean log earnings in industry k in period t .

¹⁴We follow Haltiwanger et al. (2024). The between-industry variance is $V_t^B = \sum_k s_{kt}(\bar{y}_{kt} - \bar{y}_t)^2$, where s_{kt} is industry k 's employment share, $\bar{y}_{kt}$ is mean log earnings, and $\bar{y}_t$ is overall mean log earnings. Then, $\Delta V^B = \sum_k c_k$, where $c_k = s_{k1}(\bar{y}_{k1} - \bar{y}_1)^2 - s_{k0}(\bar{y}_{k0} - \bar{y}_0)^2$ is k 's contribution. We compute endpoints by pooling two years and report contributions relative to the change in total earnings variance.

the 2000s compression, with oil and gas services and non-ferrous metal mining contributing in the opposite direction. The 2000s compression was more widespread: 206 of 302 industries contributed to the decline, compared with 157 industries contributing to the 2010s increase.¹⁵

The decomposition by firm size shows that the 2010s increase in the between-firm component is driven by changes within size bins. Panel D of Figure 4 decomposes between-firm variance using four size bins: 1–5, 6–25, 26–100, and more than 100 employees. The within-bin component accounts for most of the variance and drives its evolution. Notably, we do not observe a shift in employment toward smaller firms. Instead, Panel A of Appendix Figure 5 shows that the employment share of large firms rose from 40.2% in 1995–99 to 47.3% in 2015–19, mostly at the expense of firms with 25 or fewer employees.¹⁶

The 2010s inequality increase was driven by a relative decline in the lower tail. Figure 5 shows that, while lower-tail inequality declined in the 2000s, by 2011 both the P50–P5 and P50–P10 gaps had returned to their 1990s levels, reaching even higher levels in 2015–19. Upper-tail inequality, in contrast, increased in the 1990s and declined steadily during the 2000s and 2010s, although that decline slowed in the 2010s. Women show similar trends in overall and upper-tail inequality, with a similarly large between-firm component, as shown in Appendix Figure 6. Their lower-tail inequality, however, increased throughout the period.

The evolution of earnings inequality tracks Argentina’s macroeconomic regimes, with the 2010s increase concentrated in differences between firms and the lower tail. These patterns motivate isolating the role of firms in driving inequality trends.

2.3 Data Sources

We now summarize data sources and sample restrictions. Appendix A provides details.

¹⁵Although the contributions are broad-based, the tails are concentrated: the eight largest absolute contributions account for 43% and 41% of gross industry contributions in the two periods, respectively.

¹⁶Panel B of Appendix Figure 5 shows similar trends for formal workers in the household survey data. Panel C shows that the distribution of informal workers across size bins is more stable over time.

2.3.1 Matched employer-employee dataset

We rely on Argentina’s matched employer-employee dataset, collected by the tax authority for the *Sistema Integrado Previsional Argentino* (SIPA). The data include information on all jobs held by wage-earners in the private sector, state-owned companies, and autonomous public institutions (such as universities and banks) for 1995–2019. We use worker and firm identifiers to track workers across firms over time.¹⁷ We observe the industry and province of the firm, as well as the age and gender of workers (though not their education). Industry codes follow a custom classification based on ISIC Rev. 3.1.

We construct a worker-firm-year panel by averaging monthly pre-tax earnings, including base salary, bonuses, severance payments, and other pay components, after deflating them to 2010 Argentine pesos.¹⁸ We exclude jobs with earnings above the 99.9th percentile within each year to limit the influence of outliers. We focus on men aged 20 to 55, whom we refer to as prime-aged, a group with high and stable employment rates (Busso and Romero Fonseca 2015), reporting results for women in the appendix. Because hours are unobserved, we follow the literature and exclude jobs paying less than ARS 317 per month in 2010 pesos (about USD 80), limiting the influence of part-time jobs. We vary this threshold in robustness checks. We also drop jobs lasting fewer than six months, internships, and temporary-agency workers.¹⁹ The next section describes additional restrictions for the AKM sample.

2.3.2 Additional data sources

Household survey. We rely on Argentina’s *Encuesta Permanente de Hogares* (EPH). The survey changed format in 2003, with the newest EPH “Continua” covering 31 urban areas and representing over 70% of Argentina’s urban population. We use the EPH to measure

¹⁷The data do not include establishment identifiers. However, following the literature (e.g., Alvarez et al. 2018), we prefer to use firms, as wage-setting decisions are likely made at this level.

¹⁸We use the CPI from the National Institute of Statistics and Censuses (INDEC), except for 2007–15, when the official data were manipulated (see, e.g., Cavallo 2013). For these years, we use CPIs from provincial statistics offices and, later, an inflation measure computed by opposition parties.

¹⁹Workers in temporary employment agencies are recorded twice, as employees of both the agency and the client firm. Drenik et al. (2023) use this feature to study firms hiring outsourced workers.

informality as the share of salaried workers without regular social security contributions (International Labour Organization 2014).²⁰ We also compute the share of salaried workers earning below the hourly minimum wage as an additional marker of weak enforcement.²¹

Earnings reported in the survey data differ from those in the administrative data for two main reasons: differences in the definition of earnings and misreporting. The EPH surveys after-tax wages while SIPA registers pre-tax wages. However, differences in wage levels exceed what can be attributed to taxes and social security contributions. This is likely a consequence of misreporting, especially in the tails of the distribution (Albina et al. 2024).

Wage floors. We obtain the national minimum wage from the Secretariat of Labor. Wage floors negotiated in sectoral collective agreements (*convenios colectivos de trabajo*) are collected from a separate set of recurring resolutions that report each agreement’s mean wage floor, used to compute severance-payment caps. Because formats vary across resolutions, we harmonize the names of unions, employer associations, and firms, correct data-entry typos, and reconstruct persistent bargaining units that can be followed over time.²² We deflate wage floors to 2010 pesos as well.

The result is a monthly panel of average real wage floors at the level of the bargaining unit, which underlies Panel D of Figure 3.²³ We assign bargaining units to one or more ISIC Rev. 3.1 divisions (2-digit codes).²⁴ We retain multiple industry codes when a unit spans industries or their coverage is uncertain.

²⁰We exclude self-employment, which accounts for a quarter of the labor force according to the EPH data.

²¹The Secretariat of Labor publishes the monthly minimum wage, which we convert into an hourly rate by dividing it by 200 hours. Appendix A.2 describes how we compute hourly earnings in the survey.

²²Agreement codes and signatories may change over time in the raw data. Bargaining units fully renegotiate their agreements, which leads to new codes. Defining bargaining units by their signatories allows us to abstract from changes in agreement codes. However, the raw data sometimes omit signatories. We use manual review and automated matching to reconcile incomplete or inconsistent records. These data extend Hermo (2025) beyond the exporting sector and back to 1995 by digitizing additional resolutions.

²³An average wage floor is the mean across the wage floors of the worker categories within a bargaining unit. Because the differences across categories are typically stable, this average tracks the evolution of negotiated wages well. We replace floors that fall below the national minimum wage (MW) with the MW, as the MW is binding in those cases. This replacement has bite only for lower-wage bargaining units between 2003 and 2009, when the MW increased rapidly and some negotiated floors lagged behind.

²⁴We used AI and human review to build the classification. AI agents reviewed and suggested edits to an existing classification, which was then verified by human researchers. Appendix A.4 provides further details.

Productivity data. First, we obtain data on value added per worker for a sample of firms in 2010–12 from the *Encuesta Nacional de Dinámica de Empleo e Innovación* survey (ENDEI), collected by the Secretariat of Labor. It covers over 3,000 manufacturing firms and can be linked to SIPA. Second, we use data on sectoral productivity, collected and harmonized by the *Centro de Estudios para la Producción* (CEP XXI), for 2004–2019.

3 Methodology

To isolate the contribution of firms to inequality, we estimate the AKM model in five subperiods: 1995–99, 2000–04, 2005–09, 2010–14, and 2015–19. This section describes the estimation strategy and implementation, the variance decomposition, and the empirical analyses used to study industry productivity, negotiated wage floors, and informality.

3.1 Firms, Workers, and the AKM Variance Decomposition

Our analysis is based on the two-way fixed effects model pioneered by [Abowd et al. \(1999\)](#):

$$y_{it} = \alpha_i + \psi_{j(i,t)} + \Upsilon_t + \varepsilon_{it}, \quad (1)$$

where y_{it} is log earnings and $j(i, t)$ identifies worker i ’s employer in year t . Worker effects α_i capture attributes rewarded equally across employers within each subperiod, while firm effects ψ_j capture wage premia common to a firm’s workers. Year effects Υ_t absorb common earnings fluctuations, and ε_{it} is the residual. We include no additional worker covariates.

Firm wage effects are identified from workers moving across employers. We assume exogenous mobility ([Card et al. 2013](#), [Kline 2024](#)): $E[\varepsilon_{it} \mid \alpha_i, \{j(i, s)\}_{s \in T}, \Upsilon_t] = 0$ for all $t \in T$ where T is the set of years in each estimation sample. Namely, the residual is mean independent of a worker’s entire employer history, conditional on worker and year effects. Under this assumption, expected earnings changes for movers identify differences in firm premia after accounting for year effects. The assumption permits sorting on worker and

firm effects but rules out mobility systematically related to residual earnings. We present diagnostic evidence on the plausibility of this assumption in the next section.

Equation (1) allows us to decompose the variance of log earnings as follows:

$$\begin{aligned} \text{Var}(y_{it}) = & \overbrace{\text{Var}(\alpha_i)}^{\text{Worker}} + \overbrace{\text{Var}(\psi_{j(i,t)})}^{\text{Firm}} + \overbrace{2 \text{Cov}(\alpha_i, \psi_{j(i,t)})}^{\text{Sorting}} \\ & + \underbrace{\text{Var}(\Upsilon_t) + 2 \text{Cov}(\alpha_i, \Upsilon_t) + 2 \text{Cov}(\psi_{j(i,t)}, \Upsilon_t)}_{\text{Covariates}} + \underbrace{\text{Var}(\varepsilon_{it})}_{\text{Residual}}. \end{aligned} \quad (2)$$

Plug-in estimates of these variance components can exhibit substantial limited mobility bias (see, e.g., [Bonhomme et al. 2023](#)). Our baseline uses the heteroskedasticity-robust correction of [Kline et al. \(2020\)](#), or KSS for short. We also report uncorrected plug-in estimates.

Firm wage effects can only be identified for firms that are connected by worker mobility. Our baseline analysis uses the largest set that remains connected after removing any single worker-firm match, as required by the KSS correction. We refer to this as the leave-out-match connected set. We also report plug-in estimates for the largest connected set. For granular analyses where bias correction is infeasible, we use plug-in estimates.²⁵ Our AKM estimates are obtained using the `pytwoway` Python package ([Bonhomme et al. 2023](#)).

Following common practice in the AKM literature, we keep the highest-paying job per worker-year when workers have multiple jobs in the same year. We drop single stayers before constructing the two connected sets. Appendix Table 1 compares the full sample with the connected sets. The leave-out-match set retains 73.7% of worker-years in 1995–99 and 78.8% in 2015–19. The leave-out-match connected set drops proportionally more firms than workers, suggesting that the excluded firms are smaller on average. Despite this selection toward larger firms, earnings and age distributions remain similar to those in the full sample.

For each region and size group, we construct the connected sets and estimate a separate AKM model with the KSS correction. The groups are as follows. First, we group provinces

²⁵The KSS bias correction requires estimation of separate models for each group, which is computationally intensive and may not be feasible for granular groups with low mobility. See [Azkarate-Askasua and Zerecero \(2024\)](#) for a related discussion.

into six regions based on geographical proximity: “Buenos Aires,” “Center,” “West,” “Northwest,” “Northeast,” and “Patagonia”.²⁶ Second, we define three size bins based on the mean number of employees within each subperiod: small (25 or fewer employees), medium (more than 25 and at most 100 employees), and large (more than 100 employees).

To validate our estimates, we relate 2010–14 firm effects to value added per worker from the 2010–12 ENDEI survey. Some regressions control for firm size, its interaction with productivity, and province and industry fixed effects, weighting firms by worker-years.

3.2 The Drivers of Firm Wage Effects

We explore three potential drivers. First, motivated by the growing dispersion in productivity between industries, we study the role of industry differences. Second, as the strength of labor market institutions fluctuated significantly during our study period, we study the effect of changes in wage floors. Finally, given that the 2010s inequality increase was concentrated in the lower tail, we study the association between the informality rate, as an indicator of weak enforcement of labor regulations, and the evolution of firm wage effects.

3.2.1 Industry wage differentials

We construct industry wage differentials following [Card et al. \(2024\)](#), defined as

$$\bar{\psi}_{kp} = \frac{\sum_{k(j)=k} N_{jp} \psi_{jp}}{\sum_{k(j)=k} N_{jp}}$$

where ψ_{jp} is the (estimated) firm fixed effect for firm j in period p , $k(j)$ is the industry of firm j , and N_{jp} is the number of worker-year observations for firm j in period p .²⁷ As in

²⁶The regions are defined as follows. Buenos Aires: City of Buenos Aires and Buenos Aires Province; Center: La Pampa, Córdoba, Santa Fe, and Entre Ríos; West: Mendoza, San Juan, La Rioja, and San Luis; Northwest: Jujuy, Salta, Tucumán, Catamarca, and Santiago del Estero; Northeast: Formosa, Chaco, Misiones, and Corrientes; Patagonia: Neuquén, Río Negro, Santa Cruz, Chubut, and Tierra del Fuego.

²⁷An alternative to constructing $\{\bar{\psi}_{kp}\}$ is to estimate industry fixed effects directly, relying on workers switching industries (e.g., [Krueger and Summers 1988](#)). [Card et al. \(2024\)](#) show that such an approach suffers from “hierarchy bias,” as movers from low-wage to high-wage industries tend to move from relatively good firms in the origin industry to relatively bad firms in the destination, thereby biasing estimates of

Card et al. (2024), we normalize mean firm effects in restaurants (ISIC 5521) to zero within each period. The weighted variance of industry differentials measures the between-industry component of firm-effect variance and does not depend on this normalization.

We expect the industry wage differentials to reflect differences in mean labor productivity across sectors. To test this relationship we use CEP XXI data, which are more aggregated than our baseline industry wage differentials.²⁸ We then construct differentials at that level and correlate them with the average labor productivity within each period.

We also examine whether less productive industries show greater dispersion in firm premia. Distortions that weaken the allocation of resources toward more productive firms can both lower mean productivity and sustain wider productivity dispersion (Hsieh and Klenow 2009). Differences in compliance, including unregistered employment and wage payments, may provide another source of firm heterogeneity (Ulyssea 2018, Feinmann et al. 2022). Thus, we compute the within-sector variance of firm effects and relate it to sectoral productivity as well. We emphasize that, as the variation in productivity is not exogenous to changes in the mean and variance of firm wage effects, these analyses do not establish causality.

3.2.2 Labor market institutions

The national minimum wage and negotiated wage floors more than doubled between the late 1990s and late 2000s. We examine whether industries with larger increases in negotiated wage floors experienced greater compression in firm wage effects.

We use the newly digitized collective bargaining data to examine the relationship between changes in negotiated wage floors and the distribution of firm wage effects within ISIC divisions. We measure wage-floor growth as the change in the mean log wage floor between 2001–02 and 2008–09, the period of the largest increase in wage floors.²⁹ We estimate its

industry effects. Aggregating firm effects, as above, bypasses this problem.

²⁸The labor productivity data are available at an aggregate sectoral definition that generally corresponds to ISIC sections and is more disaggregated within some sections, such as manufacturing.

²⁹We use bargaining units that can be followed consistently from the late 1990s through 2008, and restrict the sample to industries with at least two wage-floor observations in 2001–02. After these restrictions, industries have an average of 11.2 annual wage-floor observations over 2001–02, ranging from 2 to 48.

effect on changes in the dispersion and percentiles of log earnings, firm effects, and worker effects from 1995–99 to 2005–09 and from 1995–99 to 2015–19.

Variation in negotiated wage floors may be endogenous to changes in these outcomes. To estimate their causal effect, we instrument the mean log wage floor change with the negative gap between the industry’s mean log wage floor in 2001–02 and the mean log national minimum wage in 2005–07. The exclusion restriction requires that outcomes in the initially lower wage-floor industries would have evolved similarly to those in initially higher wage-floor industries in the absence of the minimum-wage increase. Limited adjustment of negotiated wage floors during the late 1990s and early 2000s, before the minimum-wage increase, motivates this design. We further assess the validity of the instrument using pre-trend evidence and by examining its correlation with productivity growth.

3.2.3 Informality and firm wage inequality

Motivated by the concentration of rising inequality at the bottom of the earnings distribution, we examine whether local labor markets with higher informality rates experienced larger increases in firm-effect dispersion. We use the 1995–99 informality rate as a proxy for weak enforcement, measured using the survey data. We aggregate our estimated firm and worker effects to local markets, defined by combinations of regions and ISIC sections, weighting by worker-years.³⁰ Given the fine granularity, we rely on the plug-in variance estimator as well.³¹

We fit a two-way fixed effects model with local labor market and period fixed effects, interacting the informality rate in 1995–99 with period indicators.³² The interaction for 1995–99 is omitted, so our parameters of interest measure the differential change in the association between the informality rate and the outcome relative to the 1995–99 baseline.

³⁰Some ISIC sections are combined to match the aggregation level of the EPH classification, resulting in 11 economic sectors and 67 local labor markets, after dropping market-year cells with fewer than 30 observations in the EPH. To match the EPH geography, this analysis treats the City of Buenos Aires and Buenos Aires Province as separate regions, whereas the baseline variance decomposition combines them.

³¹When presenting these results, we discuss concerns about limited mobility bias and provide supporting evidence from outcomes that do not rely on the estimated AKM effects.

³²More precisely, we estimate $y_{ct} = \gamma_c + \delta_t + \sum_{s \neq 1} \beta_s I_{c1} \mathbf{1}\{t = s\} + e_{ct}$, where y_{ct} is an outcome in market c and period t , I_{c1} is the informality rate in 1995–99, and γ_c and δ_t are market and period fixed effects.

We weight by the number of worker-years and cluster standard errors at the local labor market level. While this analysis does not establish causality, it characterizes the labor market conditions associated with changes in firm wage inequality.

4 Firms and the Evolution of Earnings Inequality

This section discusses the results from the AKM variance decomposition, presents heterogeneity by firm size, pay rank, and region, and provides robustness checks.

4.1 Variance Decomposition

The firm component accounts for a significant share of earnings inequality, particularly in the 2010s. Table 1 shows estimates of the KSS-corrected decomposition for our five subperiods. Consider the first period, 1995–99, displayed in column (1). Out of the total variance of 0.554, the worker component accounts for 0.234 (42.2%), the firm component for 0.183 (33.0%), and the sorting component for 0.096 (17.3%). The variance decomposition for 2015–19, displayed in column (5), shows that the firm component accounts for 0.181 of a total variance of 0.436 (41.5%). This increase of 8.4 percentage points is fully accounted for by a decline of 9.1 percentage points in the importance of the worker component.

Earnings inequality declined by 24.5% between 1995–99 and 2005–09, driven by both the worker and firm components. Worker effects account for 60.3% of this decline and firm effects for 30.9%. The larger worker contribution is consistent with evidence emphasizing educational upgrading and declining returns to skills.

In contrast, firm premia more than account for the subsequent inequality increase. Between 2005–09 and 2015–19, firm-effect variance rose by 0.040, more than twice the 0.018 increase in the variance of log earnings, offsetting declines in other components. Firm-effect variance nearly returned to its 1990s level, while worker-effect variance remained lower.

Changes in sorting played a smaller role in the evolution of earnings inequality. Sorting

accounts for an average of 17% of earnings variance, but contributes less to its changes than worker or firm effects. The slight decline in the sorting component contrasts with evidence from advanced economies, where increasing positive assortative matching has been an important driver of *rising* inequality (e.g., Card et al. 2013, Song et al. 2019).

Estimates for women show similar trends. Appendix Figure 7 shows a decline in worker and firm effect variances from 1995–99 to 2005–09 and an increase in the firm effect variance between 2005–09 and 2015–19. However, we find a negative sorting component in all periods, which is mitigated by the variance corrections but remains slightly negative.³³

4.2 Heterogeneity by Firm Size, Pay Rank, and Region

Firm size. Column (7) of Table 2 shows that between 2005–09 and 2015–19 the variance of firm effects rose by 0.085 among small firms, 0.043 among medium firms, and 0.020 among large firms. The increase among the smallest firms was more than *four times* as large as among the largest. The 2000s show no comparable gradient: the variance changed by -0.036 , -0.052 , and -0.016 among small, medium, and large firms, respectively. Panel B shows that within-size dispersion accounts for 80.5% of the increase between 2005–09 and 2015–19.³⁴

A decline in the employment share among small firms partly offset the rise in dispersion. Panel C shows that the share of worker-years in small firms declined by 4.6 percentage points over this period, while that in large firms increased by 5.6 points. Between-size differences played a larger role in the earlier decline than in the subsequent increase (Panel B), consistent with compression of the wage-size gradient during the 2000s.

³³Appendix Table 2 replicates the sample statistics in Appendix Table 1 for women. On average, the number of worker-years in the connected set is 62.8% smaller than for men, and the share with more than one firm is 17.2% smaller, raising stronger concerns about limited mobility bias.

³⁴We construct the size decomposition as follows. For each period we estimate the variance-corrected $\text{Var}(\psi_j \mid j \in b)$ separately for each bin b . Then, using the full male leave-out-match sample for that period, we compute the worker-year weights w_b and the (weighted) mean firm effects ψ_b . The within-bin component is $\sum_b w_b \text{Var}(\psi_j \mid j \in b)$ and the between-bin component is $\sum_b w_b (\psi_b - \psi)^2$, where $\psi = \sum_b w_b \psi_b$ is the overall (weighted) mean firm effect. The total variance is the sum of the two components.

Pay rank. Appendix Figure 8 shows the evolution of the lower- and upper-tail gaps of the firm premia distribution, computed over worker-years.³⁵ Lower-tail gaps compressed substantially during the 2000s and partially reopened in the 2010s. By 2015–19, the P50–P5 gap exceeded its 1990s level, while the P50–P25 gap was flat during the 2010s, showing that the 2010s increase was concentrated among the lowest-paying firms. Upper-tail gaps were more stable, with a slight increase in 2000–04 and decline in 2010–14, relative to 1995–99.

These gaps could widen mechanically if employment shifted toward low-paying firms. Appendix Figure 9 shows the opposite: in the 2010s, employment shifted from the bottom half and top decile toward the sixth through eighth deciles.

Geographic variation. The increase in firm-effect dispersion was broad-based across regions. The between-region component accounts for only 6.6% of the variance on average across periods. Within-region dispersion accounts for 92.4% of the increase between 2005–09 and 2015–19. Appendix Figure 10 shows that less developed regions have higher levels of firm-effect dispersion, particularly the Northwest, the Northeast, and the West. The increases in firm premia dispersion in the 2010s range from 0.033 to 0.092 across regions.

4.3 Robustness and Validation

4.3.1 Testing AKM assumptions

We conduct three exercises. First, exogenous mobility implies parallel pre-move wage trends across origin-destination groups. We classify the mover’s origin and destination firms into quartiles based on their co-workers’ wages and study their wage evolution around the move.³⁶ Appendix Figure 11 shows the evolution of wages for workers moving across firms to and from the first and fourth quartiles only, for the intervals 1997–01, 2006–10, and 2013–17. The evolution of wages before the move is consistent with exogenous mobility: wages evolve

³⁵This figure relies on the largest connected set of firms and the plug-in variance estimator.

³⁶To prevent compositional changes over time we focus on movers that are observed during four consecutive years around the move. We residualize wages by year fixed effects to adjust for the macroeconomic cycle.

in parallel before the move regardless of the origin and destination firms.

Second, under exogenous mobility, the model predicts symmetric wage changes for movers between the same pair of firms.³⁷ Panel D of Appendix Figure 11 shows approximately symmetric wage changes, suggesting the symmetry assumption gives a good approximation. A slight deviation occurs between the first and fourth quartiles, where upward movers appear to experience slightly larger gains than the losses of downward movers.

Finally, we assess the additive specification by computing mean residuals within a 10-by-10 grid of worker- and firm-effect deciles. Appendix Figure 12 shows that, in all cases, the mean residuals are no larger than approximately 0.011 log points in absolute value (and are usually much smaller), suggesting that additivity is a good approximation.³⁸

4.3.2 Robustness checks

Alternative estimators. The KSS correction requires a more restrictive connected set that disproportionately excludes small firms. We therefore report the plug-in decomposition for the largest connected set in Appendix Table 3 and compare estimators holding the leave-out-match sample fixed in Appendix Figure 13. The plug-in estimator yields a larger firm component and a smaller sorting component, as expected (Bonhomme et al. 2023), but the evolution of firm-effect dispersion is similar across samples and estimators.

Minimum earnings cutoff. Appendix Figure 14 reports plug-in estimates increasing the minimum earnings cutoff. Higher cutoffs reduce the level of the firm component, but do not affect its evolution: the worker component explains most of the 2000s decline, while the firm component accounts for the increase between 2005–09 and 2015–19.

³⁷To see this, consider workers moving from firm j to firm k . Under exogenous mobility their expected wage change should be $\psi_k - \psi_j$ (up to the year fixed effects). Similarly, workers moving from k to j should experience the reverse wage change, $\psi_j - \psi_k$.

³⁸Similar to other studies (e.g., Card et al. 2013, Alvarez et al. 2018), we find the largest deviations for the low-wage workers. The mean residuals are positive for workers in the lowest deciles of worker and firm effects in 1995–99, but turn negative in subsequent periods, which may be related to the evolution of the minimum wage.

Time-varying window. Rolling-window estimates, shown in Appendix Figure 15, confirm the timing of the reversal. The firm component falls between the 2001–05 and 2004–08 windows, coinciding with the minimum-wage increase of 2004–07, and rises thereafter. The worker component declines more gradually, between the 1999–03 and 2007–11 windows, and subsequently stabilizes, paralleling the evolution of the skill premium.

4.3.3 Estimated firm wage effects

We validate our estimated firm wage effects from the 2010–14 period against data on value added per worker from the ENDEI sample of over 3,000 manufacturing firms in 2010–12. Appendix Table 4 shows results of regressions of firm effects on log value added per worker, log firm size, and their interaction, with and without controls for industry and province.

Productivity is positively associated with firm wage premia across specifications. Evaluated at the mean log firm size (corresponding to approximately 55 employees), the specifications with size interactions imply that an increase of 10 log points in value added per worker is associated with 0.9–1.0 log points higher wages, holding worker characteristics fixed. The association weakens with firm size, particularly when controlling for both industry and province.³⁹ In sum, more productive firms pay higher wages, holding worker characteristics fixed, consistent with rent-sharing between firms and workers (Card et al. 2018).

4.4 Comparison with the Literature

We compare the contribution of firm wage effects in Argentina with estimates from developing and advanced economies in Appendix Figure 16, using our plug-in estimates. The figure notes show selection criteria and estimation methods for each study.

The share of variance explained by firms in Argentina is large in international context. In 2015–19, this share exceeds those reported for the other countries shown in the left panel of

³⁹Alvarez et al. (2018, Table 6) run the analogous regression for the universe of Brazilian manufacturing firms. In 2008–12, the period closest to ours, they report coefficients on log value added per worker of 0.140 without controls and 0.120–0.128 with subsector or state controls, close to our estimates from a much smaller survey-based sample. However, their interaction with firm size is positive.

Appendix Figure 16, including developing economies like Brazil (Alvarez et al. 2018), Mexico (Pérez Pérez and Nuño-Ledesma 2024), South Africa (Bassier 2023), and Uruguay (Bergolo et al. 2025), as well as advanced economies such as West Germany (Card et al. 2013) and the US (Song et al. 2019). However, as argued by Kline (2024, p. 118), comparing variance levels may be more appropriate. Argentina’s firm-effect variance level remains larger than in advanced economies but is more comparable to other developing countries. In particular, the variance is comparable to that of Mexico (Pérez Pérez and Nuño-Ledesma 2024) and smaller than that of South Africa (Bassier 2023). The key difference between Argentina and other developing countries seems to be in the smaller variance of worker effects.

5 Potential Drivers of Firm Wage Premia Dispersion

The preceding analysis shows that firm wage premia compressed during the 2000s expansion and became more dispersed during the stagnation of the 2010s. Motivated by the descriptive evidence in Section 2, we explore three potential mechanisms: productivity dispersion across sectors, the evolution of negotiated wage floors, and informality.

5.1 Industries, Productivity, and Firm Premia Dispersion

5.1.1 Industry wage differentials and their contribution

Following Card et al. (2024), we measure industry wage differentials by averaging the estimated firm wage effects within 4-digit industries, weighting firms by worker-years. Panel B of Table 3 shows that the between-industry component accounts for 38.4% of the firm-effect variance in 1995–99 (column 1), and increases to 41.1% in 2015–19 (column 3). While these results are based on the plug-in variance estimator, the table shows that they capture the same evolution of the variance of firm effects as the KSS estimator used in Section 4.1.

Industries account for nearly half of the 2010s increase in the variance of firm effects. Panel A of Table 3 shows that the variance of firm effects rose from 0.150 in 2005–09 to 0.191

in 2015–19. The between-industry component increased from 0.060 to 0.078, accounting for 45.2%. By comparison, between-industry differences account for about a third of the earlier decline (column 4), pointing to a larger role for within-industry compression in the 2000s.

The industry rankings broadly align with the raw-earnings patterns in Section 2.2. Appendix Table 5 lists the ten 4-digit industries with the highest and lowest wage differentials in 2015–19, together with their mean worker effects and employment shares. Industries with the highest premia include non-ferrous metal mining, motor vehicle manufacturing, services incidental to oil and gas extraction, and banking, and those with the lowest premia include education, construction-related activities, used-book retail, and fishing services. Several industries at both ends of this ranking also contributed substantially to the 2010s increase in between-industry earnings inequality in the raw data: oil and gas services and non-ferrous metal mining among high-premium industries, and construction and education among low-premium industries (Appendix Figure 4). Appendix Table 6 reports differentials at the more aggregated ISIC section level, for 1995–99, 2005–09, and 2015–19.

As discussed in Section 3.2.1, hierarchy bias predicts attenuation of industry fixed effects estimated from industry movers relative to the industry wage differentials. Appendix Figure 17 confirms this prediction across our sample period.

5.1.2 Industries, firm wage premia, and labor productivity

We relate industry wage differentials to labor productivity, measured as value added per worker. Panels A and B of Figure 6 show that more productive industries pay higher firm premia in both 2005–09 and 2015–19, consistent with industry wage differentials partly reflecting productivity differences. Notably, less productive industries not only pay lower firm premia on average but also exhibit greater dispersion in the premia paid by their firms. Panels C and D of Figure 6 show that this negative association with within-industry dispersion strengthens over time. An increase of 10 log points in labor productivity is associated with a reduction in the within-industry SD of firm effects of about 0.0034 in 2005–09 and 0.0061

in 2015–19. We reject equality of the two slopes at the 5% level (p -value = 0.023).

These cross-industry patterns parallel the evolution across macroeconomic regimes. During the 2000s, aggregate productivity rose and the dispersion of firm premia declined. During the 2010s, productivity declined and both productivity gaps and the dispersion of firm premia increased.⁴⁰ The similarity between the cross-sectional and aggregate patterns is consistent with productivity playing a role in the evolution of firm wage premia.

Labor productivity is associated with the dispersion of firm effects but not of worker effects, reinforcing the interpretation that productivity may affect inequality through the firm wage-setting process. Panel A of Appendix Figure 18 shows that more productive industries employ workers with higher mean worker effects, although this gradient is weaker than for firm effects. Panel B shows no association with the within-industry dispersion of worker effects, with a coefficient close to zero and statistically insignificant.

5.1.3 International benchmark and interpretation

Industry wage differentials are more dispersed in Argentina than in the US. Figure 7 compares their distribution for Argentina (2015–19) with the US estimates of Card et al. (2024) for 2010–18, both normalized to restaurants.⁴¹ The standard deviation in Argentina (0.281) is more than twice that in the US (0.122). Most US industries pay modest positive premia relative to restaurants, whereas Argentina’s distribution is much wider.

The industry wage differentials are correlated with mean worker effects, consistent with sorting. Panel C of Appendix Figure 18 shows that the estimated slope from regressing mean worker effects on industry premia is 0.34 in 2015–19, compared with 0.90 in the US (Card et al. 2024, Figure 3). Argentina combines greater dispersion in industry premia with a substantially weaker relationship between industry premia and worker composition.

These patterns connect to development theories that emphasize productivity heterogeneity across sectors, in particular the dual-economy tradition of Lewis (1954) and the Latin

⁴⁰See Section 2.1 for productivity trends and Section 4.1 for firm-effect dispersion.

⁴¹Both classifications use 4-digit industries: ISIC Rev. 3.1 for Argentina and NAICS for the US.

American structuralist tradition of, e.g., [Prebisch \(1950\)](#) and [Furtado \(1963\)](#). The substantial dispersion of industry wage premia and their association with sectoral productivity provide a labor-market counterpart to this heterogeneity.

5.2 Labor Market Institutions

Negotiated wage floors rose during the 2000s, when firm wage effects compressed, and weakened in the 2010s, as the variance of firm wage effects increased. We now examine whether these fluctuations contributed to the evolution of firm wage effects.

5.2.1 OLS estimates

Increases in mean wage floors are associated with declines in both earnings inequality and the dispersion of firm wage effects between 1995–99 and 2005–09. Panel A of Table 4 shows that a 10 log point larger increase in the mean wage floor is associated with a decline of 0.0075 in the standard deviation (SD) of log earnings, of 0.0080 in the SD of firm effects, and of 0.0041 in the SD of worker effects (columns 1, 3, and 5, respectively), all significant at the 10% level. These correspond to 1.2%, 2.1%, and 0.8% of the respective 1995–99 levels.

5.2.2 Instrumental-variable evidence

A concern with these results is that wage floors are determined by other factors that also affect earnings dispersion. For example, productivity gains concentrated among smaller firms could both narrow firm wage gaps and encourage higher negotiated floors. To address this concern, we instrument the change in the mean log wage floor with the negative gap between the industry’s mean log wage floor in 2001–02 and the average log minimum wage in 2005–07, which captures the exposure of each industry to the minimum-wage increase.

The IV estimates imply greater compression of firm premia than OLS. Column (4) of Table 4 shows that a 10 log point larger increase in the mean wage floor implies a decline of 0.0127 in the SD of firm effects ($t = 1.91$), or 3.3% of its 0.382 level in 1995–99. The OLS

point estimate in column (3) is smaller, at 0.0080. For worker effects, the IV point estimate is also larger in absolute value than OLS, but is not statistically significant. Panel B of Table 4 shows that a 10 log point larger increase in the mean floor implies an increase of approximately 4.1 log points at the 10th percentile of the firm-effect distribution, compared with an OLS estimate of 2.5 log points. The point estimate is also positive at the median, although less precisely estimated, and is small and insignificant at the 90th percentile. The results are consistent with institutional compression operating from below.⁴²

The compressing effect of wage floors partially reversed during the 2010s. Table 5 shows that the estimated effect on the change in the SD of firm effects is negative between 1995–99 and 2005–09 and positive between 2005–09 and 2015–19, offsetting part of the 1995–99 to 2005–09 compression.⁴³ Over the full 1995–99 to 2015–19 period, the estimated effects on the SD and the 50–10 gap are statistically indistinguishable from zero, although the 90–50 gap remains significantly narrower.

Instrument validity. The instrument strongly predicts growth in wage floors. Panel A of Appendix Table 7 reports first-stage estimates, showing that a 10 log point larger initial gap predicts a 5.50 log point larger increase in the mean wage floor ($F\text{-stat} = 51$). Consistent with the institutional compression mechanism, the instrument predicts a larger increase in the lower percentiles of the wage floor distribution (columns 2–6), and a decline in the SD of wage floors (column 7). Panel A of Appendix Figure 19 shows event-study estimates: the instrument predicts increases in wage floors from 2004 onward, when the minimum wage increased, with pre-2004 coefficients close to zero and statistically insignificant.⁴⁴

A causal interpretation requires that the initial gap affect changes in firm wage effects

⁴²With only 43 industries, we verify that these estimates are robust to small-sample inference. Because the model is just identified, the wild bootstrap p -value of the reduced form, computed over 9,999 replications, is the Anderson-Rubin p -value for the null of no effect (e.g., Cameron et al. 2008). The bootstrap p -values are 0.084 for the SD of firm effects, 0.039 and 0.240 for the 10th and 50th percentiles, and 0.893 for the 90th.

⁴³For a 10 log point increase in wage floors, the SD effects are -0.0127 between 1995–99 and 2005–09 and 0.0073 between 2005–09 and 2015–19, with wild bootstrap p -values of 0.084 and 0.064, respectively.

⁴⁴We replace wage floors below the statutory minimum with that minimum (see Section 2.3). Panel A of Appendix Figure 19 shows that the first-stage pattern is similar using the original floors.

only through negotiated wage floors. The institutional history supports this view: wage floors changed little in the decade preceding the 2004–07 minimum-wage increase, which prompted essentially all bargaining units to renegotiate their wage floors.⁴⁵

Several pieces of evidence support the identifying assumption. First, Panel B of Appendix Table 7 reports reduced-form estimates relative to 1995–99. The coefficient is negative in every period, largest in magnitude in 2005–09, and statistically significant only in that period. Second, Panel B of Appendix Figure 19 shows no detectable relationship between the instrument and sectoral productivity growth between 2004 and 2007, supporting the interpretation that the instrument affects firm wage effects through negotiated wage floors rather than differential productivity growth across industries.

Economic magnitude. Changes in mean log wage floors vary substantially across industries, averaging 50.3 log points with a cross-industry SD of 23.6 log points. Scaling the IV coefficient by one SD of observed wage-floor growth implies an additional decline in the SD of firm effects of 0.030, or 7.8% of the mean within-industry dispersion of 0.382 in 1995–99. This magnitude is large relative to the compression observed over the same period, when mean within-industry dispersion fell from 0.382 to 0.325.

5.3 Informality and Firm Wage Premia Dispersion

Weak enforcement of labor regulations may have allowed low-paying firms to fall behind as the macroeconomy deteriorated. Because informality directly captures noncompliance with social security registration, we use it as a marker of weak enforcement, and examine whether it relates to the evolution of firm wage inequality. To abstract from changes in informality levels, we use the initial informality rate in 1995–99 throughout the analysis.

⁴⁵The lack of negotiations during the 1990s follows from the economic and political conditions of the time. Price stability, including mild deflation, and a political environment unfavorable to labor unions, together with the ultra-activity clause (which meant that expired agreements remained in force), discouraged negotiations (Palomino and Trajtemberg 2006). Collective bargaining revived in the second half of the 2000s.

5.3.1 Firm wage premia dispersion

Dispersion in firm premia grew more in markets with higher informality, particularly in the 2010s. Column (2) of Table 6 shows that a 10 percentage point higher initial informality rate is associated with an additional 0.0121 increase in the SD of firm effects between 1995–99 and 2015–19 ($t = 2.09$). This corresponds to 3.0% of its 0.406 baseline level. The differential change is indistinguishable from zero in 2000–04, becomes positive in 2005–09, and is larger in both 2010s periods. Column (1) shows a similar pattern for earnings dispersion.

The widening of firm premia reflect the lowest-paying firms falling behind. Columns (3) and (4) of Table 6 show that, between 1995–99 and 2015–19, a 10 percentage point higher initial informality rate is associated with an additional wage decline of 3.0 log points at the 10th percentile of firm premia, holding worker characteristics fixed ($t = 3.09$), while the effect at the 90th percentile is small and statistically indistinguishable from zero ($t = 0.51$).

5.3.2 Firm size and minimum wage compliance

High-informality markets also shifted toward smaller formal firms. Column (5) of Table 6 shows that a 10 percentage point higher informality rate is associated with a decline in mean firm size that is 4.3 log points larger between 1995–99 and 2015–19 ($t = 2.33$). Columns (1) and (2) of Appendix Table 8 show that high-informality markets also experienced a larger increase in the share of firms with 3 or fewer employees and a larger decline in the share of firms with more than 25 employees.

The association between informality and the share of salaried workers earning below the minimum wage also strengthened, further suggesting weaker enforcement of labor regulations. Column (3) of Appendix Table 8 shows that the association between informality and the share earning below the minimum wage is larger in every period relative to 1995–99, and largest in 2005–09 when the minimum wage increased sharply.

Two checks reduce concerns that estimation bias drives these findings. First, local market fixed effects absorb permanent differences in plug-in bias. A remaining concern is that bias

grows more in initially high-informality markets as their firms become smaller. This pattern would bias downward the estimated covariance between worker and firm effects in those markets, making the differential change in the covariance increasingly negative. Instead, column (4) of Appendix Table 9 shows the opposite pattern, with the association becoming more positive over the period.⁴⁶ Second, the results for firm size, the firm size distribution, and earnings dispersion do not rely on estimated firm effects and display the same pattern.

6 Conclusions

Argentina’s earnings inequality decline and reversal had different sources. During the 2000s expansion, compression in both worker and firm effects contributed to declining inequality. During the 2010s stagnation, rising dispersion in firm wage effects more than accounted for the increase in earnings inequality, while worker-effect dispersion remained broadly stable. The reversal was concentrated among small, low-paying firms, suggesting that inequality reductions can prove fragile when macroeconomic conditions deteriorate.

Industry differences and labor market institutions help explain these patterns. Widening industry wage differentials accounted for nearly half of the 2010s increase in firm-effect variance. Less productive industries paid lower premia and exhibited greater dispersion across firms. Wage floors compressed firm effects from below during the 2000s, but this compression weakened in the 2010s. Low-paying firms also fell further behind in more informal local labor markets, consistent with weak enforcement limiting the protection of pay at the bottom.

Our findings suggest avenues for future research. Longitudinal productivity data covering small firms would help assess whether productivity divergence drives widening firm wage premia and distinguish changes within firms from entry and exit. Cross-country comparisons of industry wage differentials would help establish whether industry differences contribute more to firm wage inequality in developing economies.

⁴⁶Appendix Table 9 reports results for the variance of firm effects, worker effects, and their covariance. The point estimates for all three components are positive in the 2010s. Firm effects account for about 39% of the differential increase in the variance of log earnings in the formal sector.

References

- Abbate, N. and Jiménez, B. (2026). Do minimum wage hikes lead to employment destruction? Evidence from a regression discontinuity design in Argentina. *Journal of Development Economics*, 178:103558.
- Abowd, J. A., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2):251–333.
- Acosta, P., Cruces, G., Galiani, S., and Gasparini, L. (2019). Educational upgrading and returns to skills in Latin America: Evidence from a supply–demand framework. *Latin American Economic Review*, 28(1):18.
- Albina, I., Laguinge, L., Gasparini, L., Tornarolli, L., Cruces, G., and Afonso, S. (2024). Ajustando la imagen de la distribución del ingreso en Argentina: Encuestas y registros administrativos. Documentos de Trabajo del CEDLAS 336, CEDLAS-Universidad Nacional de La Plata.
- Alvaredo, F., Bourguignon, F., Ferreira, F. H. G., and Lustig, N. (2025). Inequality bands: Seventy-five years of measuring income inequality in Latin America. *Oxford Open Economics*, 4(Supplement 1):i9–i35.
- Alvarez, J., Benguria, F., Engbom, N., and Moser, C. (2018). Firms and the decline in earnings inequality in Brazil. *American Economic Journal: Macroeconomics*, 10(1):149–189.
- Azkarate-Askasua, M. and Zerecero, M. (2024). No more limited mobility bias: Exploring the heterogeneity of labor markets. *Available at SSRN 5039828*.
- Bassier, I. (2023). Firms and inequality when unemployment is high. *Journal of Development Economics*, 161:103029.
- Beccaria, L., Maurizio, R., and Vázquez, G. (2015). Recent decline in wage inequality and formalization of the labour market in Argentina. *International Review of Applied Economics*, 29(5):677–700.
- Bergolo, M. L., Ceni, R., Fondo, M., and Vergara, D. (2025). Minimum wages and the

- distribution of firm wage premia. Working Paper 34188, National Bureau of Economic Research.
- Bhuller, M., Moene, K. O., Mogstad, M., and Vestad, O. L. (2022). Facts and fantasies about wage setting and collective bargaining. *Journal of Economic Perspectives*, 36(4):29–52.
- Blanco, A., Diaz de Astarloa, B., Drenik, A., Moser, C., and Trupkin, D. R. (2022). The evolution of the earnings distribution in a volatile economy: Evidence from Argentina. *Quantitative Economics*, 13(4):1361–1403.
- Bonhomme, S., Holzheu, K., Lamadon, T., Manresa, E., Mogstad, M., and Setzler, B. (2023). How much should we trust estimates of firm effects and worker sorting? *Journal of Labor Economics*, 41(2):291–322.
- Briskar, J., Di Porto, E., Rodríguez Mora, J. V., and Tealdi, C. (2024). The role of industries in rising inequality. *IZA Discussion Paper*, 16693.
- Busso, M., Madrigal, L., and Pagés, C. (2010). *Productivity from the Bottom Up: Firms and Resource Allocation in Latin America*, pages 69–96. Palgrave Macmillan US, New York.
- Busso, M. and Romero Fonseca, D. (2015). Female labor force participation in Latin America: Patterns and explanations. Documento de Trabajo 187, Universidad Nacional de La Plata, Centro de Estudios Distributivos, Laborales y Sociales (CEDLAS).
- Bustos, P. (2011). Trade liberalization, exports, and technology upgrading: Evidence on the impact of MERCOSUR on Argentinian firms. *American Economic Review*, 101(1):304–40.
- Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics*, 90(3):414–427.
- Card, D. and Cardoso, A. R. (2022). Wage flexibility under sectoral bargaining. *Journal of the European Economic Association*, 20(5):2013–2061.
- Card, D., Cardoso, A. R., Heining, J., and Kline, P. (2018). Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics*, 36(S1):S13–S70.
- Card, D., Heining, J., and Kline, P. (2013). Workplace heterogeneity and the rise of West German wage inequality. *Quarterly Journal of Economics*, 128(3):967–1015.
- Card, D., Rothstein, J., and Yi, M. (2024). Industry wage differentials: A firm-based ap-

- proach. *Journal of Labor Economics*, 42(S1):S11–S59.
- Cardoso, A. R. and Portugal, P. (2005). Contractual wages and the wage cushion under different bargaining settings. *Journal of Labor economics*, 23(4):875–902.
- Cavallo, A. (2013). Online and official price indexes: Measuring Argentina’s inflation. *Journal of Monetary Economics*, 60(2):152–165.
- Ciaschi, M., Galeano, L., and Gasparini, L. (2021). Estructura productiva y desigualdad salarial: Evidencia para América Latina. *El Trimestre Económico*, 88(349):77–106.
- Derenoncourt, E., Gerard, F., Lagos, L., and Montialoux, C. (2025a). Minimum wages and informality. Working Paper 34445, National Bureau of Economic Research.
- Derenoncourt, E., Gerard, F., Lagos, L., and Montialoux, C. (2025b). What do (thousands of) unions do? Union-specific pay premia and inequality. Working Paper 34139, National Bureau of Economic Research.
- Dix-Carneiro, R. and Kovak, B. K. (2015). Trade liberalization and the skill premium: A local labor markets approach. *American Economic Review*, 105(5):551–57.
- Drenik, A., Jäger, S., Plotkin, P., and Schoefer, B. (2023). Paying outsourced labor: Direct evidence from linked temp agency-worker-client data. *The Review of Economics and Statistics*, 105(1):206–216.
- Engbom, N. and Moser, C. (2022). Earnings inequality and the minimum wage: Evidence from Brazil. *American Economic Review*, 112(12):3803–47.
- Eslava, M., Meléndez, M., Ulyssea, G., Urdaneta, N., and Flores, I. (2025). Businesses and inequality in Latin America. *Oxford Open Economics*, 4(Supplement 1):i334–i348.
- Feinmann, J., Hsu Rocha, R., and Lauletta, M. (2022). Payments under the table: Employer-employee collusion in Brazil. *Available at SSRN 4270665*.
- Fernández, M. and Messina, J. (2018). Skill premium, labor supply, and changes in the structure of wages in Latin America. *Journal of Development Economics*, 135:555–573.
- Furtado, C. (1963). *The Economic Growth of Brazil: A Survey from Colonial to Modern Times*. University of California Press, Berkeley.
- Galiani, S. and Sanguinetti, P. (2003). The impact of trade liberalization on wage inequality:

- Evidence from Argentina. *Journal of Development Economics*, 72(2):497–513.
- Gasparini, L. and Cruces, G. (2010). A distribution in motion: The case of Argentina. In Lustig, N. and Lopez-Calva, L. F., editors, *Declining Inequality in Latin America: A Decade of Progress?* Brookings Institution and UNDP, Washington DC.
- Gasparini, L., Cruces, G., and Tornarolli, L. (2016). Chronicle of a deceleration foretold: Income inequality in Latin America in the 2010s. *Revista de Economía Mundial*.
- Gasparini, L. and Lustig, N. (2011). *The Rise and Fall of Income Inequality in Latin America*. Oxford University Press.
- Gopinath, G. and Neiman, B. (2014). Trade adjustment and productivity in large crises. *American Economic Review*, 104(3):793–831.
- Graña, J. M. and Terranova, L. (2022). Neither mechanical nor premature: Deindustrialization and the New International Division of Labour (1970–2019). *Revista de Historia Industrial*, 31(86):11–46.
- Haanwinckel, D. (2025). Supply, demand, institutions, and firms: A theory of labor market sorting and the wage distribution. *American Economic Review*, 115(12):4137–82.
- Haanwinckel, D. and Soares, R. R. (2021). Workforce composition, productivity, and labour regulations in a compensating differentials theory of informality. *The Review of Economic Studies*, 88(6):2970–3010.
- Haltiwanger, J., Hyatt, H. R., and Spletzer, J. R. (2024). Rising top, falling bottom: Industries and rising wage inequality. *American Economic Review*, 114(10):3250–83.
- Hermo, S. (2017). The structure of wages in Argentina 1992-2016: The role of demand and supply. In *Anales, LII Reunión Anual*. Asociación Argentina de Economía Política.
- Hermo, S. (2025). Collective bargaining networks and the propagation of shocks. *Working paper*.
- Hsieh, C.-T. and Klenow, P. J. (2009). Misallocation and manufacturing TFP in China and India*. *The Quarterly Journal of Economics*, 124(4):1403–1448.
- International Labour Organization (2014). *Women and Men in the Informal Economy: A Statistical Picture*. International Labour Office, Geneva, second edition edition.

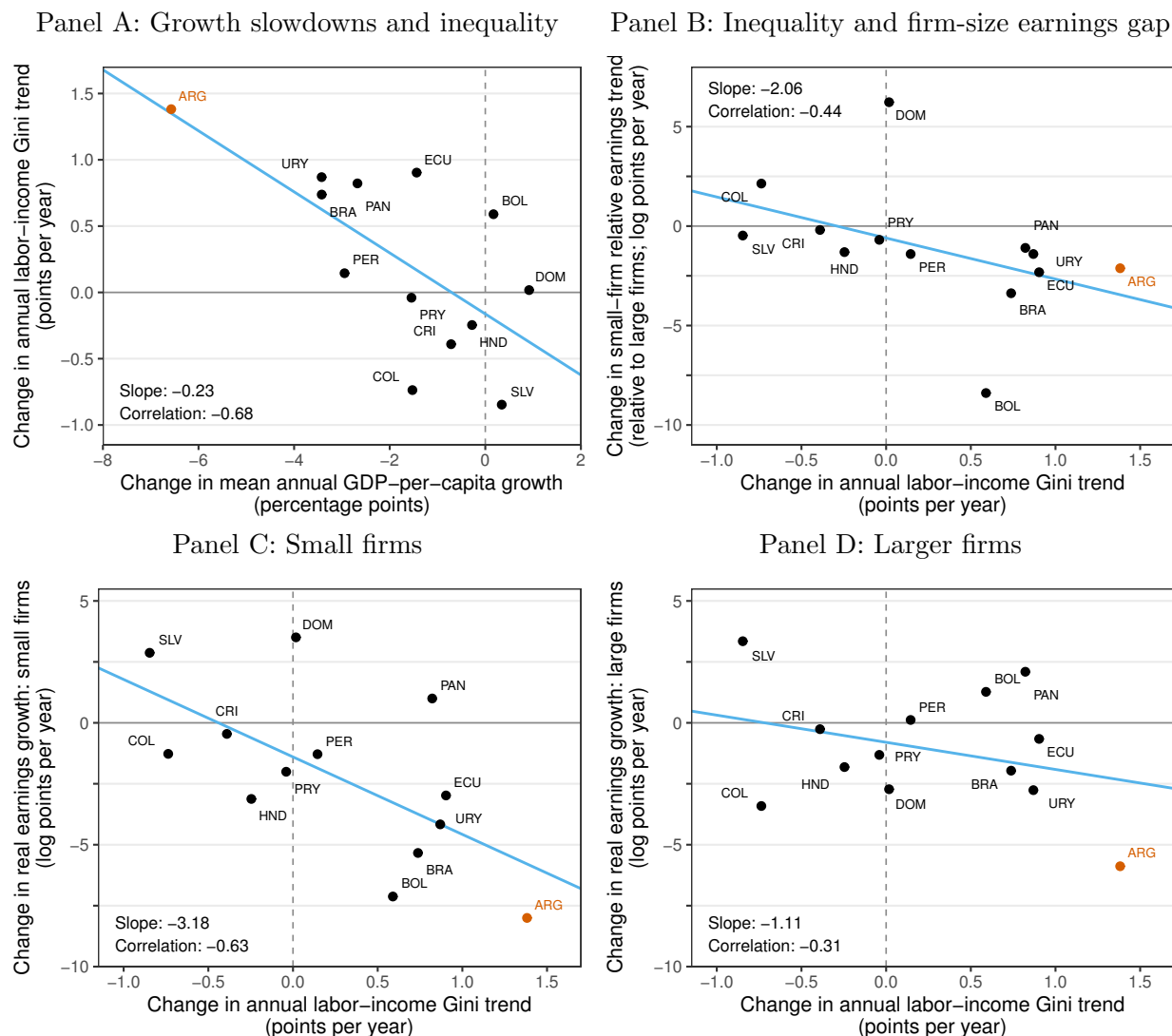
- Katz, L. F. and Autor, D. H. (1999). Chapter 26 - Changes in the wage structure and earnings inequality. volume 3 of *Handbook of Labor Economics*, pages 1463–1555. Elsevier.
- Kline, P. (2024). Chapter 2 - Firm wage effects. In Dustmann, C. and Lemieux, T., editors, *Handbook of Labor Economics*, volume 5 of *Handbook of Labor Economics*, pages 115–181. Elsevier.
- Kline, P., Saggio, R., and Sølvesten, M. (2020). Leave-out estimation of variance components. *Econometrica*, 88(5):1859–1898.
- Krueger, A. B. and Summers, L. H. (1988). Efficiency wages and the inter-industry wage structure. *Econometrica: Journal of the Econometric Society*, pages 259–293.
- Lachowska, M., Mas, A., Saggio, R., and Woodbury, S. A. (2023). Do firm effects drift? Evidence from Washington administrative data. *Journal of Econometrics*, 233(2):375–395.
- Levy, S. (2008). *Good Intentions, Bad Outcomes: Social Policy, Informality, and Economic Growth in Mexico*. Brookings Institution Press, Washington, DC. First edition, published May 6, 2008.
- Lewis, W. A. (1954). Economic development with unlimited supplies of labour. *The Manchester School*, 22(2):139–191.
- Lombardo, C. and Martinez-Correa, J. (2019). Convenio colectivo, sindicatos y dispersión salarial: Evidencia de Argentina. Manuscript.
- Lustig, N., Lopez-Calva, L. F., Ortiz-Juarez, E., and Monga, C. (2016). Deconstructing the decline in inequality in Latin America. In *Inequality and Growth: Patterns and Policy*, pages 212–247. Palgrave Macmillan UK.
- Machado Parente, R., Brotherhood, L., and Iachan, F. S. (2026). Minimum wages, inequality, and the informal sector. Working paper.
- Manacorda, M., Sánchez-Páramo, C., and Schady, N. (2010). Changes in returns to education in Latin America: The role of demand and supply of skills. *ILR Review*, 63(2):307–326.
- Maurizio, R. and Vazquez, G. (2016). Distribution effects of the minimum wage in four Latin American countries: Argentina, Brazil, Chile and Uruguay. *International Labour Review*,

155(1):97–131.

- Messina, J. and Silva, J. (2019). Twenty years of wage inequality in Latin America. *The World Bank Economic Review*, 35(1):117–147.
- Oberfield, E. (2013). Productivity and misallocation during a crisis: Evidence from the Chilean crisis of 1982. *Review of Economic Dynamics*, 16(1):100–119.
- Palomino, H. and Trajtemberg, D. (2006). Una nueva dinámica de las relaciones laborales y la negociación colectiva en la Argentina. *Revista de trabajo*, 2(3).
- Pérez Pérez, J. (2020). The minimum wage in formal and informal sectors: Evidence from an inflation shock. *World Development*, 133:104999.
- Pérez Pérez, J. and Nuño-Ledesma, J. G. (2024). Workers, workplaces, sorting, and wage dispersion in Mexico. *Economía*, 23(1):pp. 311–332.
- Ponczek, V. and Ulyssea, G. (2021). Enforcement of labour regulation and the labour market effects of trade: Evidence from Brazil. *The Economic Journal*, 132(641):361–390.
- Prebisch, R. (1950). *The economic development of Latin America and its principal problems*. United Nations Department of Economic Affairs, Lake Success, NY.
- Ramírez Leira, L., Lombardo, C., and Gasparini, L. (2025). Wage floors set in collective bargaining: Evidence on wages and employment in Argentina. Working Paper 0353, CEDLAS, Universidad Nacional de La Plata.
- Schteingart, D., Trombetta, M., and Pascuariello, G. (2022). Primas salariales sectoriales en Argentina. *Económica*, 68.
- Song, J., Price, D., Guvenen, F., Bloom, N., and von Wachter, T. (2019). Firming up inequality. *Quarterly Journal of Economics*, 134(1):1–50.
- Ulyssea, G. (2018). Firms, informality, and development: Theory and evidence from Brazil. *American Economic Review*, 108(8):2015–47.

Tables and Figures

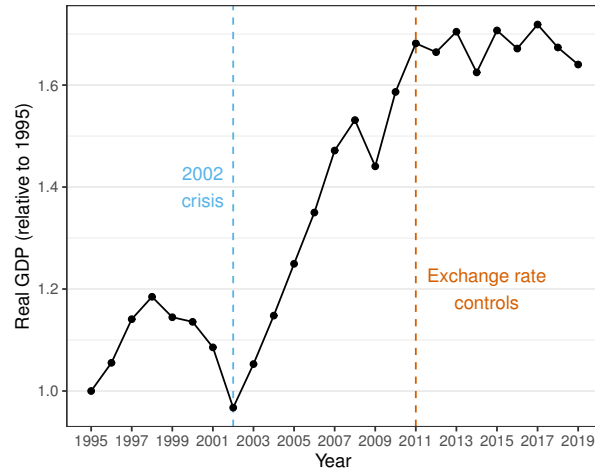
Figure 1: Growth, inequality, and firm-size earnings gaps in Latin America



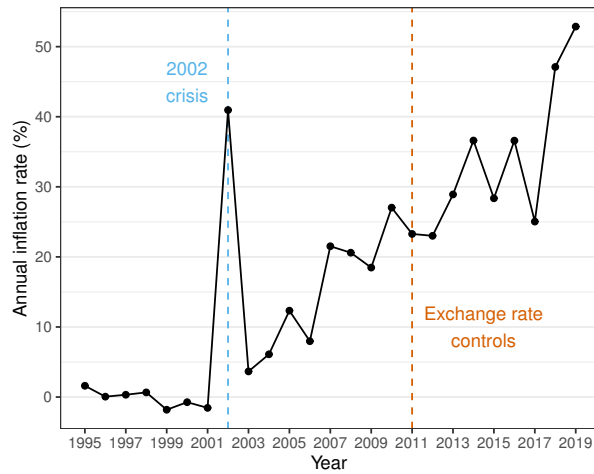
Notes: Data are from the Socio-Economic Database for Latin America and the Caribbean (SEDLAC, CEDLAS and the World Bank) and the World Development Indicators. All changes are measured as the value for 2012–19 minus that for 2003–11. Panel A plots the change in the annual trend of the labor-income Gini among all workers (on a 0–100 scale) against the change in mean annual real GDP-per-capita growth. Panel B plots the change in the annual trend of small-firm relative earnings against the change in the Gini trend. Relative earnings are defined as 100 times the log ratio of mean monthly labor income at small firms, with fewer than 5 workers, to that at larger firms, with 5 or more workers. Panels C and D plot the change in real earnings growth at small and larger firms, respectively, against the change in the Gini trend. Earnings growth is measured as the annual trend in 100 times the log of mean real monthly labor income. All earnings measures refer to private salaried workers.

Figure 2: Macroeconomic indicators for Argentina, 1995–2019

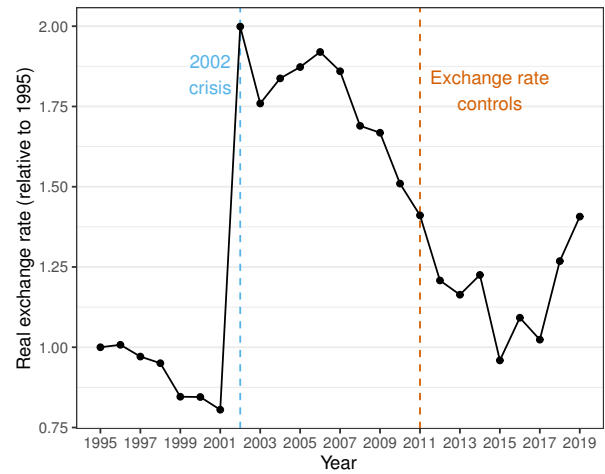
Panel A: Real gross domestic product



Panel B: Annual inflation

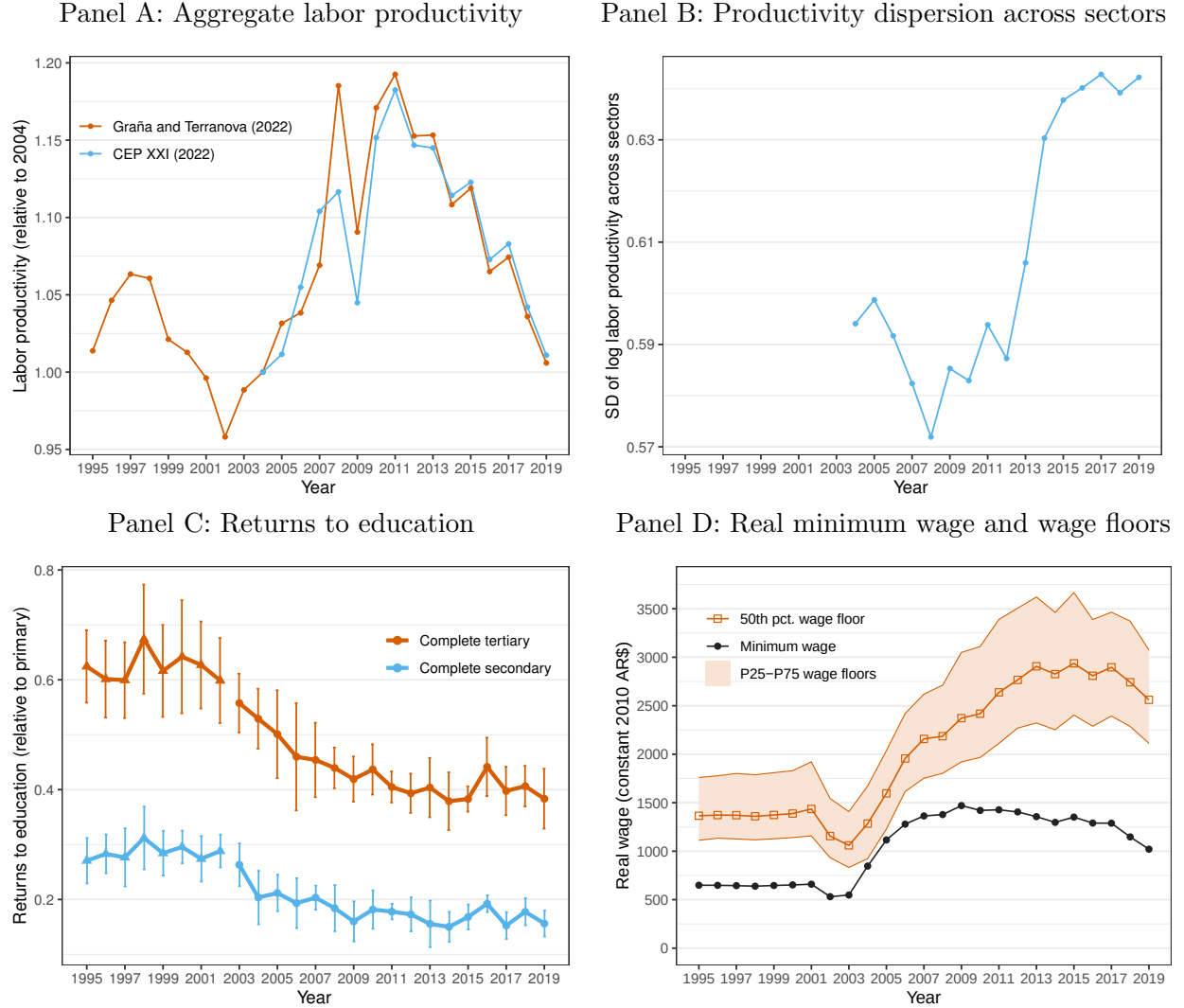


Panel C: Real exchange rate (pesos per USD)



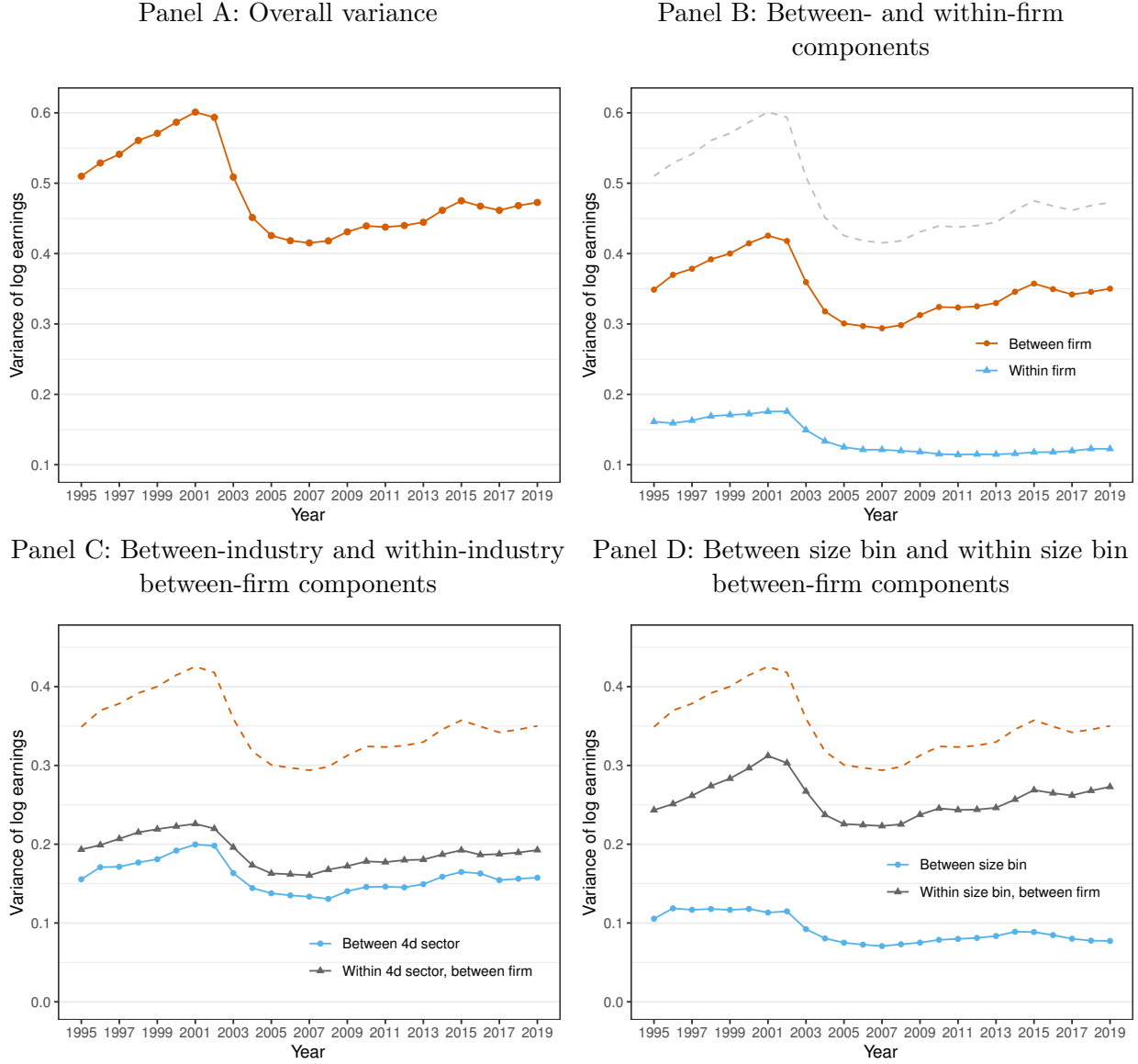
Notes: Data are from the National Institute of Statistics and Censuses (INDEC) and the National Accounts Office (DNCN). The figure shows the evolution of key macroeconomic indicators for Argentina between 1995 and 2019. Panel A shows the evolution of the real Gross Domestic Product (GDP). Panel B shows the annual inflation rate, constructed as the percent change in the Consumer Price Index (CPI) between December of the previous year and December of the current year. Panel C shows the evolution of the real exchange rate. We use alternative sources for the CPI index between 2007 and 2015 as the official data are widely considered to have been manipulated.

Figure 3: Correlates of wage inequality in Argentina, 1995–2019



Notes: Data are from [Graña and Terranova \(2022\)](#), CEP XXI, the Permanent Household Survey (EPH), and the Secretariat of Labor. The figure shows the evolution of three potential determinants of earnings inequality in Argentina between 1995 and 2019. Panel A shows aggregate labor productivity, measured as real output per worker normalized to 2004 = 1. The series from [Graña and Terranova \(2022\)](#) covers 1995–2019, while the series from CEP XXI starts in 2004. Panel B shows the standard deviation of log labor productivity across the 34 sectors of the CEP XXI data in 2004–2019, weighting each sector by its number of jobs. Panel C shows the coefficients of a Mincerian wage regression within a given year controlling for gender, age (linear and quadratic), region, and sector. The omitted category is workers with incomplete secondary education or less. “Complete secondary” corresponds to complete secondary and incomplete tertiary education, and “Complete tertiary” to complete tertiary education. Robust standard errors are clustered at the region level. Different shape markers indicate the change in the EPH survey format in 2003. Panel D shows the real minimum wage, obtained from the Secretariat of Labor and deflated by the CPI, and the percentiles 25, 50, and 75 of average wage floors, obtained from resolutions of the Secretariat of Labor.

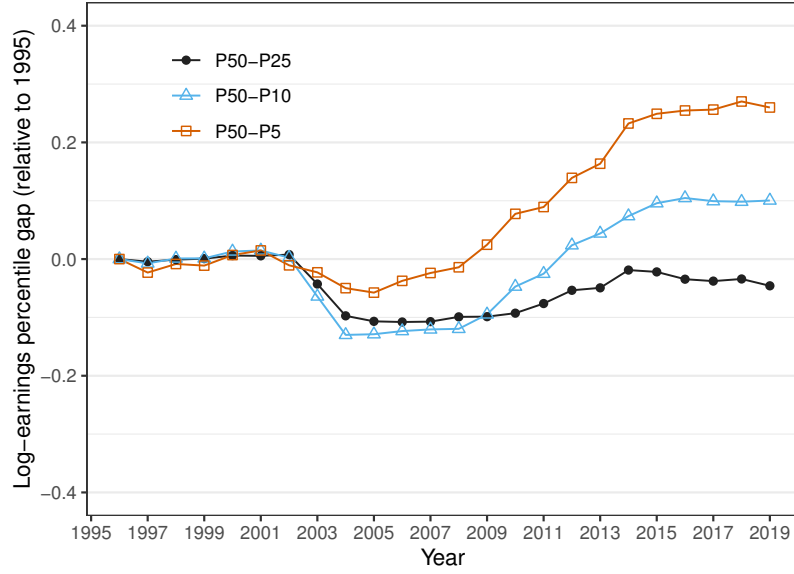
Figure 4: Variance of log earnings in the formal labor market, prime-aged men



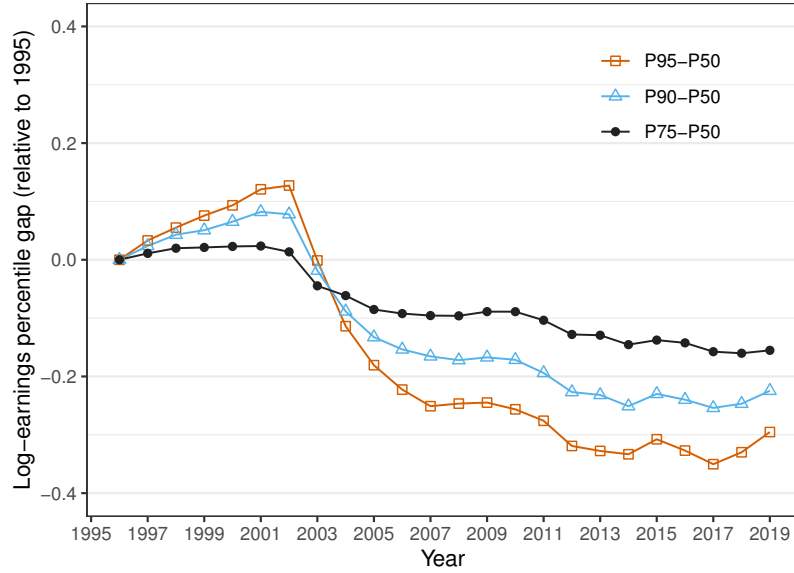
Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The figure shows the evolution of inequality, defined as the variance of log earnings, between 1995 and 2019. Panel A shows the overall variance of log earnings, and Panel B decomposes the variance into the between- and within-firm components. Panel C decomposes the between-firm component into between-industry and within-industry between-firm components. Similarly, Panel D decomposes the between-firm component into between-size-bin and within-size-bin between-firm components. Earnings are measured as average monthly total real earnings. We exclude earnings above the 99.9th percentile of the distribution, and below USD 75 per month, and worker-firm-year cells that correspond to jobs shorter than 6 months and those labeled as internships.

Figure 5: Percentile gaps in log earnings in Argentina relative to 1995

Panel A: Lower-tail inequality



Panel B: Upper-tail inequality



Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The figure shows the evolution of inequality as measured by differences between percentiles of the log real earnings distribution. Earnings are measured as average monthly total real earnings. We exclude earnings above the 99.9th percentile of the distribution, and below USD 75 per month, and worker-firm-year cells that correspond to jobs lasting fewer than six months or internships.

Figure 6: Firm wage effects and sectoral productivity in 2005–09 and 2015–19

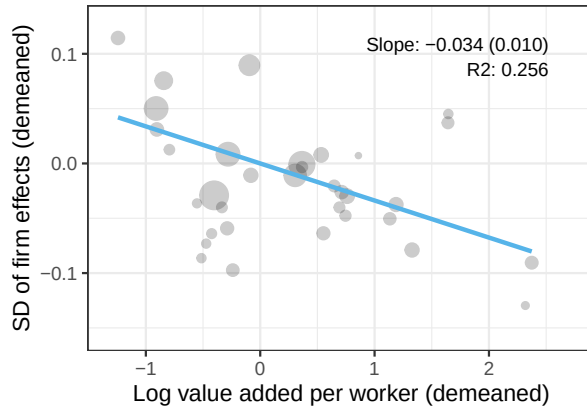
Panel A: Mean firm effect, 2005–09



Panel B: Mean firm effect, 2015–19



Panel C: SD of firm effects, 2005–09

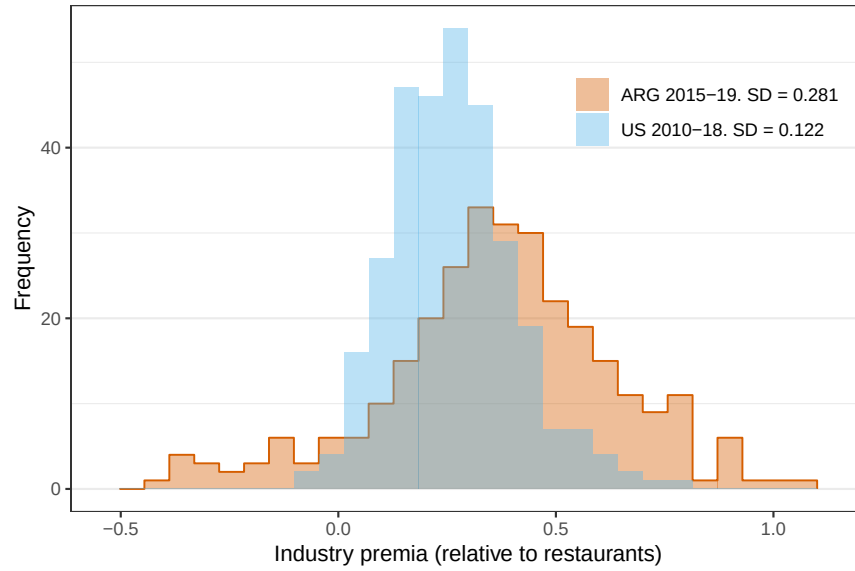


Panel D: SD of firm effects, 2015–19



Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55 and from CEP XXI. The figure shows the relationship between firm effects and sectoral productivity in Argentina for the periods 2005–09 and 2015–19. Panels A and B show a scatter of the average firm wage effect and sectoral productivity, while Panels C and D show a scatter plot of the SD of firm wage effects and sectoral productivity. The measure of sectoral productivity is an average of value added per worker across relevant years. Variables are demeaned within each period using worker-year weights. Reported standard errors are clustered by sector. Sectors follow CEP XXI's classification based on ISIC Rev. 3.1, with selected aggregations and subdivisions.

Figure 7: Distribution of industry wage premia, Argentina and the US



Notes: Data are from Argentina's social security system (SIPA) for 2015–2019 and from [Card et al. \(2024\)](#) for the US in 2010–2018. The figure shows the distribution of industry wage premia in Argentina and the US, with industry premia calculated relative to restaurants in both cases. Industries are defined at the 4-digit level: ISIC Rev. 3.1 for Argentina and NAICS for the US.

Table 1: Variance decomposition of AKM estimates by period, KSS bias-corrected estimates

	1995–99		2000–04		2005–09		2010–14		2015–19		Change 1995–2009		Change 2005–2019	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
Variance of log earnings	0.554	(100.0)	0.572	(100.0)	0.418	(100.0)	0.415	(100.0)	0.436	(100.0)	-0.136	(100.0)	0.018	(100.0)
Variance of worker effects	0.234	(42.2)	0.240	(42.0)	0.152	(36.3)	0.142	(34.3)	0.144	(33.0)	-0.082	(60.3)	-0.008	(-41.8)
Variance of firm effects	0.183	(33.0)	0.192	(33.7)	0.141	(33.7)	0.158	(38.0)	0.181	(41.5)	-0.042	(30.9)	0.040	(219.0)
Variance of year effects	0.002	(0.3)	0.009	(1.6)	0.016	(3.7)	0.004	(0.9)	0.001	(0.2)	0.014	(-10.1)	-0.015	(-81.1)
2×Cov. of worker and firm effects	0.096	(17.3)	0.084	(14.7)	0.077	(18.5)	0.079	(19.0)	0.073	(16.7)	-0.019	(13.9)	-0.004	(-24.8)
2×Cov. of worker and year effects	-0.002	(-0.4)	-0.001	(-0.2)	-0.007	(-1.6)	-0.002	(-0.6)	0.000	(0.1)	-0.004	(3.2)	0.007	(39.3)
2×Cov. of firm and year effects	-0.001	(-0.3)	-0.001	(-0.2)	0.000	(0.1)	-0.000	(-0.0)	0.000	(0.0)	0.002	(-1.4)	-0.000	(-2.3)
Variance of residual	0.043	(7.8)	0.048	(8.4)	0.039	(9.3)	0.035	(8.3)	0.037	(8.6)	-0.004	(3.2)	-0.001	(-8.2)
Millions of ...														
...worker years	8.08		7.46		11.18		12.75		12.78					
...firms	0.11		0.09		0.15		0.15		0.13					
R^2	0.955		0.949		0.943		0.950		0.951					

Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The table shows estimates of the variance decomposition of models of log earnings on worker fixed effects, firm fixed effects, and year fixed effects following [Kline et al. \(2020\)](#). The models are estimated separately for the periods 1995–99, 2000–04, 2005–09, 2010–14, and 2015–19, using the largest leave-out-match connected set of firms in each period. Columns (1) through (5) show the estimates of the variance of each component for each period. Column (6) shows the change in the variance of each component between 1995–99 and 2005–09, and column (7) shows the change between 2005–09 and 2015–19, both in levels and as a percentage of the change in the variance of log earnings. The top eight rows show estimates of the variance of different components of log earnings, with the numbers in parentheses showing the variance normalized by the variance of log earnings in the period or the change in the variance of log earnings between two periods. The bottom three rows show the number of worker years, the number of firms, and the R^2 of the model.

Table 2: Variance of AKM firm wage effects by firm size and period, KSS bias-corrected estimates

	1995–99	2000–04	2005–09	2010–14	2015–19	Change 1995–2009	Change 2005–2019
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Variance of firm effects by size							
Small firms (≤ 25)	0.167	0.177	0.131	0.176	0.215	-0.036 (74.9)	0.085 (190.7)
Medium firms (> 25 to 100)	0.194	0.203	0.143	0.162	0.185	-0.052 (106.9)	0.043 (96.2)
Large firms (> 100)	0.120	0.147	0.104	0.106	0.124	-0.016 (33.2)	0.020 (45.0)
Panel B: Decomposition of total variance							
Total (within+between)	0.199	0.212	0.151	0.171	0.195	-0.048 (100.0)	0.044 (100.0)
Between size bin	0.050	0.045	0.031	0.037	0.040	-0.019 (39.5)	0.009 (19.5)
Within size bin	0.149	0.167	0.120	0.134	0.155	-0.029 (60.5)	0.036 (80.5)
Panel C: Share of worker-years by size							
Small firms (≤ 25)	0.230	0.207	0.234	0.214	0.189	0.004	-0.046
Medium firms (> 25 to 100)	0.241	0.239	0.239	0.228	0.229	-0.002	-0.010
Large firms (> 100)	0.529	0.553	0.527	0.558	0.582	-0.003	0.056

Notes: Data are from Argentina’s social security system (SIPA) for men aged 20 to 55. The table shows the decomposition of the variance of firm wage effects by firm size bin, using the heteroskedasticity-robust correction of [Kline et al. \(2020\)](#) on the leave-out-match connected set constructed within each bin. Firms are classified into three size bins based on average employment: small (25 or fewer workers), medium (more than 25 and at most 100 workers), and large (more than 100 workers). Panel A reports the variance of firm effects estimated separately within each size bin. Panel B decomposes the variance of firm effects into a between-bin component, which captures differences in mean firm effects across size classes, and a within-bin component, which captures dispersion among firms of similar size. The total in Panel B is computed as the sum of the within-bin and between-bin components, so it is internally consistent with the decomposition shown in the table. Because the size bins are estimated separately, this total differs from the economy-wide variance of firm effects reported in Table 1. Numbers in parentheses in columns (6) and (7) express each change as a percentage of the change in the total variance of firm effects in Panel B over the same period. Panel C reports the share of worker-years accounted for by each size bin.

Table 3: Industry wage differentials and the evolution of firm wage effects by period

	1995–99	2005–09	2015–19	Change 1995–2009		Change 2005–2019	
	(1)	(2)	(3)	(4)		(5)	
Panel A: Variance of firm effects, leave-out-match sample							
KSS corrected	0.183	0.141	0.181	-0.042		0.040	
Plug-in	0.195	0.150	0.191	-0.045	(100.0)	0.041	(100.0)
Panel B: Decomposition of plug-in variance							
Between industries	0.075	0.060	0.078	-0.015	(33.0)	0.018	(45.2)
Within industries	0.120	0.090	0.112	-0.030	(67.0)	0.022	(54.8)
Between share (%)	38.4	40.0	41.1				

Notes: Data are from Argentina’s social security system (SIPA) for men aged 20 to 55. Panel A reports the variance of firm wage effects in the largest leave-out-match connected set of firms. The first row uses the heteroskedastic correction of [Kline et al. \(2020\)](#), while the second row reports the corresponding plug-in variance estimate on the same sample. Panel B decomposes the plug-in variance of firm effects into the variance of industry wage differentials, defined as the mean firm effect within each 4-digit industry weighted by worker-years, which corresponds to the between-industries component, and the variance of firm effects within industries. Columns (4) and (5) show changes between 1995–99 and 2005–09, and between 2005–09 and 2015–19. Numbers in parentheses in Panel B express each change as a percentage of the corresponding change in the plug-in variance of firm effects. The last row of Panel B reports the between-industries component as a percentage of the plug-in variance of firm effects in each period. By construction, the between-industries and within-industries components add up to the plug-in variance of firm effects.

Table 4: Negotiated wage floors and changes in earnings and AKM effects, 1995–2009

Panel A: Standard deviation of log earnings, firm effects, and worker effects						
	SD log earnings		SD firm effects		SD worker effects	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Change in mean	-0.0754	-0.0956	-0.0805	-0.1269	-0.0407	-0.0583
log wage floor	(0.0311)	(0.0467)	(0.0436)	(0.0665)	(0.0238)	(0.0378)
R^2	0.0973	0.0886	0.1013	0.1427	0.0763	0.0886
Observations	43	43	43	43	43	43
Panel B: Percentiles of firm-effect distribution						
	10th percentile		50th percentile		90th percentile	
	OLS	IV	OLS	IV	OLS	IV
	(7)	(8)	(9)	(10)	(11)	(12)
Change in mean	0.2540	0.4127	0.0186	0.1376	0.0223	0.0116
log wage floor	(0.0941)	(0.1414)	(0.0864)	(0.0953)	(0.0621)	(0.0825)
R^2	0.1836	0.2749	0.0023	0.0700	0.0033	0.0005
Observations	43	43	43	43	43	43

Notes: Data are from Argentina’s social security system (SIPA) for men aged 20 to 55 and from Secretariat of Labor resolutions reporting average wage floors. The table shows estimates of the effect of changes in negotiated wage floors on changes in inequality measures at the ISIC Rev. 3.1 division level between 1995–99 and 2005–09. The industry’s mean log negotiated wage floor is computed between 2001–02 and 2008–09, and uses bargaining units observed consistently from the late 1990s through 2008 and sectors with at least two wage-floor observations. The dependent variables are changes between 1995–99 and 2005–09 in the standard deviation (SD) of log earnings, the SD of firm effects, the SD of worker effects, and the 10th, 50th, and 90th percentiles of the firm-effect distribution. Odd-numbered columns report OLS estimates. Even-numbered columns report IV estimates that instrument the change in the mean log wage floor with the negative gap between the industry’s mean log wage floor in 2001–02 and the average log real national minimum wage in 2005–07. Heteroskedasticity-robust standard errors are reported in parentheses.

Table 5: Timing and persistence of wage-floor effects

	Moments of firm-effect distributions			
	SD (1)	50–10 gap (2)	90–50 gap (3)	90–10 gap (4)
<i>1995–99 to 2005–09 (baseline)</i>	-0.127 (0.066)	-0.275 (0.158)	-0.126 (0.055)	-0.401 (0.170)
<i>2005–09 to 2010–14</i>	0.051 (0.029)	0.184 (0.069)	0.071 (0.044)	0.254 (0.080)
<i>2005–09 to 2015–19</i>	0.073 (0.033)	0.188 (0.087)	-0.072 (0.072)	0.116 (0.131)
<i>1995–99 to 2015–19</i>	-0.054 (0.073)	-0.087 (0.197)	-0.198 (0.077)	-0.285 (0.231)
Observations	43	43	43	43
First-stage F	51.27	51.27	51.27	51.27

Notes: Data are from Argentina’s social security system (SIPA) for men aged 20 to 55 and Secretariat of Labor resolutions reporting average wage floors. The table shows IV estimates of the effect of changes in negotiated wage floors on changes in the standard deviation (SD) and percentile gaps of the firm-effect distribution at the ISIC Rev. 3.1 division level. All regressions use the change in the industry’s mean log negotiated wage floor between 2001–02 and 2008–09, instrumented with the negative gap between the industry’s mean log wage floor in 2001–02 and the average log real national minimum wage in 2005–07, as in Table 4. The dependent variables are changes between the periods indicated in each row. The wage-floor treatment and instrument are the same across rows. Heteroskedasticity-robust standard errors are reported in parentheses.

Table 6: Informality, the dispersion of firm wage effects, and firm size

	SD log earnings (1)	SD firm effects (2)	10th ptile. firm effect (3)	90th ptile. firm effect (4)	Log mean firm size (5)
Informality $\times$ 2000–04	0.004 (0.019)	-0.005 (0.021)	-0.069 (0.042)	-0.135 (0.074)	-0.138 (0.134)
Informality $\times$ 2005–09	0.122 (0.045)	0.079 (0.037)	-0.144 (0.079)	-0.031 (0.103)	-0.206 (0.146)
Informality $\times$ 2010–14	0.194 (0.059)	0.135 (0.052)	-0.271 (0.069)	-0.005 (0.122)	-0.434 (0.164)
Informality $\times$ 2015–19	0.193 (0.062)	0.121 (0.058)	-0.304 (0.099)	-0.053 (0.104)	-0.432 (0.186)
Time and local market effects	Yes	Yes	Yes	Yes	Yes
R^2	0.877	0.800	0.941	0.907	0.974
Observations	335	335	335	335	335

Notes: Data are from Argentina’s social security system (SIPA) for men aged 20 to 55 and from the Permanent Household Survey (EPH). The table shows estimates of the association between labor informality and the dispersion of earnings and firm wage effects across local labor markets, together with average firm size. The unit of observation is a region-sector cell, defined by the seven EPH regions and the sections of ISIC Rev. 3.1, some of which are combined to match the EPH classification. The dependent variables are the standard deviation of log earnings in column (1), the standard deviation and the 10th and 90th percentiles of the estimated AKM firm effects in columns (2) through (4), and the log of average firm size in column (5). The regressor is the informality rate in 1995–99, defined as the share of salaried workers not registered with the social security system, interacted with period indicators. The 1995–99 interaction is omitted, so the table reports differential changes relative to that period. The estimation sample is restricted to cells with at least 30 EPH observations. Firm effects are measured with the plug-in estimator, and firm size is computed over the connected set of men. All specifications include period and region-sector fixed effects, and observations are weighted by the number of worker-years in the cell. Standard errors clustered at the region-sector level are reported in parentheses.

Appendix for

“Firms and the Fragility of Inequality Reduction: Evidence from Argentina”

(Not for publication)

A Data Appendix

A.1 Administrative Data (SIPA)

The *Sistema Integrado Previsional Argentino* (SIPA) contains administrative records of all employment relationships registered with Argentina’s social security system. The data cover the period 1995–2019 and include all private-sector wage employment, employment in state-owned enterprises (e.g., YPF, Aerolíneas Argentinas), and employment in autonomous public institutions (e.g., national universities, provincial banks). The data exclude public-sector employees in central, provincial, and municipal government, as well as self-employed workers and informal employees. Each record contains a unique worker identifier and firm identifier that allow us to track individuals across employers over time.

The SIPA microdata are confidential and cannot be publicly redistributed. Researchers seeking access must contact Argentina’s Secretariat of Labor. Access is subject to the Secretariat’s authorization.

Earnings Variable. For each worker-firm-month observation, we observe total pre-tax compensation, which includes base salary, regular bonuses (e.g., the 13th-month salary), overtime pay, severance payments (when applicable), and other taxable compensation.

We process earnings as follows. First, we convert nominal earnings to constant December 2010 pesos using the Consumer Price Index (CPI). Second, we construct an average monthly

earnings variable for each worker-firm pair within each calendar year. Third, we exclude observations above the 99.9th percentile of the earnings distribution within each year to limit the influence of outliers, such as unusually large severance payments or bonuses. Fourth, we exclude observations with average monthly real earnings at or below ARS 317.25, roughly USD 80 at the December 2010 exchange rate. We verify robustness to thresholds of 1.33, 1.67, 2, and 2.67 times this baseline.

Sample Restrictions. We restrict our baseline sample to men aged 20 to 55. We exclude worker-firm-year observations corresponding to jobs that lasted fewer than 6 months within the calendar year, as well as observations explicitly coded as internships or training contracts using the hiring modality variable (*modalidad de contratación*) of the SIPA data. We also exclude workers employed by temporary employment agencies, who appear in the data as employed by both the agency and the client firm, and firms classified as temporary employment agencies in the BADE (Base de Análisis de la Dinámica del Empleo) firm registry. Employment in state-owned enterprises and autonomous public institutions is retained. When a worker holds multiple jobs within a year, we keep only the highest-paying job, following standard practice in the AKM literature.

Firm and Worker Characteristics. The administrative data include firm-level information on 4-digit industry classification (based on ISIC Rev. 3.1) and the province where the firm is registered (available from the BADE firm registry). At the worker level, the data contain age (computed from year of birth recorded in the social security system) and gender. Worker education is not available.

Connected Sets. Estimation of the AKM models requires a set of firms connected by worker mobility. We define two connected sets. The first is the largest connected set: the largest set of firms such that any two firms can be linked through a chain of worker moves. The second is the leave-out-match connected set: the largest set of firms that remains connected after removing any single worker-firm match, a more restrictive sample required

for the bias correction method of [Kline et al. \(2020\)](#). Following standard practice, we drop single stayers—workers who never change employers and are observed only once—before computing connected sets, as these observations do not contribute to identification of either worker or firm effects.

A.2 Household Survey Data (EPH)

The *Encuesta Permanente de Hogares* (EPH) is Argentina’s main labor force survey, conducted by the National Institute of Statistics and Censuses (INDEC). The survey underwent a major methodological change in 2003: the original format (“Puntual” EPH, 1995–2002) was conducted twice per year (May and October) in 28 urban agglomerations, while the revised format (“Continua” EPH, 2003–2019) collects data quarterly in 31 urban agglomerations. We use the October wave for 1995–2002 and the fourth quarter for 2003–2019, except for 2015 when we use the second quarter due to data availability limitations (the survey was temporarily suspended).

Variable Definitions. We classify individuals as employed if they report having worked at least one hour in the reference week or having a job from which they were temporarily absent.⁴⁷ We define informal salaried employment as jobs where the employer does not make regular contributions to the social security system. This definition excludes self-employment, which accounts for approximately one-quarter of the labor force. Earnings correspond to monthly after-tax labor income from the main job (*ingreso de la ocupación principal*), and are also deflated to 2010 ARS using the CPI. To classify workers as earning below the minimum wage, we compare their hourly earnings with the hourly national minimum wage, defined as the monthly minimum wage published by the Secretariat of Labor divided by 200 hours.⁴⁸ Establishment size is reported by workers as the number of employees at their

⁴⁷Individuals are classified as unemployed if they are not employed and are actively seeking work in the reference week. Appendix Figure 1 shows the evolution of the employment-to-population ratio and the unemployment rate.

⁴⁸The “Puntual” EPH reports hourly earnings directly, which we compare with the minimum wage in force in the fourth quarter of each year. For the “Continua” EPH we divide monthly earnings in the main

workplace, which we group into 1–5, 6–25, 26–100, and more than 100 employees.

We construct six education categories based on the highest level attained: primary incomplete (less than 7 years of education), primary complete (7 years), secondary incomplete (8–11 years), secondary complete (12 years), tertiary incomplete (13–16 years), and tertiary complete (17+ years). Industry codes, which vary across survey waves, are harmonized to a consistent classification at the section level of ISIC Rev. 3.1.

Sample Restrictions. For comparability with the administrative data, we restrict the EPH sample to salaried workers (excluding self-employed workers and employers) aged 20 to 55 with positive reported earnings and valid responses on formality status.

A.3 Firm Survey Data (ENDEI)

The first wave of the *Encuesta Nacional de Dinámica de Empleo e Innovación* (ENDEI), conducted in 2013–14, collects data on firm activities during 2010–12. The survey is representative of manufacturing firms with 10 or more employees, covering approximately 3,700 firms in the first round. Key variables include value added (total sales minus intermediate inputs, reported annually) and employment (number of employees), which allow computation of value added per worker as a productivity measure. Firm identifiers allow us to match these firms with the SIPA data.

A.4 Bargaining-Unit Industry Classification

We map bargaining units in the negotiated wage-floor data to one or more ISIC Rev. 3.1 divisions (2-digit codes). AI agents using OpenAI’s GPT 5.6 Sol reviewed this classification across multiple sessions. Relying on the names of the union and employer signatories, the bargaining agreement codes, and, when needed, online searches for additional information, the agents suggested edits to the existing classification. Human researchers validated the job by usual weekly hours times 30/7, and compare them with the quarterly average of the minimum wage.

suggested edits to build the final classification. We retain multiple industry codes when a bargaining unit spans industries or its coverage is uncertain.

B Additional Tables and Figures

Appendix Table 1: Summary statistics of SIPA estimation sample, prime-aged men

Period	Millions of			Log earnings		Age		Mean N. firms	Share movers
	Worker years	Workers	Firms	Mean	SD	Mean	SD		
Panel A: Entire sample									
1995–99	10.97	3.51	0.44	7.73	0.73	35.64	9.56	1.273	0.232
2000–04	10.38	3.31	0.42	7.68	0.74	35.99	9.42	1.236	0.205
2005–09	14.10	4.36	0.50	8.00	0.65	35.51	9.38	1.292	0.245
2010–14	15.99	4.74	0.52	8.19	0.66	35.91	9.21	1.273	0.228
2015–19	16.20	4.72	0.50	8.16	0.68	36.83	9.06	1.255	0.213
Panel B: Connected set									
1995–99	8.87	2.36	0.21	7.82	0.74	35.73	9.39	1.391	0.330
2000–04	8.20	2.13	0.18	7.78	0.75	36.01	9.24	1.349	0.301
2005–09	12.00	3.13	0.26	8.06	0.65	35.50	9.20	1.396	0.331
2010–14	13.67	3.44	0.27	8.25	0.65	35.90	9.02	1.366	0.305
2015–19	13.71	3.42	0.23	8.23	0.66	36.79	8.87	1.343	0.285
Panel C: Leave-out-match connected set									
1995–99	8.08	2.15	0.11	7.87	0.74	35.74	9.38	1.378	0.321
2000–04	7.46	1.94	0.09	7.82	0.76	35.99	9.23	1.335	0.290
2005–09	11.18	2.92	0.15	8.09	0.65	35.45	9.19	1.383	0.321
2010–14	12.75	3.21	0.15	8.28	0.64	35.85	9.01	1.354	0.295
2015–19	12.78	3.19	0.13	8.26	0.66	36.75	8.85	1.333	0.277

Notes: Data are from Argentina’s social security system (SIPA) for men aged 20 to 55. The table shows summary statistics of the administrative data for different periods. Panel A shows the entire sample, Panel B shows the largest connected set of firms, and Panel C shows the leave-out-match connected set: the largest set of firms that remains connected after we leave out any worker–firm match. Real earnings are computed as the mean of monthly total real earnings for every worker–firm pair within each year. We then exclude real earnings above the 99.9th percentile of the distribution, and below USD 75 per month, within each year. We also exclude worker–firm–year cells that correspond to jobs shorter than 6 months and those labeled as internships. The last two columns show the average number of firms per worker (“Mean N. firms”) and the share of workers with more than one firm (“Share movers”).

Appendix Table 2: Summary statistics of SIPA estimation sample, prime-aged women

Period	Millions of			Log earnings		Age		Mean N. firms	Share movers
	Worker years	Workers	Firms	Mean	SD	Mean	SD		
Panel A: Entire sample									
1995–99	4.27	1.44	0.26	7.56	0.65	34.55	9.66	1.201	0.177
2000–04	4.37	1.42	0.24	7.54	0.67	35.07	9.42	1.184	0.164
2005–09	5.63	1.85	0.30	7.83	0.60	34.88	9.24	1.214	0.185
2010–14	6.69	2.11	0.33	8.01	0.61	35.48	9.04	1.198	0.172
2015–19	6.95	2.12	0.33	8.02	0.63	36.72	8.87	1.183	0.160
Panel B: Connected set									
1995–99	3.02	0.83	0.08	7.67	0.67	34.53	9.48	1.315	0.274
2000–04	3.14	0.81	0.07	7.64	0.69	34.96	9.22	1.290	0.256
2005–09	4.38	1.17	0.11	7.90	0.60	34.80	9.02	1.319	0.275
2010–14	5.23	1.34	0.12	8.09	0.60	35.42	8.83	1.291	0.251
2015–19	5.36	1.36	0.10	8.11	0.62	36.63	8.66	1.266	0.231
Panel C: Leave-out-match connected set									
1995–99	2.65	0.73	0.04	7.71	0.69	34.57	9.48	1.291	0.255
2000–04	2.77	0.71	0.03	7.67	0.70	34.93	9.21	1.272	0.240
2005–09	3.95	1.06	0.05	7.92	0.61	34.77	9.00	1.297	0.257
2010–14	4.73	1.22	0.06	8.11	0.61	35.40	8.81	1.269	0.233
2015–19	4.85	1.23	0.05	8.14	0.62	36.60	8.63	1.248	0.216

Notes: Data are from Argentina’s social security system (SIPA) for women aged 20 to 55. The table shows summary statistics of the administrative data for different periods. Panel A shows the entire sample, Panel B shows the largest connected set of firms, and Panel C shows the leave-out-match connected set: the largest set of firms that remains connected after we leave out any worker–firm match. Real earnings are computed as the mean of monthly total real earnings for every worker–firm pair within each year. We then exclude real earnings above the 99.9th percentile of the distribution, and below USD 75 per month, within each year. We also exclude worker–firm–year cells that correspond to jobs shorter than 6 months and those labeled as internships. The last two columns show the average number of firms per worker (“Mean N. firms”) and the share of workers with more than one firm (“Share movers”).

Appendix Table 3: Variance decomposition of AKM estimates by period, plug-in estimates

	1995–99		2000–04		2005–09		2010–14		2015–19		Change 1995–2009		Change 2005–2019	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
Variance of log earnings	0.548	(100.0)	0.564	(100.0)	0.416	(100.0)	0.417	(100.0)	0.438	(100.0)	-0.132	(100.0)	0.022	(100.0)
Variance of worker effects	0.266	(48.5)	0.278	(49.3)	0.179	(43.1)	0.172	(41.1)	0.177	(40.4)	-0.087	(65.6)	-0.003	(-11.4)
Variance of firm effects	0.212	(38.8)	0.225	(39.9)	0.163	(39.1)	0.184	(44.0)	0.208	(47.6)	-0.050	(37.6)	0.046	(207.0)
Variance of year effects	0.002	(0.3)	0.009	(1.6)	0.015	(3.7)	0.004	(0.9)	0.001	(0.2)	0.014	(-10.4)	-0.015	(-66.0)
2×Cov. of worker and firm effects	0.048	(8.8)	0.026	(4.7)	0.042	(10.0)	0.040	(9.7)	0.031	(7.0)	-0.006	(4.8)	-0.011	(-49.6)
2×Cov. of worker and year effects	-0.002	(-0.4)	-0.001	(-0.2)	-0.007	(-1.6)	-0.002	(-0.5)	0.000	(0.1)	-0.004	(3.2)	0.007	(31.1)
2×Cov. of firm and year effects	-0.001	(-0.3)	-0.001	(-0.2)	0.000	(0.1)	-0.000	(-0.0)	0.000	(0.0)	0.002	(-1.4)	-0.000	(-1.7)
Variance of residual	0.024	(4.3)	0.028	(4.9)	0.023	(5.5)	0.020	(4.8)	0.021	(4.8)	-0.001	(0.5)	-0.002	(-9.5)
Millions of ...														
...worker years	8.87		8.20		12.00		13.67		13.71					
...firms	0.21		0.18		0.26		0.27		0.23					
R^2	0.957		0.951		0.945		0.952		0.952					

Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The table shows estimates of the variance decomposition of models of log earnings on worker fixed effects, firm fixed effects, and year fixed effects following [Abowd et al. \(1999\)](#). The models are estimated separately for the periods 1995–99, 2000–04, 2005–09, 2010–14, and 2015–19, using the largest connected set of firms in each period. Columns (1) through (5) show the estimates of the variance of each component for each period. Column (6) shows the change in the variance of each component between 1995–99 and 2005–09, and column (7) shows the change between 2005–09 and 2015–19, both in levels and as a percentage of the change in the variance of log earnings. The top eight rows show estimates of the variance of different components of log earnings, with the numbers in parentheses showing the variance normalized by the variance of log earnings in the period or the change in the variance of log earnings between two periods. The bottom three rows show the number of worker years, the number of firms, and the R^2 of the model.

Appendix Table 4: Regressions of firm effects on productivity and size, 2010–12 ENDEI sample

	Dependent variable: firm wage effect								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log VA per worker	0.1446 (0.0166)		0.1028 (0.0062)	0.1317 (0.0211)		0.0954 (0.0137)	0.0984 (0.0158)		0.1190 (0.0092)
Log firm size		0.1131 (0.0088)	0.1030 (0.0233)		0.1089 (0.0093)	0.1060 (0.0084)		0.1033 (0.0080)	0.1946 (0.0139)
Log VA pw * Log firm size			-0.0001 (0.0015)			-0.0006 (0.0006)			-0.0081 (0.0006)
Province FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
ISIC division FE	No	No	No	No	No	No	Yes	Yes	Yes
Num. of firms	3,028	3,028	3,028	3,028	3,028	3,028	3,028	3,028	3,028
Num. of worker-years	1,363,444	1,363,444	1,363,444	1,363,444	1,363,444	1,363,444	1,363,444	1,363,444	1,363,444
R^2	0.1617	0.3725	0.4495	0.2433	0.4496	0.5094	0.3689	0.5424	0.5733
R^2 within				0.1451	0.3782	0.4457	0.0890	0.3394	0.3841

Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55 and from the *Encuesta Nacional de Dinámica de Empleo e Innovación* (ENDEI). The table shows regressions of estimated firm wage effects on log value added per worker, log firm size, and their interaction, for firms observed in the 2010–12 ENDEI sample. Firm effects are obtained from an AKM model estimated on SIPA data for 2010–14. The unit of observation is a worker-year, so that firms are weighted by their number of worker-years, and standard errors are clustered at the ISIC division (2-digit codes) and province levels. Value added per worker is calculated from self-reported ENDEI data for 2010–12, averaging the values for those three years to obtain one value for the period. Data below the 1st percentile and above the 99th percentile of the log value-added-per-worker distribution are trimmed to prevent extreme values from driving the results.

Appendix Table 5: Top and bottom 10 industry wage differentials, 2015–19

Rank	Code	Industry name	Mean log earnings	Industry premium	Mean Worker Effect	Percent of workforce
		(1)	(2)	(3)	(4)	(5)
		Across industry mean	8.261	0.390	0.000	
		Across industry SD	0.393	0.281	0.151	
1	1320	Mining of non-ferrous metal ores	9.160	1.129	0.159	0.34
2	3410	Manufacture of motor vehicles	9.030	1.108	0.051	0.93
3	1120	Service activities incidental to oil and gas	9.324	1.072	0.382	1.44
4	1110	Crude oil and gas extraction	9.448	1.007	0.573	0.49
5	6030	Transport via pipelines	9.230	0.956	0.405	0.05
6	4011	Production of electricity	9.263	0.926	0.466	0.30
7	6521	Services of banking financial institutions	9.069	0.917	0.281	1.15
8	2330	Processing of nuclear fuel	8.862	0.913	0.079	0.02
9	2320	Manufacture of refined petroleum products	9.038	0.899	0.265	0.17
10	2230	Reproduction of recorded media	9.082	0.890	0.322	0.00
291	0112	Vegetable growing and nursery	7.448	-0.258	-0.166	0.03
292	4549	Building completion	7.320	-0.268	-0.282	0.01
293	0150	Hunting and game services	7.326	-0.277	-0.268	0.24
294	4542	Finishing and covering of walls and floors	7.261	-0.321	-0.290	0.03
295	0502	Fish farms and other aquatic products	7.651	-0.324	0.104	0.00
296	0503	Fishing services	7.413	-0.337	-0.128	0.00
297	8000	Education	7.288	-0.374	-0.210	0.02
298	4511	Building demolition	7.570	-0.376	0.076	0.00
299	4544	Painting and decorating work	7.630	-0.376	0.135	1.94
300	5242	Retail sale of used books	7.203	-0.430	-0.238	0.05

Notes: Data are from Argentina’s social security system (SIPA), with industry wage differentials calculated following [Card et al. \(2024\)](#). Worker effects are obtained from the AKM model estimated on men aged 20 to 55 for the 2015–19 period. The table shows the 10 industries with the largest and smallest industry wage differentials in 2015–19, at the 4-digit level of disaggregation. Column (1) shows the name of the industry, shortened for display purposes. Column (2) shows the average of log earnings, column (3) the industry wage differentials, and column (4) the average worker effect, all weighted by the number of worker-years. Column (5) shows the percentage of the total number of worker-years in the given industry, with “0.00” indicating that the industry represents fewer than .01% of worker-years.

Appendix Table 6: Industry wage differentials across broad industries, relative to restaurants

Code	Industry description	Industry wage differential			Share of worker-years		
		1995–99	2005–09	2015–19	1995–99	2005–09	2015–19
A	Agriculture, hunting and forestry	-0.070	-0.085	0.002	0.044	0.054	0.046
B	Fishing	0.649	0.632	0.484	0.003	0.004	0.003
C	Mining and quarrying	0.727	0.904	0.988	0.017	0.021	0.026
D	Manufacturing	0.361	0.367	0.483	0.361	0.289	0.268
E	Electricity, gas and water supply	0.646	0.602	0.738	0.021	0.014	0.018
F	Construction	-0.009	0.127	0.068	0.056	0.099	0.108
G	Wholesale and retail trade	0.228	0.238	0.422	0.133	0.152	0.155
H	Hotels and restaurants	0.084	0.095	0.143	0.021	0.024	0.022
I	Transport, storage and communications	0.517	0.477	0.568	0.136	0.120	0.129
J	Financial intermediation	0.598	0.520	0.735	0.039	0.025	0.023
K	Real estate and business activities	0.154	0.165	0.301	0.085	0.122	0.118
M	Education	-0.518	-0.412	-0.376	0.017	0.017	0.019
N	Health and social work	0.300	0.265	0.406	0.021	0.017	0.023
O	Other community and social service activities	0.271	0.283	0.408	0.045	0.041	0.041

Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The table shows industry wage differentials aggregated at the section level for 1995–99, 2005–09, and 2015–19. Industry wage differentials are computed relative to restaurants. Sections are defined according to ISIC Rev. 3.1. The last three columns report each section's share of worker-years in the corresponding period.

Appendix Table 7: First-stage and reduced-form estimates for negotiated wage floors

Panel A: First-stage regressions							
	Change in log negotiated wage floor						
	Mean	10th ptile.	25th ptile.	50th ptile.	75th ptile.	90th ptile.	Std. dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Negative pre-treatment wage-floor gap	0.5497 (0.0768)	0.7247 (0.0728)	0.6323 (0.0786)	0.5682 (0.0829)	0.4993 (0.0968)	0.3263 (0.1019)	-0.1703 (0.0409)
R^2	0.5671	0.6070	0.6024	0.5668	0.4477	0.1877	0.2356
First-stage F statistic	51.27	99.01	64.76	46.97	26.58	10.25	17.37
Observations	43	43	43	43	43	43	43
Panel B: Initial wage-floor gap and changes in the SD of firm effects							
	1995–99	2000–04	2005–09	2010–14	2015–19		
	(8)	(9)	(10)	(11)	(12)		
Negative pre-treatment wage-floor gap	0	-0.0391 (0.0247)	-0.0697 (0.0339)	-0.0417 (0.0423)	-0.0299 (0.0393)		
R^2	—	0.1021	0.1427	0.0398	0.0179		
Observations	—	43	43	43	43		

Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55 and from Secretariat of Labor resolutions reporting average wage floors. The table shows first-stage and reduced-form estimates of the effect of the wage-floor gap on changes in negotiated wage floors (Panel A) and in the SD of firm effects (Panel B), at the ISIC Rev. 3.1 division level. The wage-floor gap is the negative gap between the industry's mean log wage floor in 2001–02 and the average log real national minimum wage in 2005–07. In Panel A, the dependent variables are changes between 2001–02 and 2008–09 in the mean, indicated percentiles, and standard deviation of log wage floors, which use bargaining units observed consistently from the late 1990s through 2008 and sectors with at least two wage-floor observations. The first-stage F statistic tests whether the coefficient on the wage-floor gap is zero. In Panel B, the dependent variable is the change in the SD of firm effects between 1995–99 and each indicated period, with 1995–99 normalized to zero. Heteroskedasticity-robust standard errors are reported in parentheses.

Appendix Table 8: Informality, enforcement, and the size distribution of firms

	Share firms ≤ 3 employees (1)	Share firms > 25 employees (2)	Share less than MW (3)
Informality $\times$ 2000–04	0.011 (0.021)	-0.024 (0.006)	0.213 (0.053)
Informality $\times$ 2005–09	0.022 (0.025)	-0.017 (0.009)	0.550 (0.119)
Informality $\times$ 2010–14	0.053 (0.028)	-0.046 (0.010)	0.492 (0.075)
Informality $\times$ 2015–19	0.074 (0.032)	-0.063 (0.012)	0.328 (0.061)
Time and local market effects	Yes	Yes	Yes
R^2	0.979	0.980	0.880
Observations	335	335	322

Notes: Data are from Argentina’s social security system (SIPA) for men aged 20 to 55 and from the Permanent Household Survey (EPH). The table shows estimates of the association between labor informality, compliance with the minimum wage, and the size distribution of firms across local labor markets. The unit of observation is a region-sector cell, defined by the seven EPH regions and the sections of ISIC Rev. 3.1, some of which are combined to match the EPH classification. The dependent variables are the shares of firms in the two tails of the size distribution, measured in the social security records, in columns (1) and (2), and the share of salaried workers earning less than the minimum wage, measured in the EPH, in column (3). The regressor is the informality rate in 1995–99, defined as the share of salaried workers not registered with the social security system, interacted with period indicators. The 1995–99 interaction is omitted, so the table reports differential changes relative to that period. The estimation sample is restricted to cells with at least 30 EPH observations. The size distribution is computed over the connected set of men. All specifications include period and region-sector fixed effects, and observations are weighted by the number of worker-years in the cell. Standard errors clustered at the region-sector level are reported in parentheses.

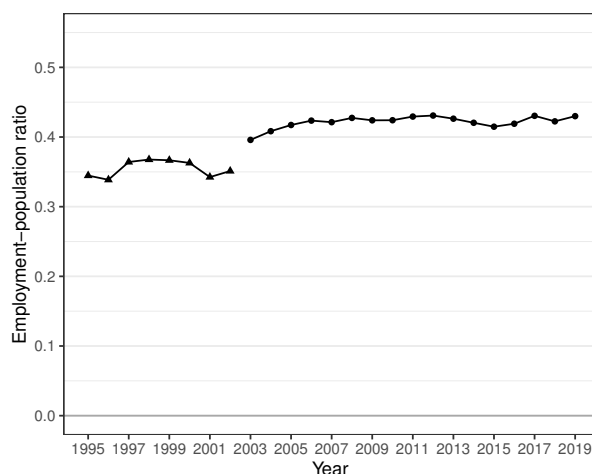
Appendix Table 9: Informality and the variance decomposition of log earnings

	Var. log earnings (1)	Var. firm effects (2)	Var. worker effects (3)	2× Cov. firm, worker effects (4)
Informality × 2000–04	-0.003 (0.026)	-0.005 (0.017)	0.001 (0.013)	-0.000 (0.024)
Informality × 2005–09	0.176 (0.062)	0.061 (0.030)	0.080 (0.016)	0.026 (0.029)
Informality × 2010–14	0.260 (0.082)	0.107 (0.040)	0.109 (0.022)	0.037 (0.036)
Informality × 2015–19	0.260 (0.085)	0.102 (0.045)	0.115 (0.023)	0.040 (0.033)
Time and local market effects	Yes	Yes	Yes	Yes
R^2	0.867	0.798	0.954	0.896
Observations	335	335	335	335

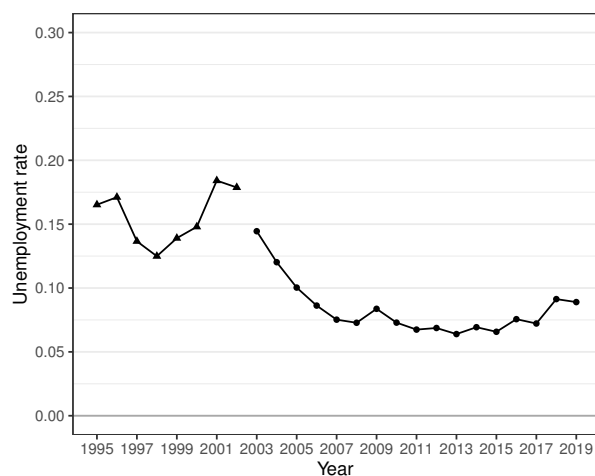
Notes: Data are from Argentina’s social security system (SIPA) for men aged 20 to 55 and from the Permanent Household Survey (EPH). The table shows estimates of the association between labor informality and the variance of log earnings across local labor markets, decomposed into the contributions of worker effects, firm effects, and sorting. The unit of observation is a region-sector cell, defined by the seven EPH regions and the sections of ISIC Rev. 3.1, some of which are combined to match the EPH classification. The dependent variables are the variance of log earnings and the components of its decomposition into the variance of the estimated AKM worker and firm effects and twice their covariance. The regressor is the informality rate in 1995–99, defined as the share of salaried workers not registered with the social security system, interacted with period indicators. The 1995–99 interaction is omitted, so the table reports differential changes relative to that period. The estimation sample is restricted to cells with at least 30 EPH observations. Column (1) is the sum of columns (2), (3), and (4), and of the variance of the residual and of the time-varying covariates, so the first three components need not add up to the total. Variances are computed with the plug-in estimator. All specifications include period and region-sector fixed effects, and observations are weighted by the number of worker-years in the cell. Standard errors clustered at the region-sector level are reported in parentheses.

Appendix Figure 1: Labor market indicators for Argentina, 1995–2019

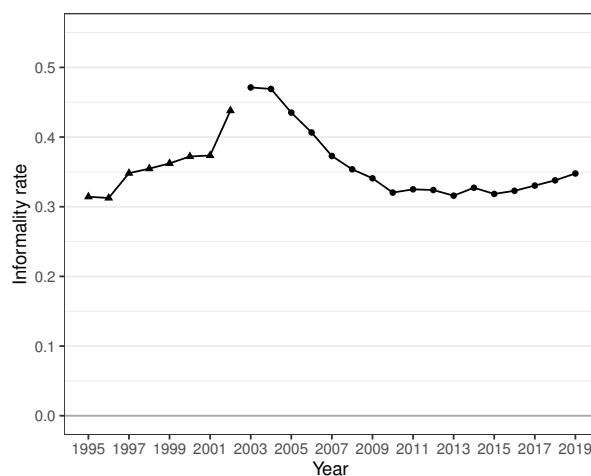
Panel A: Employment to population ratio



Panel B: Unemployment rate

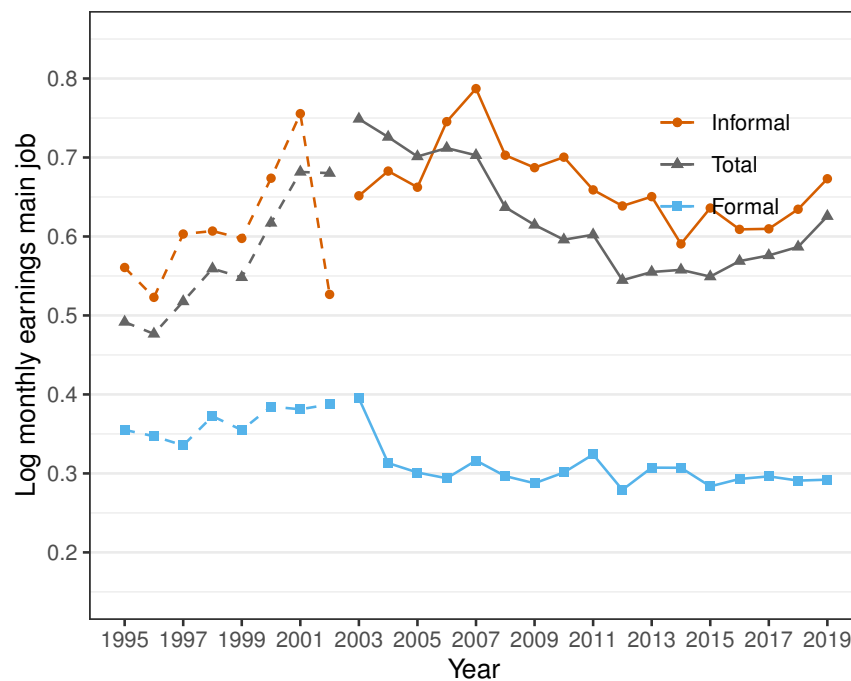


Panel C: Informality rate



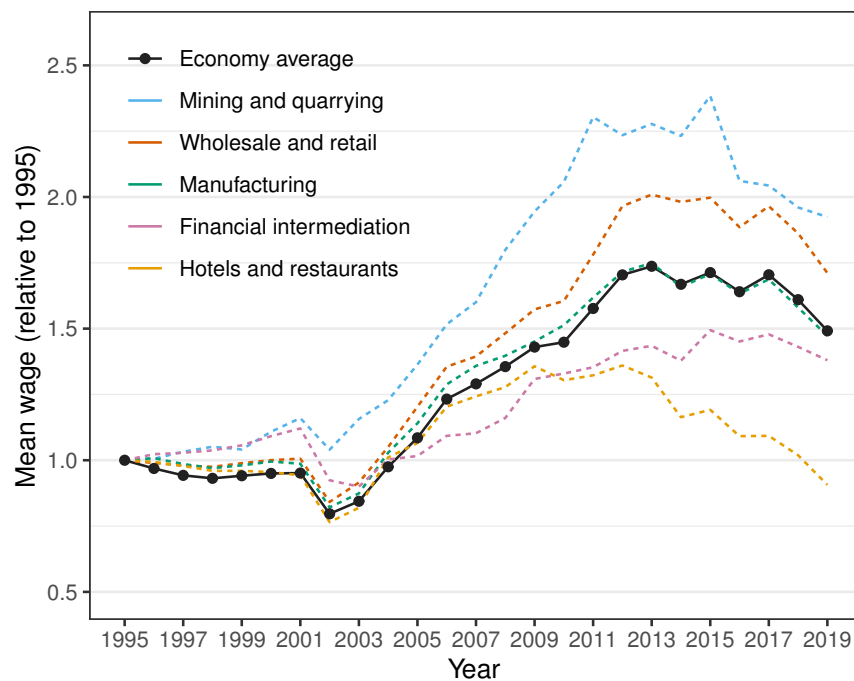
Notes: Data are from the Permanent Household Survey (EPH) of the National Institute of Statistics and Censuses (INDEC). The figure shows the evolution of key labor market indicators for Argentina between 1995 and 2019. Panel A shows the employment to population ratio, Panel B the unemployment rate (as a percentage of the economically active population), and Panel C the informality rate among salaried workers (as a percentage of the total salaried workers). The informality rate is defined as the proportion of salaried workers who report that no contributions to social security are made by their employers. The format of the EPH changed in 2003, which is indicated by different shape markers in the graphs.

Appendix Figure 2: Variance of log earnings between 1995 and 2019, household survey data



Notes: Data are from the Permanent Household Survey (EPH) for individuals aged 20 to 55. The figure shows the evolution of the variance of log real earnings in Argentina between 1995 and 2019, separately for formal, informal, and total workers. Data include earnings from the primary job of the worker only.

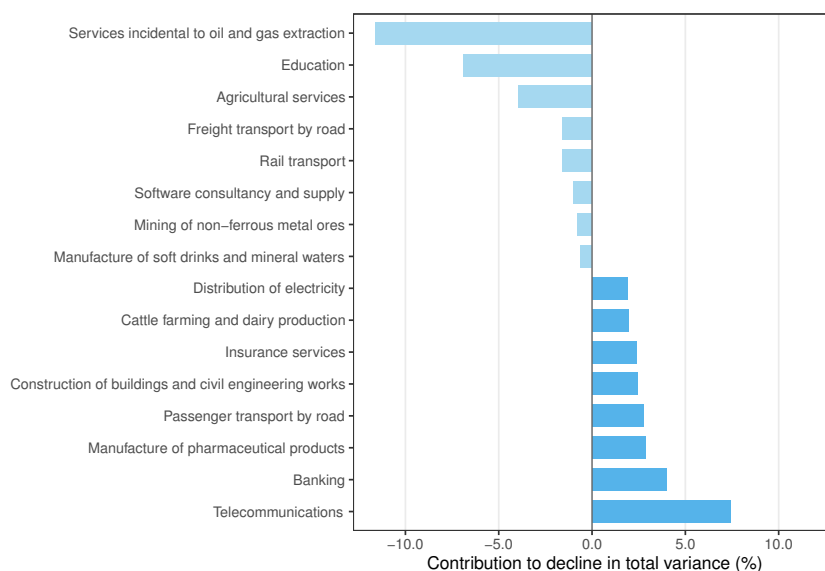
Appendix Figure 3: Mean real wages across selected sectors in Argentina, 1995–2019



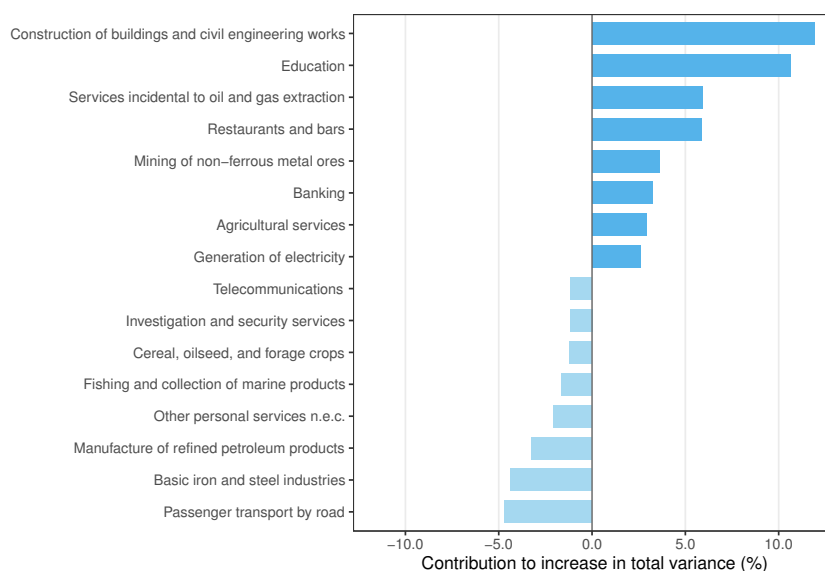
Notes: Data on average monthly wages by sector are obtained from the Secretariat of Labor and then deflated by the CPI to obtain real values. The figure shows the evolution of average real monthly wages across selected broad sectors, each normalized to its own 1995 level. The economy average is shown as a solid line with markers.

Appendix Figure 4: Industry contributions to changes in between-industry earnings inequality

Panel A: 1995–2009



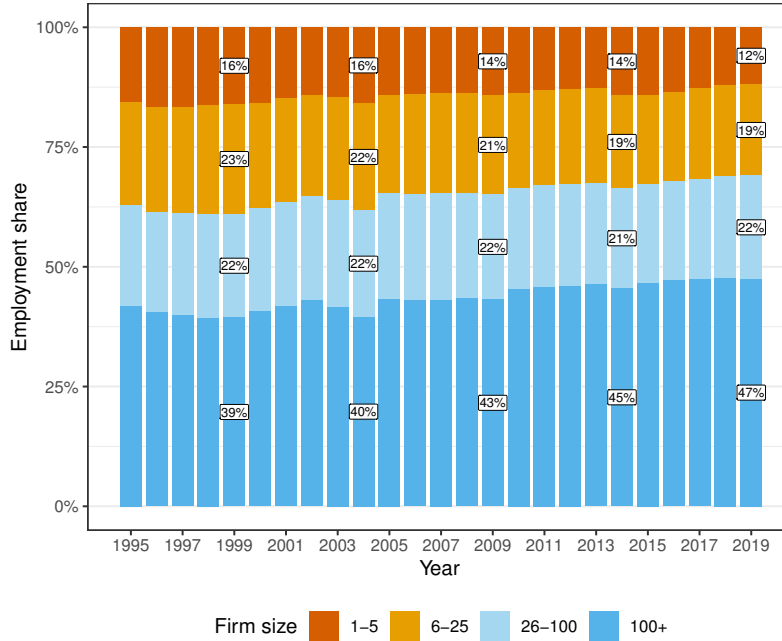
Panel B: 2005–2019



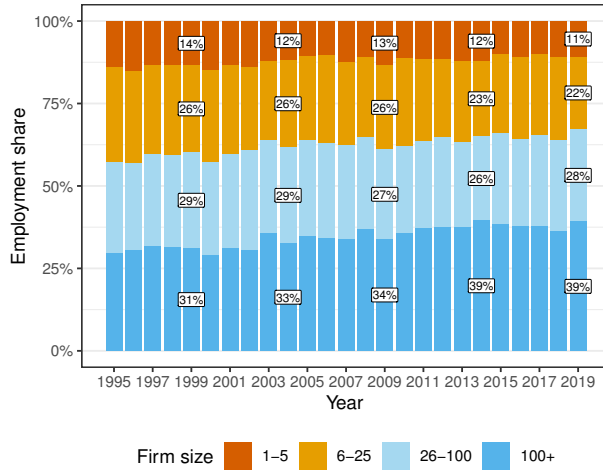
Notes: Data are from Argentina’s social security system (SIPA) for men aged 20 to 55. The figure shows the eight industries with the largest and the eight industries with the smallest level contributions to the change in the between-industry component of the variance of log earnings. Panel A compares 1995–1996 with 2008–2009, and Panel B compares 2005–2006 with 2018–2019. Industry employment shares and mean log earnings are calculated by pooling observations over the two years at each endpoint. An industry’s contribution is the change between endpoints in the product of its employment share and its squared mean log earnings differential relative to the overall mean. Industries are selected and ordered using this contribution in levels. The values displayed divide each level contribution by the change in the total variance of log earnings. The sample excludes earnings above the 99.9th percentile or below USD 75 per month, jobs lasting fewer than six months, and internships.

Appendix Figure 5: Employment share by firm size bin

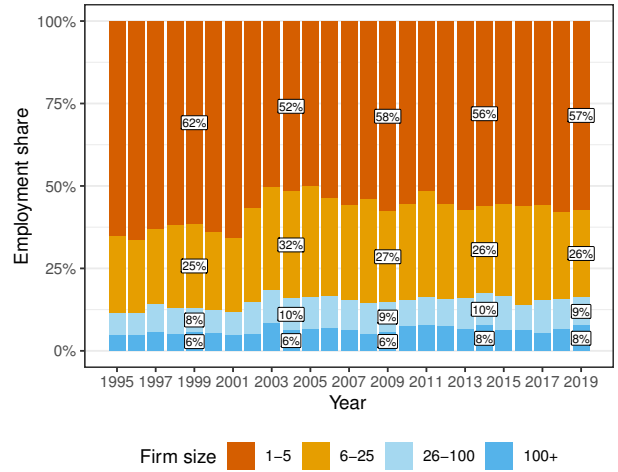
Panel A: Administrative data SIPA



Panel B: Formal workers in EPH

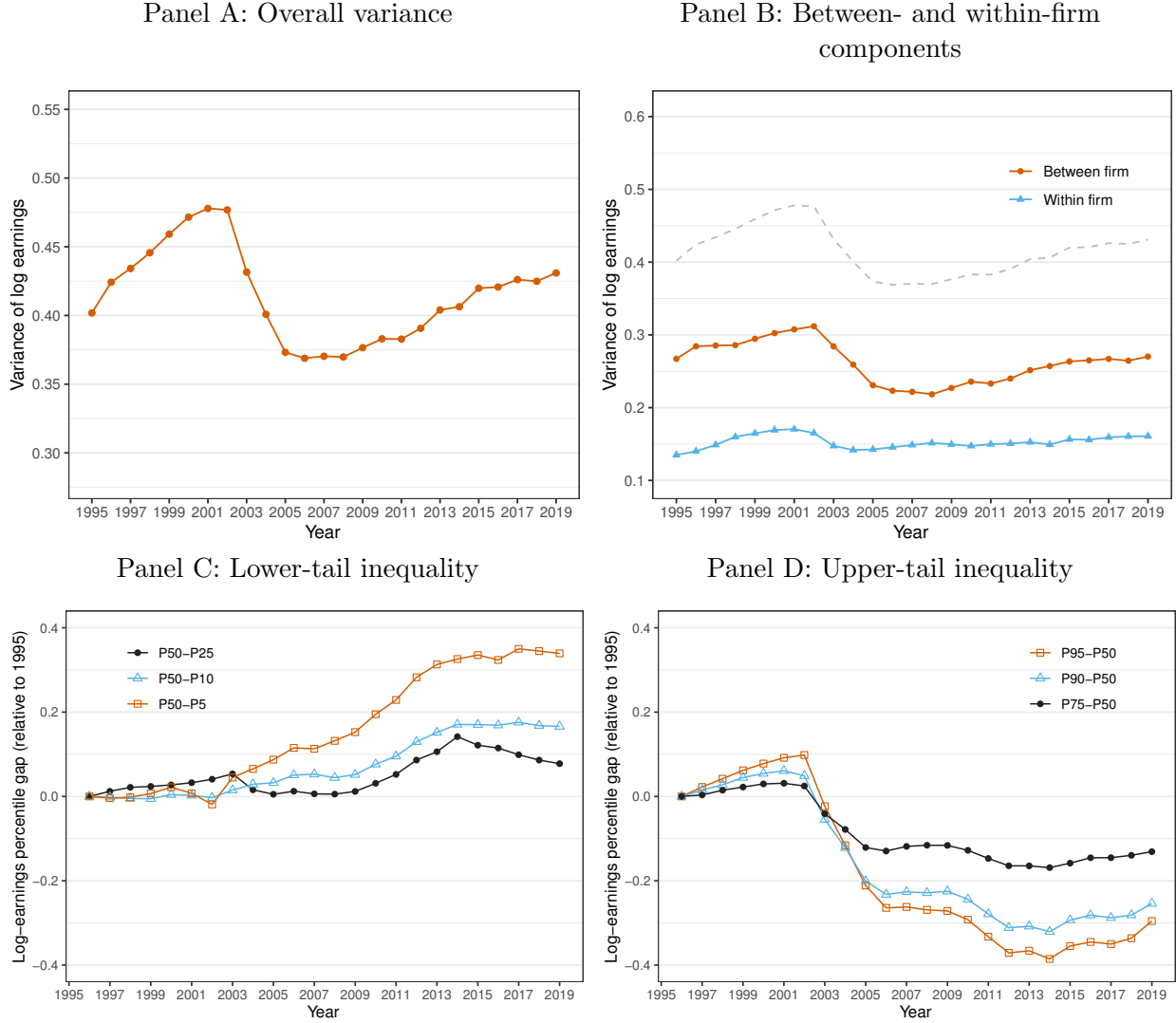


Panel C: Informal workers in EPH



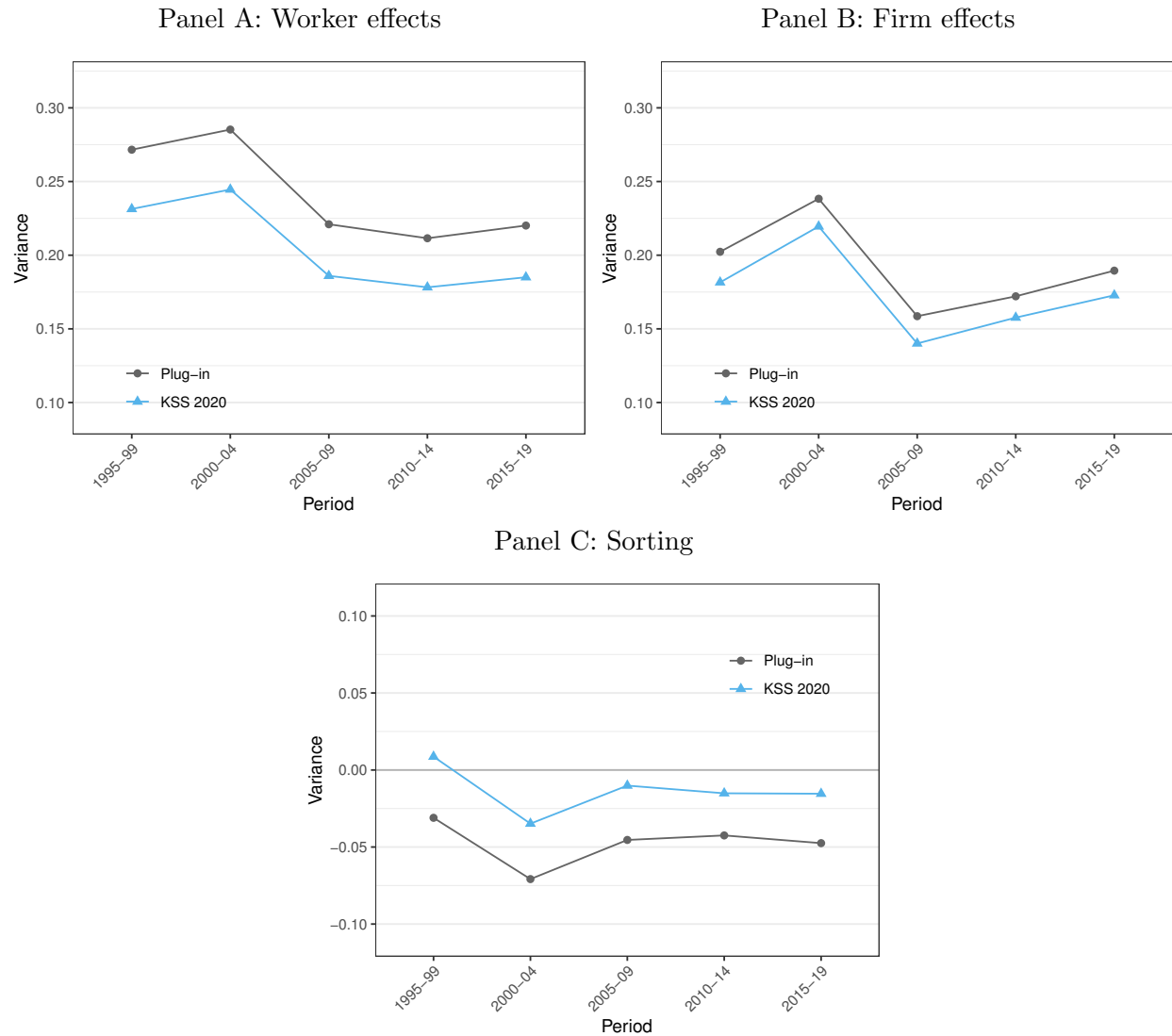
Notes: Data are from Argentina's social security system (SIPA) and from the Permanent Household Survey (EPH), for individuals aged 20 to 55. This figure shows the distribution of the number of workers across firm size bins using stacked bars, explicitly indicating the percentages for the years 1995, 2004, 2009, 2014, and 2019. In Panel A, firm size bins are defined by the number of employees at the firm: 1-5, 6-25, 26-100, and more than 100. In Panels B and C, workplace size bins are defined by the number of employees at the workplace, as declared by the worker.

Appendix Figure 6: Earnings inequality in the formal labor market, prime-aged women



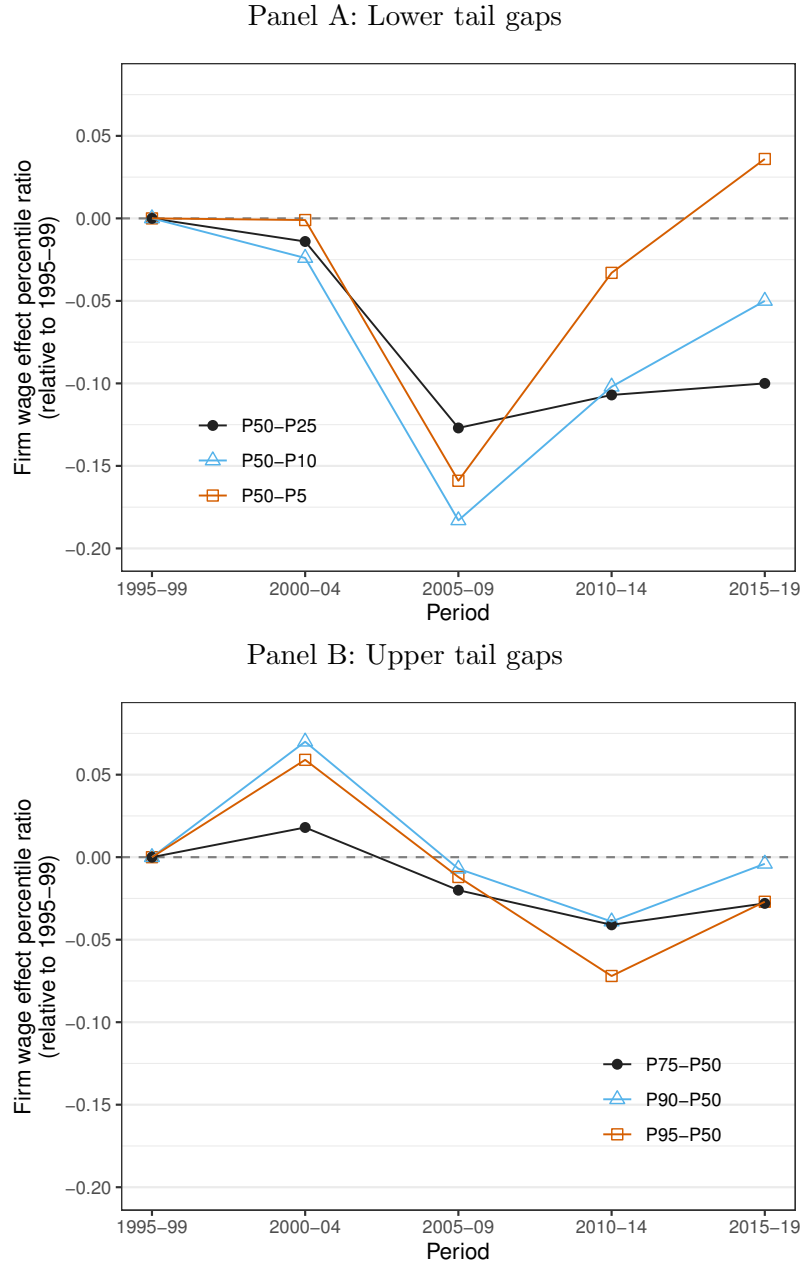
Notes: Data are from Argentina's social security system (SIPA) for women aged 20 to 55. The figure shows the evolution of earnings inequality between 1995 and 2019. Panel A shows the overall variance of log earnings, and Panel B decomposes the variance into the between- and within-firm components. Panels C and D show inequality as measured by differences between percentiles of the log real earnings distribution, for the lower and upper tails respectively. Earnings are measured as average monthly total real earnings. We exclude earnings above the 99.9th percentile of the distribution, and below USD 75 per month, and worker-firm-year cells that correspond to jobs shorter than 6 months and those labeled as internships.

Appendix Figure 7: Variance decomposition of AKM estimates by period, KSS bias-corrected estimates, prime-aged women



Notes: Data are from Argentina’s social security system (SIPA) for women aged 20 to 55. The figure shows the contribution of each component of the variance decomposition of log earnings, correcting the estimates of the variance terms, on the largest leave-out-match connected set of firms. “Plug-in” refers to the computation of the variance components directly using the AKM estimates. “KSS 2020” refers to the variance decomposition proposed by [Kline et al. \(2020\)](#), which allows for heteroskedasticity in the error term. The sorting component is twice the covariance between worker and firm effects.

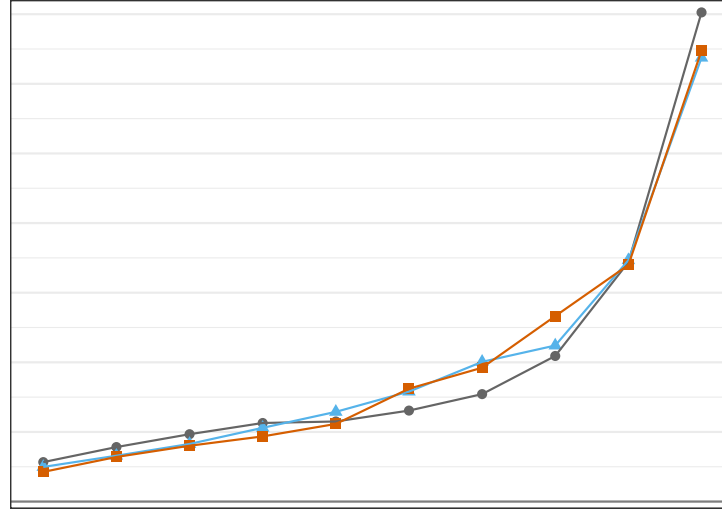
Appendix Figure 8: Percentile gaps of the firm wage effect distribution



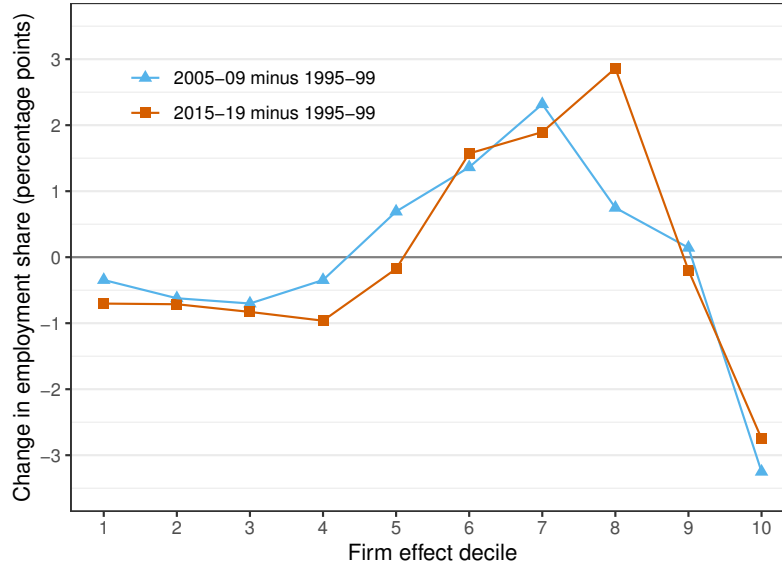
Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The figure shows the evolution of percentile gaps of the estimated firm wage effect distribution across the five subperiods, normalized relative to 1995–1999 (so that all gaps equal zero in the first period). Panel A shows lower tail gaps: P50–P5, P50–P10, and P50–P25. Panel B shows upper tail gaps: P95–P50, P90–P50, and P75–P50. Firm effects are estimated separately within each five-year period on the largest connected set of firms. Percentiles are computed over worker-years, so that each firm contributes in proportion to its employment.

Appendix Figure 9: Employment shares across firm wage effect deciles

Panel A: Employment shares

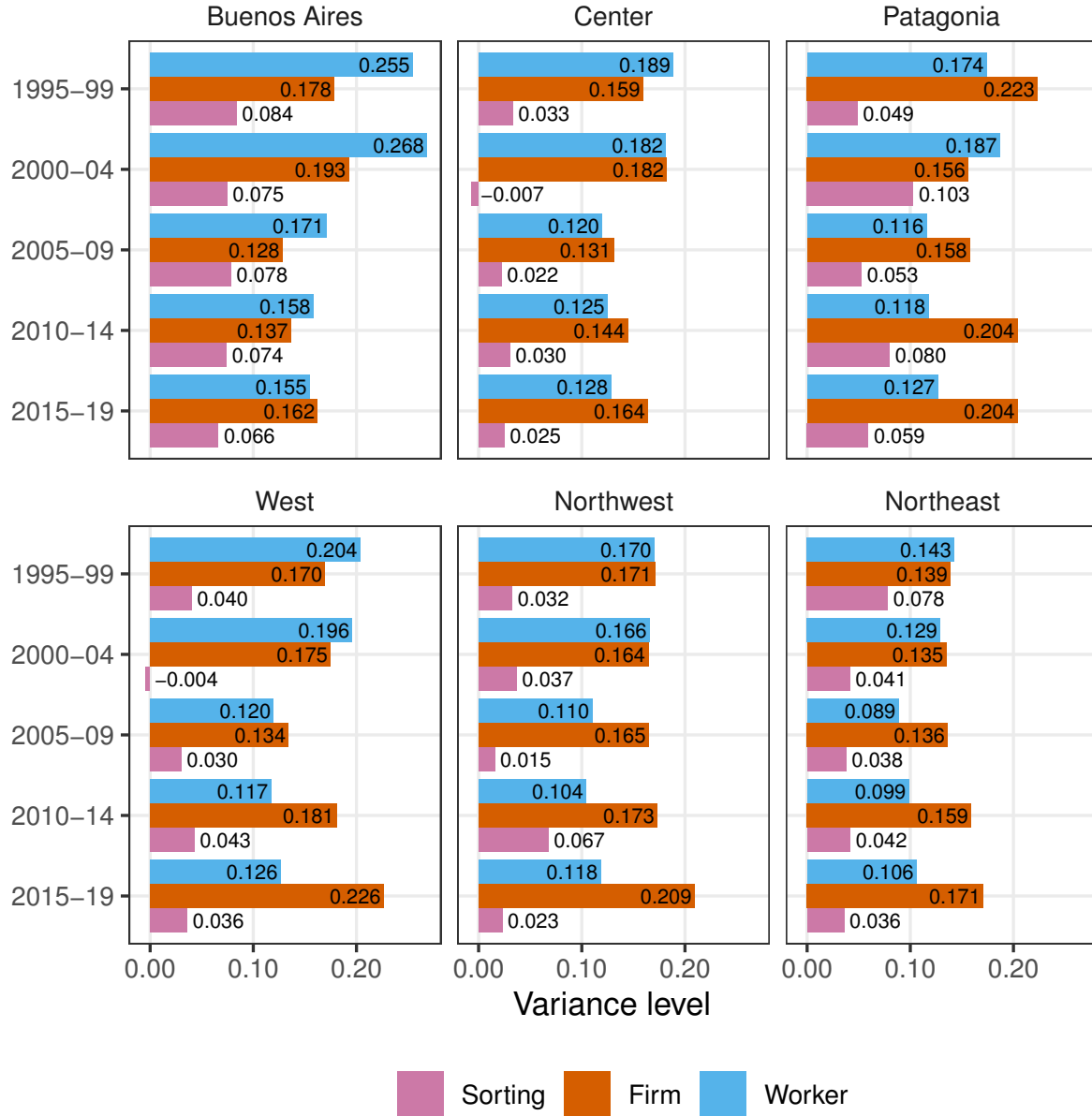


Panel B: Changes relative to 1995–99



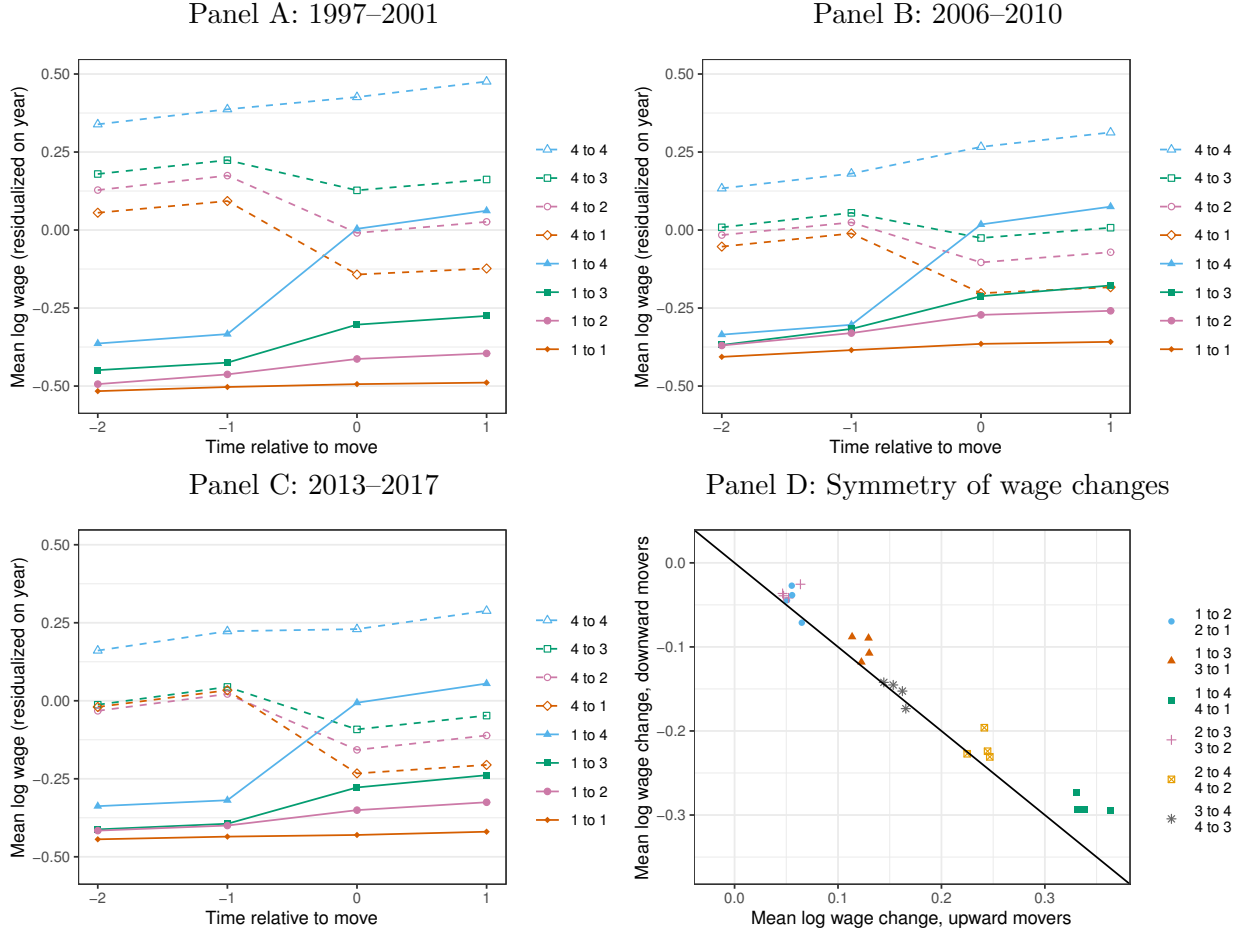
Notes: Data are from Argentina’s social security system (SIPA) for men aged 20 to 55. The figure shows the employment share of firms by firm wage effect decile in 1995–99, 2005–09, and 2015–19. Panel A shows the employment share in each firm-effect decile. Panel B shows the percentage-point change in each decile’s employment share relative to 1995–99. Firm effects are estimated separately within each five-year period on the largest connected set of firms. Within each period, firms are ranked by their estimated firm wage effect and grouped into deciles with equal weight. Employment shares are then computed as each decile’s share of total worker-years, and sum to 100% within each period.

Appendix Figure 10: AKM-based variance decomposition by region



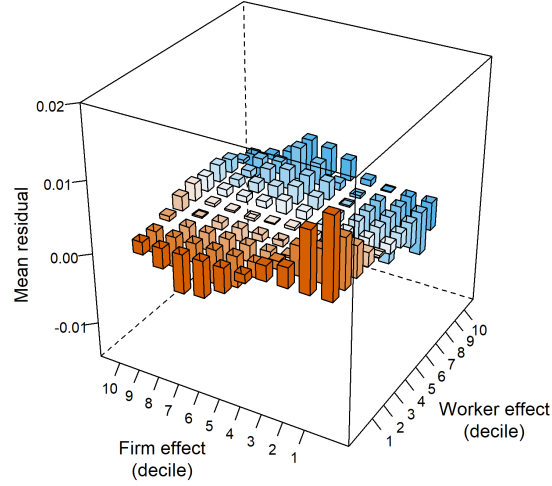
Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The figure shows the AKM variance decomposition by geographical region. The regions are defined as follows: "Buenos Aires" includes both the City of Buenos Aires and the Province of Buenos Aires; "Center" includes the provinces of Entre Ríos, Santa Fe, Córdoba, and La Pampa; "Patagonia" includes Río Negro, Neuquén, Chubut, Santa Cruz and Tierra del Fuego; "West" includes Mendoza, San Luis, La Rioja, and San Juan; "Northwest" includes Jujuy, Salta, Catamarca, Tucumán, and Santiago del Estero; and "Northeast" includes Misiones, Corrientes, Chaco, and Formosa.

Appendix Figure 11: Evolution of wages for workers moving across firms

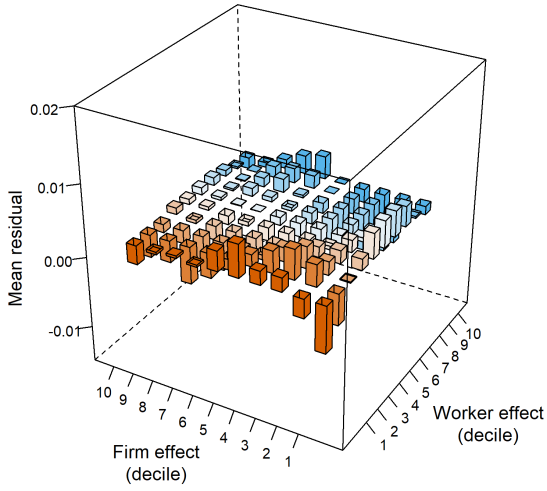


Appendix Figure 12: AKM residuals across deciles of worker and firm fixed effects

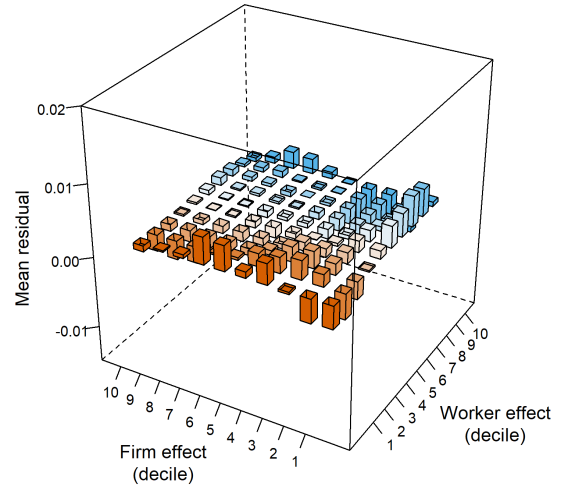
Panel A: 1995–1999



Panel B: 2005–2009

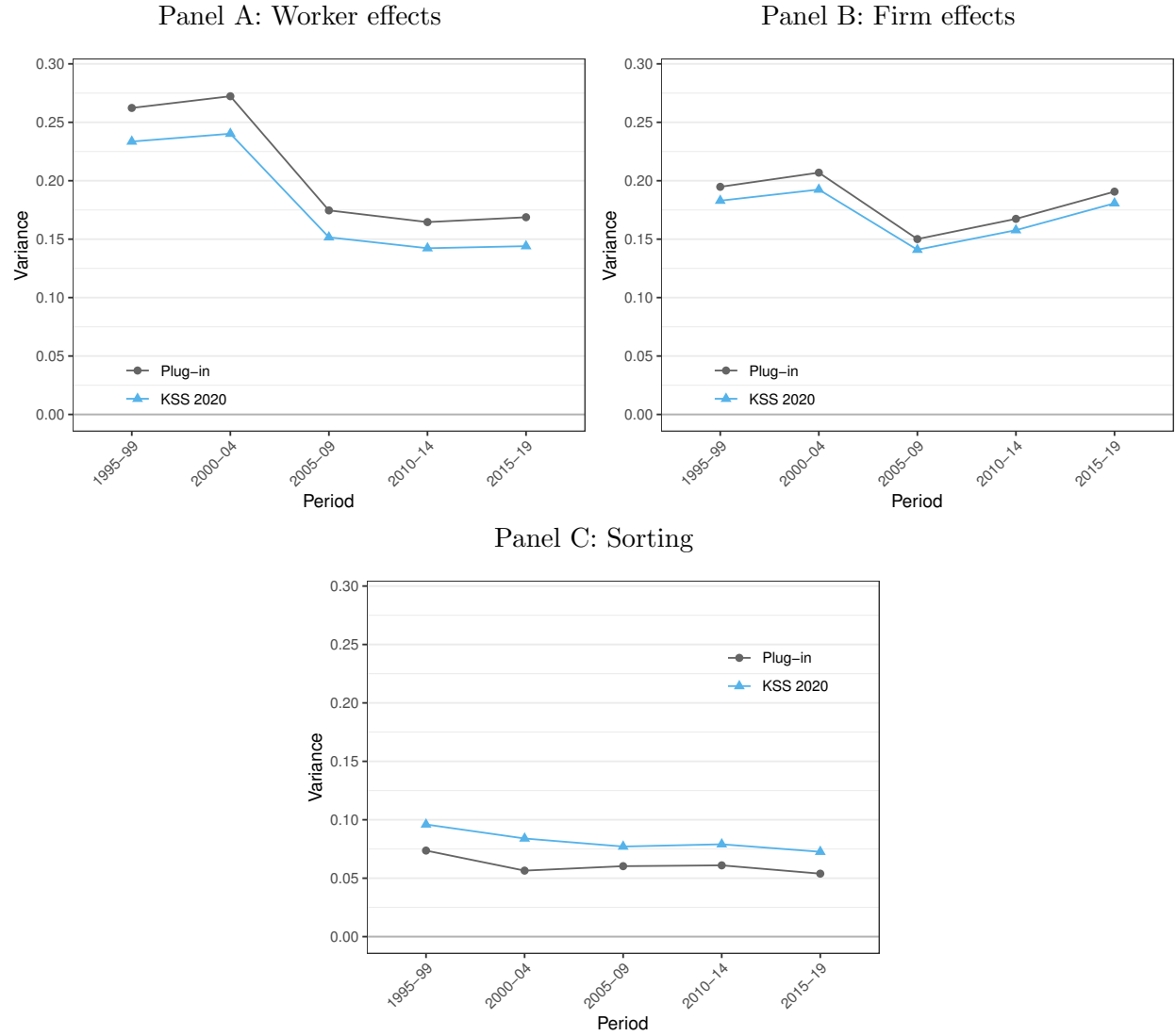


Panel C: 2015–2019



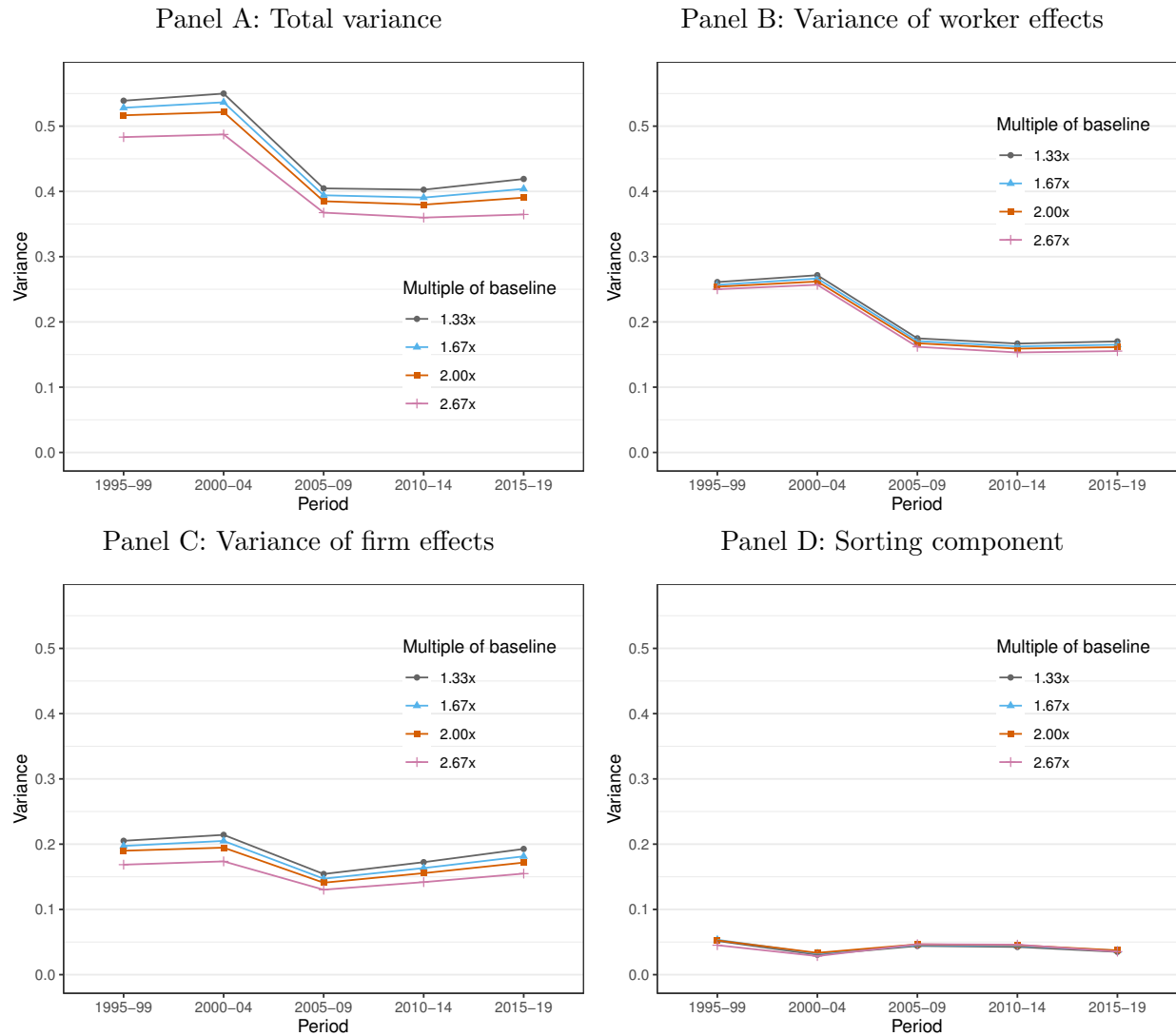
Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The figure shows the mean residual of the estimated AKM models by deciles of worker and firm effects. Panels A, B, and C show, respectively, mean residuals of models estimated in 1995–1999, 2005–2009, and 2015–2019, using the largest connected set of firms in each period.

Appendix Figure 13: Variance decomposition of AKM estimates on the leave-out-match set, prime-aged men



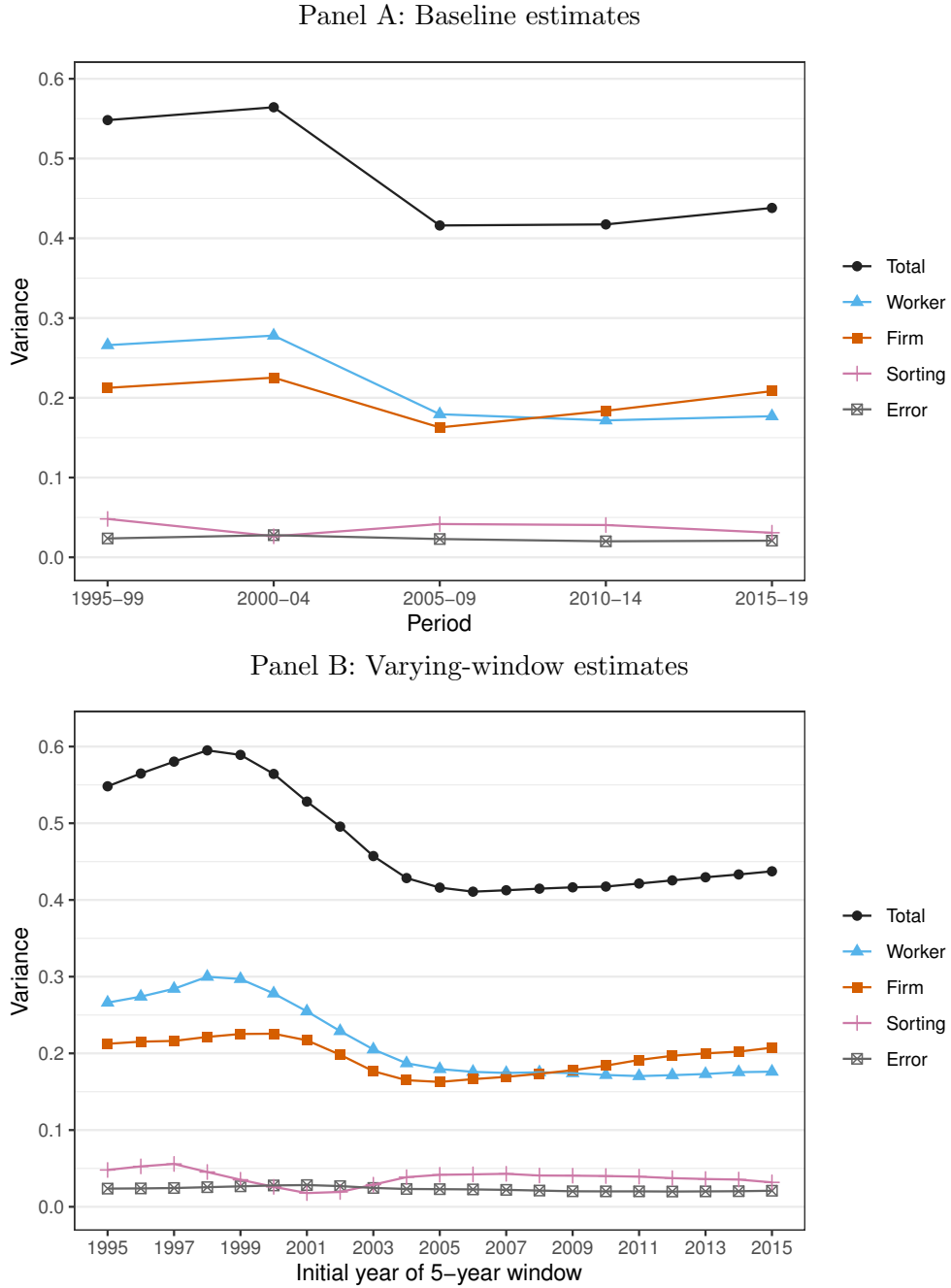
Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The figure shows the contribution of each component of the variance decomposition of log earnings, correcting the estimates of the variance terms, on the largest leave-out-match connected set of firms. "Plug-in" refers to the computation of the variance components directly using the AKM estimates. "KSS 2020" refers to the variance decomposition proposed by [Kline et al. \(2020\)](#), which allows for heteroskedasticity in the error term. The sorting component is twice the covariance between worker and firm effects.

Appendix Figure 14: Variance decomposition of log earnings according to AKM model by minimum earnings cutoff



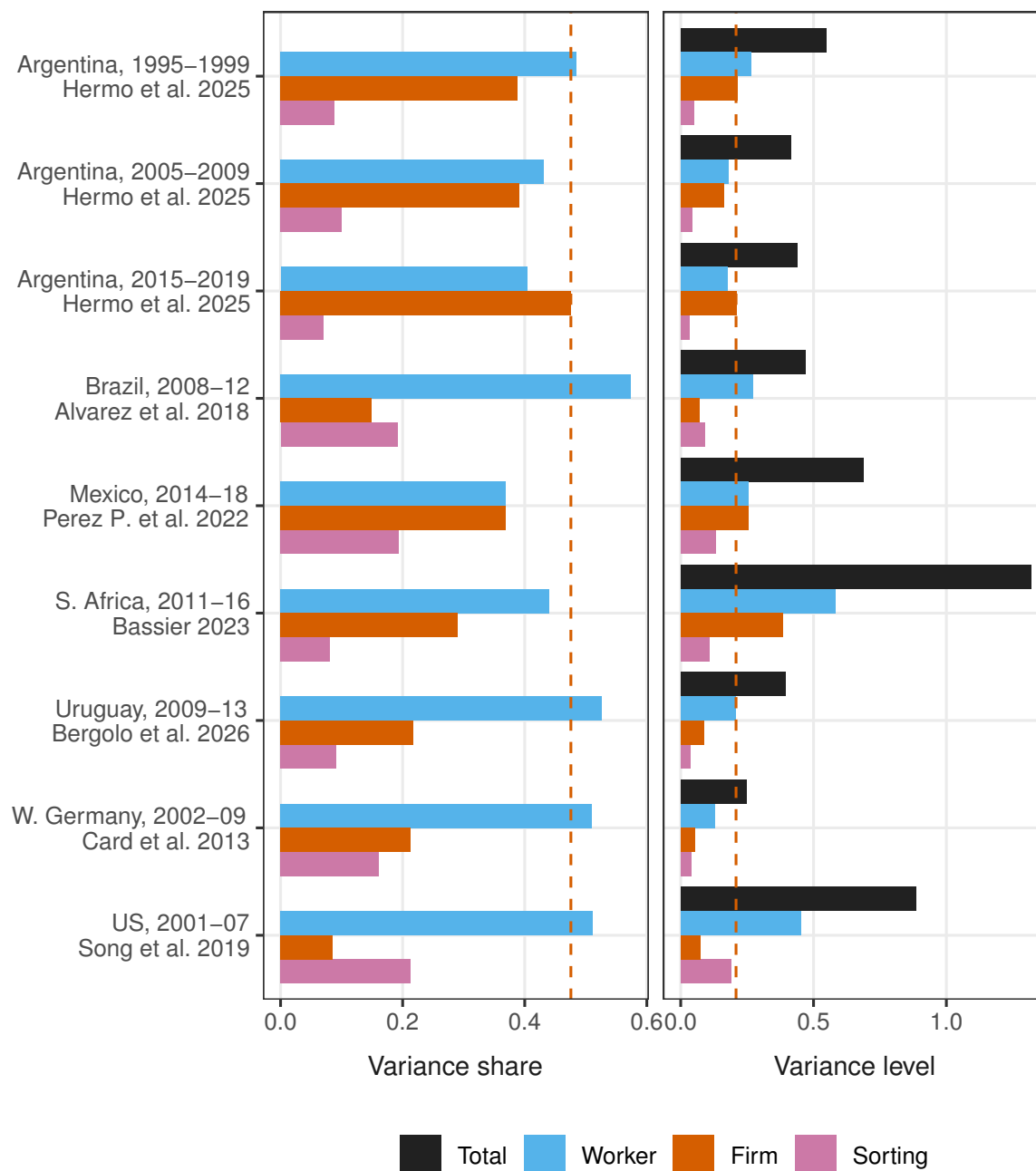
Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The figure shows estimates of the variance decomposition of a model of log earnings on worker fixed effects, firm fixed effects, and year fixed effects following [Abowd et al. \(1999\)](#), for different values of the level of minimum earnings to be included in the sample. Cutoffs are expressed as multiples of the baseline cutoff of ARS 317.25 in 2010 pesos (about USD 80). Panel A shows the total variance of log earnings. Panel B shows the variance of worker fixed effects. Panel C shows the variance of firm fixed effects. Panel D shows the sorting component, twice the covariance between worker and firm effects. Plug-in variance estimates are calculated on the largest connected set of firms.

Appendix Figure 15: Variance decomposition of log earnings with a time-varying window



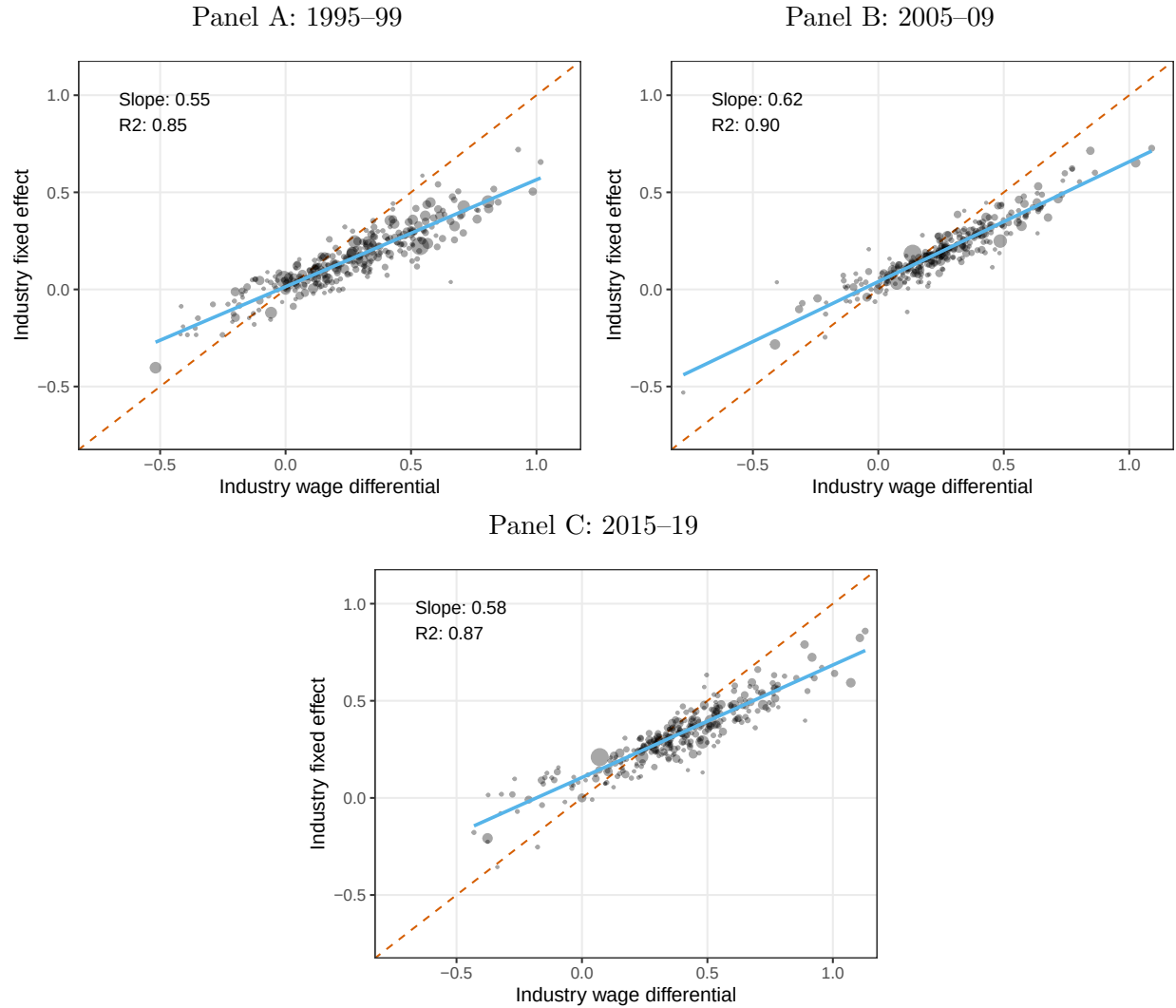
Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The figure shows estimates of the variance decomposition of a model of log earnings on worker fixed effects, firm fixed effects, and year fixed effects following [Abowd et al. \(1999\)](#), on the largest connected set of firms. Panel A replicates the baseline estimates from Table 3. Panel B shows results of models estimated separately for five-year periods with initial year ranging from 1995 through 2014.

Appendix Figure 16: Comparing AKM-based variance decomposition across countries



Notes: Data are from Argentina’s social security system (SIPA) for Argentina and from the selected studies cited below each country. The figure compares the AKM variance decomposition of log earnings across selected countries. The left panel shows the share of the worker, firm, and sorting components out of the total variance. The right panel shows the levels of the variances, including the total variance of log wages. The red line signals the variance level or variance share for Argentina in 2015–2019. Plug-in estimates of the variance components are chosen in all countries to ensure comparability. All reported estimations include year fixed effects as controls. [Alvarez et al. \(2018\)](#) also control for worker age, and [Card et al. \(2013\)](#) additionally control for education. All studies focus on men, with the exception of [Bassier \(2023\)](#) who includes both men and women.

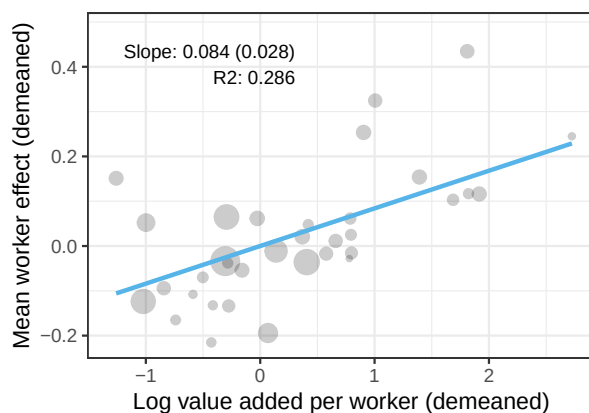
Appendix Figure 17: Industry wage differentials and industry fixed effects



Notes: Data are from Argentina’s social security system (SIPA) for men aged 20 to 55. The figure compares industry wage differentials with industry fixed effects at the 4-digit industry level. Industry wage differentials are computed as weighted averages of AKM firm effects within industries, normalized relative to restaurants. Industry fixed effects are obtained from a leave-out-match AKM model in which industries are treated as workplaces, again normalized relative to restaurants. Each point is a 4-digit industry and point size is proportional to worker-years. The dashed line is the 45-degree line, while the solid blue line shows a weighted linear fit.

Appendix Figure 18: Worker effects, sectoral productivity, and industry wage differentials in 2015–19

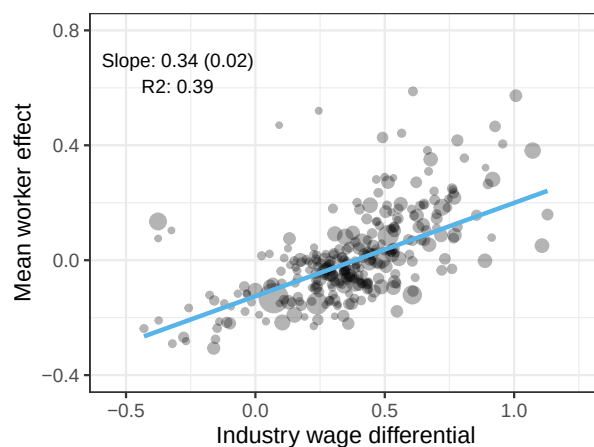
Panel A: Mean worker effect and productivity



Panel B: SD of worker effects and productivity



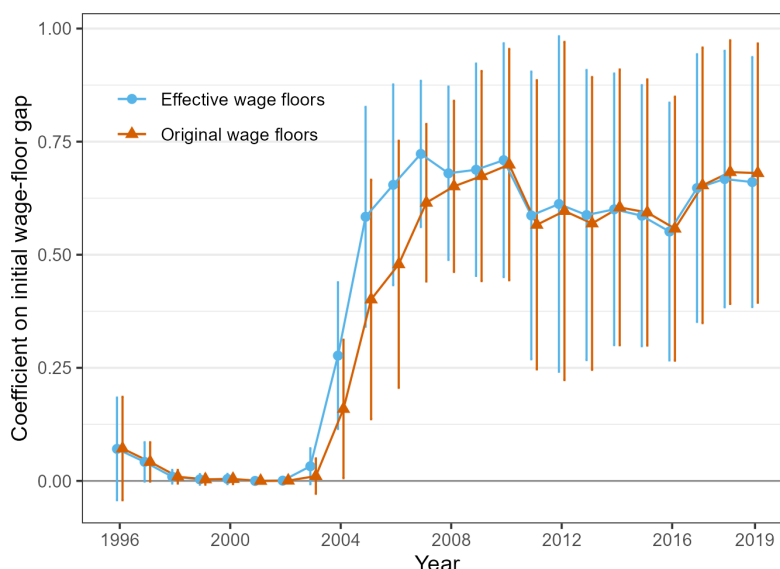
Panel C: Industry differentials and worker effects



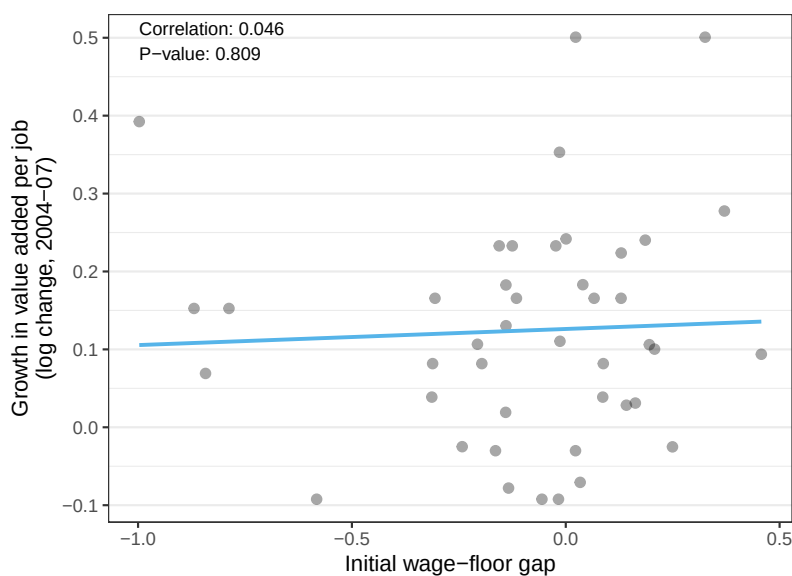
Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55 and from CEP XXI. Panels A and B show scatter plots of the mean and the standard deviation of worker effects against sectoral productivity. The measure of sectoral productivity is an average of value added per worker across relevant years. Variables are demeaned within each period using worker-year weights. Reported standard errors are clustered by sector. Sectors follow CEP XXI's classification based on ISIC Rev. 3.1, with selected aggregations and subdivisions. Panel C shows the correlation between industry wage premia and the mean worker effect in each industry.

Appendix Figure 19: Initial wage-floor gaps, productivity growth, and wage-floor adjustment

Panel A: Minimum wage increase and wage floor adjustment



Panel B: Growth in value added per job, 2004–07



Notes: Data are from Secretariat of Labor wage-floor records and CEP XXI. This figure shows the relationship between initial wage-floor gaps, productivity growth, and wage-floor adjustment. The initial gap is the negative difference between the industry’s mean log wage floor in 2001–02 and the average log real minimum wage in 2005–07. Panel A shows annual coefficients from regressions of changes in mean log real wage floors relative to 2001 on the initial gap. The unit of observation is the ISIC division by year, and the mean wage floor is computed using all observed bargaining units in a year. “Effective” wage floors replace the observed wage floor with the statutory minimum when the latter is higher, while “original” floors retain the recorded agreement amounts. Bars show 95% confidence intervals based on heteroskedasticity-robust standard errors. Panel B shows the relationship between the initial gap and growth in real value added per job in 2004–07 for the 43 ISIC divisions in the IV sample. The reported p -value tests a zero slope, with standard errors clustered by 30 productivity groups.