Firms and the Evolution of Earnings Inequality in Argentina's Volatile Economy*

(Preliminary and Incomplete. Please Do Not Circulate.)

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July 23, 2025

Abstract

This paper studies the role of firms in the evolution of earnings inequality in Argentina between 1995 and 2019. After the increasing trend in the 1990s, we find that inequality followed a U-shaped pattern, with a large reduction following the 2001–2002 crisis and a mild increase amidst the stagnation of the 2010s. Leveraging Argentina's matched employer-employee dataset and high-dimensional fixed-effects models following Abowd et al. (1999), we decompose the variance of log earnings into three components: worker characteristics, firm characteristics, and assortative matching. Firms contributed to the reduction in inequality in the early 2000s and fully account for the increase in inequality in the 2010s. The contribution of the firm wage effects to inequality is large and increased by 8.8percentage points between 1995–99 and 2015–19. We aggregate our estimated effects to the sectoral and regional levels to explore the drivers of the firm component. The large contribution of firms to inequality is negatively related to sectoral productivity, negatively related to the wage floors negotiated in collective agreements, and positively related to the levels of informality. Then, we study drivers of the firm component of earnings inequality between the 2000s and the 2010s. We argue that an increase in the dispersion of productivity, coupled with weakening labor market institutions—declining minimum wage and negotiated wages floors—-can explain the increase in the firm component of earnings inequality.

Keywords: earnings inequality, firm wage effects, AKM, Argentina.
JEL codes: E24, J20, J31, O15.

*We are thankful to Jorge Pérez Pérez and José G. Nuño-Ledesma for invaluable comments and suggestions. We also thank participants at seminars at the Instituto de Investigaciones Económicas (Universidad Nacional de La Plata) and JILAEE (Universidad del CEMA) for useful feedback. Finally, we are grateful to Victoria Castillo of the Ministry of Labor for granting access to the administrative data. Santiago Hermo gratefully acknowledges support from the Sarmiento Fellowship at Brown University. All errors are our own.

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1 Introduction

Earnings inequality in Latin America has declined strongly between the 1990s and 2000s (Gasparini and Lustig 2011; Messina and Silva 2019). However, the reduction of inequality slowed down and even stagnated in the 2010s (Gasparini et al. 2016; Gasparini and Cruces 2021). Despite this decline the region remains the most unequal in the world (Lustig 2015). At the same time, the large macroeconomic and institutional changes the region has gone through provide a rich environment to assess how the sources of inequality evolve as economic conditions change. Understanding the sources of these fluctuations in earnings inequality, and how they relate to macroeconomic and institutional changes, is crucial to the design of effective labor market policies in the region.

This paper studies the evolution of earnings inequality and its sources in Argentina, one of the largest countries in Latin America, between 1995 and 2019. The case of Argentina is of particular interest for several reasons. First, the country experienced large fluctuations in earnings inequality that are in line with regional trends (Lustig et al. 2016; Gasparini et al. 2016). Similarly, Argentina has experienced similar macroeconomic and institutional shifts as the rest of the region, including liberalization of the economy in the 1990s, robust economic growth in the 2000s, and growth deceleration in the 2010s, which suggests that the Argentine case can provide insights into the sources of inequality in Latin America as a whole. Finally, a large administrative dataset that contains all formal employment relationships in Argentina during this 25-year period allows us to tease out the sources of inequality at a detail that is not possible with household survey data, which is the most common source of data in the literature, yielding novel insights into the sources of inequality in a developing country over 25 years.

We decompose earnings inequality into three components: worker characteristics (such as worker ability), firm characteristics (such as firm productivity), and assortative matching between workers and firms (or "sorting"). To do so, we exploit our rich matched employer-employee dataset to fit models of log earnings as a function of worker and firm fixed effects, following Abowd et al. (1999) (AKM hereafter), and estimate the variance of log earnings that can be attributed to each component. Furthermore, by repeatedly estimating this model for 5-year intervals between 1995 and 2019, we can track the evolution of the contribution of each component of earnings inequality over time. Then, we aggregate the estimated firm wages effects at the industry and region levels to conduct several exercises that explore the drivers of the evolution of the firm component. First, we study the role of economic sectors by computing industry wage differentials following Card et al. (2023) for the entire period. We additionally match our data with value added at broader economic sectors available for the last 15 years of our sample. Second, we collect novel data on the wage floors negotiated in collective bargaining agreements and match them to sectors to study the role of labor market institutions. Finally, we explore the relationship between the firm component of earnings inequality and the informality rate across different local labor markets using household survey data.

The main finding of this paper is that firms play a large role in shaping earnings inequality in Argentina, and their contribution has increased over time. Changes in the dispersion of firm wage effects can explain the decline in inequality between the 1990s and 2000s, following the 2001–02 debt crisis, and the mild increase in the 2010s amidst the stagnation of the Argentine economy. We then move to the aggregate analysis to explore the drivers of the firm component of earnings inequality. We find that industry affiliation has become more predictive of firm wage effects over time, and that the dispersion of industry wage differentials has increased, indicating that a widening gap between sectors has contributed to the increase in firm inequality. We bring in data on sectoral productivity and negotiated wage floors and find that sectors with declines in average productivity and negotiated wage floors saw increases in the within-sector dispersion of firm wage effects. Finally, we find that across local labor markets increases in informality rates coincided with increases in the dispersion of firm wage effects.

We start our analysis by documenting the evolution of earnings inequality among prime-age men between 1995 and 2019 using our administrative data.[1] The variance of log earnings increased in the 1990s up to a peak of 0.601 in 2001, driven by strong growth at the top of the distribution. The 2001–02 crisis led to a sharp reduction in inequality, with the variance declining by −38.6% to its minimum of 0.369 in 2006. This reduction was driven by faster growth in earnings at the bottom of the distribution. Pushed mainly by declining wages at the bottom, the variance of log earnings increased consistently for the rest of the period, reaching 0.473 in 2019. We observe a widening gap between wages of different broad economic sectors throughout the period. Additionally, a simple decomposition of the variance into between- and within-firm components shows that the between-firm component is the main driver of changes in inequality. These patterns are suggestive of an important role for industries and firms in shaping the evolution of earnings inequality.

We estimate models of log earnings following AKM at 5-year intervals to track the evolving contributions of workers, firms, and assortative matching to earnings inequality over time. AKM models decompose log earnings into worker and firm effects, identifying firm wage effects based on earnings changes of workers as they move between firms (Abowd et al. 1999; Card et al. 2013; Kline 2024). The key assumption of the model is "exogenous mobility," which states that worker mobility is not driven by the unobserved component of earnings. Following the suggestions of Card et al. (2013), we assess the fit of the AKM model and find that its underlying assumptions are approximately satisfied in our data. Another concern is potential bias in variance estimates due to limited mobility between firms (Andrews et al. 2008; Kline et al. 2020; Bonhomme et al. 2023). We present results for both the uncorrected and corrected estimates, finding very similar conclusions regarding the contribution of the different components to earnings inequality.

[1]The AKM literature has mostly focused on men, so we follow this sample selection to facilitate comparisons. We provide complementary evidence for women in an appendix. However, we also note that, just like in many Latin American countries, female labor force participation in Argentina has increased over the period we study (Busso and Fonseca 2015), which complicates the interpretation of the results.

Our estimates show a large contribution of firm wage effects to earnings inequality in Argentina. Roughly two-thirds of the decline in the variance of log earnings between 1995–99 and 2005–09 can be attributed to a reduction in the variance of worker effects, while the remaining third is due to a reduction in the variance of firm effects. In contrast, the rise in the variance of log earnings from 2005–09 to 2015–19 can be fully attributed to the firm component. In fact, the increase in inequality during the 2010s would have been even greater if not for the offsetting influence of other components. We find that the contribution of assortative matching to the evolution of earnings inequality is smaller in magnitude, and pushed towards reducing inequality throughout the period.

A recent review of the literature on firm wage effects by Kline (2024) finds that the contribution of firms to the variance of log earnings seems to be larger in developing than developed countries. Our results for Argentina are in line with this finding. The uncorrected variance estimates indicate that 38.8% of the total variance of log earnings can be attributed to firms in 1995–1999, and this share increases to 47.6% in 2015–2019.[2] Additionally, the estimates for 2015–2019 imply that moving to a one standard deviation higher paying firm would increase worker earnings by 57.8%.[3] We study potential drivers of this large role of firms. Using a survey of manufacturing firms in 2010–12, we find that the firm fixed effects are strongly correlated with firm productivity, measured as value added per worker. We also find a robust negative association at the sectoral level between the variance of firm wage effects and (1) the average productivity of the sector and (2) the average wage floor negotiated in collective agreements. Our interpretation is that low-productivity sectors feature larger dispersion in productivity, and therefore in firm wage effects.

We perform several exercises that suggest fluctuations in productivity are responsible for the evolution of the firm component of earnings inequality. First, to focus on the entire period we look at the evolution of industry wage differentials, which are constructed from the estimated firm wage effects as in Card et al. (2023). We find that industries explain XXX percent of the variation in firm wage effects, and that the dispersion of industry wage differentials has increased over time. This indicates that a widening gap in productivity between sectors has contributed to the increase in firm inequality. We bring in data on sectoral productivity for the period 2005–19 and find that sectors with declines in average productivity saw increases in the within-sector dispersion of firm wage effects.

We collect data on the wage floors negotiated in collective agreements to explore the role of labor market institutions in shaping the firm component of earnings inequality. We find that the strong increase in the real minimum wage in the early 2000s coincided with a large reduction in the dispersion of wage floors relative to the late 1990s. This was a period of strong reduction

[2]Correcting for limited mobility bias using the method proposed by Kline et al. (2020) lowers these shares to 33.0% and 41.5%, respectively, but the increase over time remains.

[3]Our estimate of the standard deviation of firm wage effects is 0.456, implying that $100 \times [\exp(0.456) - 1] = 57.8\%$. Using our estimates on the leave-out sample used for the variance correction the increase is 53.0%.

in the dispersion of firm wage effects and, in particular, industry wage differentials, suggesting that labor market institutions may have played a role in the reduction of firm inequality. The data quality improves after 2005, and we are able to match the wage floors to sectors for the years 2005–19. We find that increases in the average negotiated wage floor within a sector are associated with declines in the within-sector dispersion of firm wage effects, consistent with the idea that labor market institutions can shape the firm component of earnings inequality.

Finally, we explore the relationship between the firm component of earnings inequality and the informality rate across different local labor markets. This suggests that the aforementioned larger dispersion of productivity in low-productivity sectors results in either more informal hiring or in the emergence of economic units that operate fully in the informal economy.

Our work has several limitations. First, we do not observe firm productivity. We construct industry wage differentials and bring in data on sectoral productivity to explore this issue, but we cannot directly quantify the contribution of changes in firm-level productivity to changes in firm wage effects. Second, as most studies that rely on administrative data, we do not have information on the informal sector. This is important since approximately one third of the salaried workforce in Argentina is not registered in the social security system. While we cannot directly quantify the contribution of informality to changes in inequality, we provide suggestive evidence that the prevalence of informality is related to the dispersion of firm wage effects.

This paper makes several contributions to the literature. First, we contribute to the understanding of the determinants of earnings inequality in Latin America by quantifying the importance of workers and firms in the fluctuations of earnings inequality in Argentina. Perhaps due to the paucity of administrative data identifying firms, most studies in the region have focused on the role of worker characteristics. Some studies link the 1990s inequality rise to a higher skill premium from increased demand for skilled workers amid liberalization policies. (Galiani and Sanguinetti 2003; Bustos 2007; Dix-Carneiro and Kovak 2015). Accordingly, Lustig et al. (2016), Manacorda et al. (2010), Fernández and Messina (2018), and Acosta et al. (2019) argue that the reduction in the 2000s across many Latin American countries was driven to large extent by a reduction in the skill premium.[4] Our results suggest that factors related to worker characteristics were the primary drivers of the reduction in inequality in Argentina in the 2000s. However, we show that a large part of the decrease in inequality in the 2000s and the entire increase in the 2010s can be attributed to changes in firm wage effects.

Similarly, several studies focus on the industrial composition of the economy and the role of labor market institutions as driver of earnings inequality in Argentina (Maurizio and Vazquez 2016; Ciaschi et al. 2021; Schteingart et al. 2022). Our contribution is to take a bottom-up approach to construct industry wage differentials from the estimated firm wage effects, in the spirit of recent work by Card et al. (2023), and show that the dispersion of industry wage differentials has increased over time. To the best of our knowledge, this is the first time that

[4]Pietro and Pedace (2008) and Hermo (2017) make a similar argument for Argentina. ADD MORE CITES FOR OTHER LATAM COUNTRIES.

this approach is used in a developing country. Additionally, we contribute by digitizing and matching wage floors negotiated in collective agreements to sectors, and showing that negotiated wage floors are associated with the dispersion of firm wage effects.[5]

Second, we contribute to the literature estimating firm wage effects using the AKM methodology, especially in developing countries, providing new evidence on the importance of firms in shaping earnings inequality in a large middle-income country across changing macroeconomic and institutional conditions. Alvarez et al. (2018) find that the reduction in inequality in Brazil in 1996–2012 was partially driven by firms, similar to our results in 1995–2009. Bassier (2023) and Pérez Pérez and Nuño-Ledesma (2024) find that the contribution of firm wage effects to earnings inequality in South Africa and Mexico is larger than in developed countries. Additionally, Pérez Pérez and Nuño-Ledesma (2024) find that the contribution of firms in Mexico has increased between 2004 and 2018, similar to our results between 2005 and 2019. Kline (2024) reviews the literature and argues that the dispersion of firm wage effects tends to be higher in developing countries, flagging this as an important area for future research. Our contribution is to provide suggestive evidence that productivity changes and labor market institutions may drive the evolution of the firm component. We also show that local labor markets with higher informality rates have a larger dispersion of firm wage effects, consistent with the idea that the firm inequality may be related to the prevalence of small and unproductive firms.

The rest of the paper is structured as follows. Section 2 provides context on the Argentine economy and details on the data we use. Section 3 describes the AKM model and the decomposition of earnings inequality. Section 4 presents the main results of the paper. Section 5 explores the drivers of the firm component of earnings inequality. Section 6 concludes.

2 Context and Data

In this section we discuss the macroeconomic and institutional context of Argentina, the data used in the analysis, and trends in labor market inequality.

2.1 Argentina's macroeconomic and institutional context

In the 25 years between 1995 and 2019, Argentina has experienced a wide range of macroeconomic conditions and varied policy environments. As shown in Figure 1, a period of high growth and low inflation in the 1990s was followed by a deep recession in 2001-2002, a strong recovery in the 2000s, and a period of stagnation with increasing inflation in the 2010s. The pattern of economic growth was quite different in the 1990s and 2000s, while the former featured structural reforms that spurred economic growth, such as trade liberalization, the latter was characterized

[5] Hermo (2024) also studies the role of negotiated wage floors in determining firm pay in Argentina, constructing a dataset of wage floors from observed bunching in the wage distribution within collective agreements and occupations. This method can only recover wage floors since 2011. In this paper we rely on a different source of data, allowing us to obtain information since the late 1990s.

by a depreciated exchange rate that favored the expansion of the local manufacturing industry and a shift towards more active labor market policies. The increasing inflation rate in the 2000s and appreciation of the peso led to the adoption of exchange rate controls in 2011, and the economy entered a period of stagnation with increasing inflation rates. These fluctuations were reflected in the labor market. Appendix Figure 1 shows that the unemployment rate decreased in the 2000s from a relatively high level in the 1990s. Additionally, it shows that informality was high throughout the period and peaked around the 2001–02 crisis.

These macroeconomic shifts and policy changes likely influenced earnings inequality, both by affecting returns to worker skills and the distribution of firm wage effects. The 1990s saw an expansion of high-skill sectors alongside skill-biased technical change, driving up the skill premium (Galiani and Sanguinetti 2003; Acosta and Gasparini 2007; Bustos 2007). Conversely, the 2000s expansion of local manufacturing, coupled with workforce upskilling (Cruces et al. 2014), resulted in a decline in the skill premium (Hermo 2017; Acosta et al. 2019). This is supported by the evolution of the skill premium shown in Panel A of Appendix Figure 2 and the sectoral wage trends in Panel B. In the 1990s, wages increased in high-skill sectors like Financial Intermediation and Mining, while the 2000s saw more broad-based wage growth. The stagnation of the 2010s was coupled with a similar stagnation in the skill premium and a widening of wage differentials across sectors (Ciaschi et al. 2021; Schteingart et al. 2022). Furthermore, the 1990s featured a stagnant minimum wage and discouraged collective bargaining, while the 2000s saw substantial minimum wage increases and a resurgence of collective bargaining (Palomino and Trajtemberg 2006), alongside labor formalization efforts (Kutscher et al. 2013). These efforts waned during the 2010s stagnation, as the minimum wage fell behind inflation. The trajectory of the real minimum wage shown in Panel C of Appendix Figure 2 reflects these policy shifts.

2.2 Data

2.2.1 Matched employer-employee dataset

Our baseline data source is Argentina's matched employer-employee dataset. The data are collected by the tax authority under a system known as *Sistema Integrado Previsional Argentino*, or SIPA for short, for the purpose of registering Argentine workers' contributions to the social security system. We accessed a version of these data maintained by the Ministry of Labor and Social Security. The data include information on all jobs held by wage-earners in the private sector, as well as jobs in state-owned companies and independent public institutions such as universities and banks for the period 1995–2019. We use worker and firm identifiers to track workers across firms over time.[6] The data include information on the industry and province of the firm, as well as the age and gender of workers (though not their education level).

[6]The data do not include establishment identifiers. However, we prefer to use firm identifiers, as wage-setting decisions are likely made at this level, consistent with other work in the AKM literature (e.g., Alvarez et al. 2018).

Our main variable of interest is the monthly nominal pre-tax compensation of each worker-firm-year cell. For each job, we observe the sum of several monthly pay components, including a base salary, bonuses, severance payments (if applicable), and other. Our first step is to deflate these earnings to 2010 Argentine pesos using the CPI.[7] Second, we aggregate the data to the annual level by averaging the real monthly earnings within each year. We drop jobs with yearly earnings above the 99.9th percentile within each year, which ensures that the analysis is not affected by outliers such as unusually high bonuses or severance payments. We do not observe hours worked, so to limit the influence of part-time employment we exclude jobs with a monthly compensation lower than the equivalent of $75 USD per month at 2010 prices. We change this threshold in the robustness checks.

We impose several additional restrictions on our data. First, we focus on men aged 20 to 55, a group for with relatively high and stable employment rates (Busso and Fonseca 2015). We provide results for women in the appendix. Second, we drop jobs that lasted fewer than 6 months, jobs explicitly labeled as internships, and workers in temporal employment agencies.[8]

2.2.2 Household survey data

We complement the analysis of the administrative data with data obtained from the main national household survey, known as *Encuesta Permanente de Hogares*, or EPH for short. These data allows us to incorporate the informal sector into our analysis. The survey data collects information from the 31 largest Argentine cities and is representative of over 60% of total population and over 70% of urban population.

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

we define informal work as all salaried jobs that do not feature regular contributions to social security. This definition implies that we exclude self-employment, which accounts for about a quarter of the labor force in Argentina according to the EPH data.

[7]The CPI was obtained from the National Institute of Statistics and Censuses (INDEC), except for the period 2007–2015, for which we use alternative sources, as the official data were manipulated (see, e.g., Cavallo 2013). The alternative sources include the CPI data from several provincial statistical offices in the first years and an alternative inflation measure computed by the opposition parties in the later years of this period.

[8]Workers in temporal employment agencies are recorded twice, appearing both as employees of the agency and as employees of the firm where they are assigned. Drenik et al. (2023) use this feature of the Argentine data to study wage-setting practices of firms hiring outsourced workers.

2.2.3 Firm survey data

Finally, we also exploit firm survey data obtained from the *Encuesta Nacional de Dinámica del Empleo y la Innovación*, or ENDEI for short. ENDEI is a representative sample of over 3,000 firms in the manufacturing sector. It provides information on variables that are not available in administrative datasets, such as productivity (measured as value added per worker), thus enabling an analysis of association between firm effects and individual firm productivity.

Data collected by ENDEI is provided by a representative chosen by each firm, through two distinct questionnaires, one that is self-administered and another one that is applied by a survey taker. We use the first round of ENDEI, which contains data collected in 2012 for the 2010–2012 period.

2.3 Inequality trends in Argentina from 1995 through 2019

Panel A of Figure 2 shows that Argentina's macroeconomic fluctuations coincided with large changes in the variance of wages in the administrative data, with a significant increase in inequality in the 1990s, a strong reduction in the 2000s and stagnation and a mild increase in the 2010s. As discussed by Lustig et al. (2016), the pattern of increasing inequality in the 1990s and decreasing inequality in the 2000s is common to most Latin American countries. Gasparini et al. (2016) argue that the deceleration of the reduction in inequality in the 2010s is also common to the region. Appendix Figure 3 shows that the trends in inequality are similar when using survey data and are also present in the informal segment of the labor market.[9]

Observational evidence suggests that workplace factors may play an important role in shaping inequality. Panel B of Figure 2 decomposes the variance of log earnings into a between- and a within-firm component.[10] Approximately two-thirds of the variance of log earnings can be attributed to differences *between firms*. The between-firm component declined in the 2000s and increased back to 1990s levels in the 2010s. Panel C of Figure 2 further decomposes the between-firm component into a between-industry and a within-industry between-firm component, using 4-digit industry codes, showing that nearly half of the between-firm variance can be attributed to differences *between industries*.[11]

Figure 3 explores the evolution of the distribution of earnings by plotting the log ratio of percentiles over time. The increase in inequality in the 1990s is driven by a stretching of the upper tail of the distribution, with no changes in the lower tail. During the 2000s the entire distribution contracts: the lowest percentiles get closer to the median, and the median gets closer

[9]The survey data shows a stagnation of inequality in the 2010s but no clear increase. This fact can be explained by the under-reporting of the tails of the distribution in the survey data (Albina et al. 2024).

[10]Formally, let y_{it} denote log earnings for worker i in period t. Then, $\mathrm{Var}(y_{it}) = \mathrm{Var}(\bar{y}_{j(i)}) + \mathrm{Var}(y_{it}|i \in j)$, where $j(i)$ is the firm of worker i and $\bar{y}_j$ is the average wage in j. The first component shows the between-firm variance, and the second component shows the within-firm variance.

[11]Formally, $\mathrm{Var}(\bar{y}_j) = \mathrm{Var}(\bar{y}_{s(j)}) + \mathrm{Var}(\bar{y}_j|j \in s)$, where $s(j)$ is the industry of firm j and $\bar{y}_s$ is the average wage in s. The first component shows the between-industry variance and the second one the within-industry variance.

to the upper tail. The decrease in upper tail inequality persisted in the 2010s, however, the trend in the lower tail reversed. The increase and later decline in upper tail inequality may be driven by the evolution of the skill premium (Fernández and Messina 2018; Acosta et al. 2019). The evolution of lower tail inequality may be more related to the evolution of the minimum wage (Maurizio and Vazquez 2016) and the fluctuations in formality rates (Beccaria et al. 2015).

These patterns are similar for women. Appendix Figure 2 shows similar trends in inequality for this group, and that the between-firm component is also large for women. Appendix Figure 5 shows upper tail inequality evolved similarly to men, though lower tail inequality increased throughout the study period.

3 Methodology

The evidence in the previous subsection suggests that firm-specific factors may play a large role in shaping earnings inequality in Argentina. To estimate the contribution of firms to inequality, we fit two-way fixed effects models to the universe of formal employment relationships in Argentina separately for the sub-periods 1995–1999, 2000–2004, 2005–2009, 2010–2014, and 2015–2019. These models allow us to control for unobserved worker heterogeneity when estimating firm wage effects. They also allow for a natural decomposition of the variance of log earnings into worker-specific, firm-specific, and assortative matching (or "sorting") components.

3.1 The AKM model

AKM pioneered the estimation of firm wage effects posing the following model:

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

where y_{it} is the log of earnings of worker i at time t, α_i is a worker fixed effect, $j(i,t)$ is a function that gives the identity of the firm where worker i is employed at time t, and ψ_j is a firm fixed effect. We do not control for worker characteristics in the main specification and interpret the worker fixed effects as a summary of a worker's attributes that are rewarded equally across employers in a particular sub-period. Likewise, we interpret the firm fixed effects ψ_j as a proportional wage premium that a firm pays to all its workers. Our only control is the year fixed effect Υ_t, which controls for the strong macroeconomic cycle in Argentina. Finally, ε_{it} is the residual component of earnings.

It is informative to consider the implications of the model for the wage changes of workers that switch firms. The expected wage change for workers moving from firm j to firm k between periods $t-1$ and t is

$$\begin{aligned}\mathrm{E}\left[y_{i,t} - y_{i,t-1} | j(i,t-1) = j, j(i,t) = k\right] = {} & (\psi_k - \psi_j) + (\Upsilon_t - \Upsilon_{t-1}) \\ & + E\left[\varepsilon_{it} - \varepsilon_{i,t-1} | j(i,t-1) = j, j(i,t) = k\right].\end{aligned}$$

The average wage change captures the difference in firm wage effects between firms, the difference in the year fixed effects, and the average difference in the unobserved component of earnings. The difference in year effects is controlled for in the model, so in order to identify the firm fixed effects we need the so called "exogenous mobility" assumption:

$$\mathrm{E}[\varepsilon_{it}|\alpha_i, \psi_j, \Upsilon_t] = 0$$

for all t. This assumption will be violated if workers sort into firms based on the unobserved component of earnings. For example, worker mobility that systematically follows match-specific wage effects beyond what is captured by the firm wage effects, as predicted by Roy-type models French and Taber (2011), would be inconsistent with this assumption. Following Card et al. (2013), we examine this assumption by studying the wage changes of workers that switch across firms. Importantly, this assumption allows workers to sort based on the fixed effects, for instance, it allows workers with high fixed effects to sort into firms with high firm fixed effects.

Variance decomposition Equation (1) allows us to decompose the variance of log earnings in the following components:

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

It is understood that plugging model estimates into the decomposition may yield biased estimates of the variance components, and that such bias may be substantial Bonhomme et al. (2023). Andrews et al. (2008) show that this bias arises from low mobility across firms and propose a bias correction formula under the assumption that the error term is homoskedastic. Kline et al. (2020), or KSS for short, proposes a generalization that allows for heteroskedastic errors across worker-years. We implement these bias correction methods in our analysis.

Connectedness and Implementation Firm wage effects can only be identified for a set of firms that are connected by worker mobility (Abowd et al. 1999; Card et al. 2013; Kline 2024). Intuitively, if no worker moves to or from a firm, we cannot distinguish between the firm effect and the worker effect. We estimate the model under the largest set of firms that are connected by worker mobility. Additionally, the KSS bias correction method requires a set of firms that remains connected after we leave out any one worker–firm match. We proceed by reporting the results of the plug-in variance decomposition on the largest connected set of firms, and then apply the bias correction methods in the leave-match-out connected set. We use the publicly available `pytwoway` python package to implement the estimation and bias correction methods (Bonhomme et al. 2023).

Analysis sample The restrictions discussed in Section 2.2.1 do not preclude the possibility that a worker may be observed in multiple firms within a year. Following common practice in the AKM literature, we keep the highest-paying job per worker-year in those cases. We then select the largest connected set of firms and the largest set of firms that remains connected after we leave out any worker–firm pair. When doing so, we drop single-stayers, that is, worker-firm pairs that are observed only once within the sample period.

Table 1 shows sample statistics for the set of men that we use in our baseline analysis. Panel A shows the entire sample, Panel B shows the largest connected set of firms, and Panel C shows the largest leave-out-match connected set. We observe a secular decline in mobility both in the full sample and the connected sets, as shown in the last two columns of the table, with a particularly sharp drop in the 2000–2004 period, which coincides with the 2001–2002 crisis. The share of worker-years in the full sample that remain in the connected set increases from 80.9% in 1995–1999 to 84.6% to 2015–2019 (for the leave-out-match connected set the increase is from 73.7% to 78.8%). We observe a larger proportional decline in the number of firms than in the number of workers across the connected sets over time, suggesting that the connected sets mostly drop small firms. Despite these differences, the summary statistics of worker-years in the connected sets are quite similar to those of the full sample. Average log earnings are only slightly larger, and the evolution of the standard deviations across periods is similar to that of the full sample. As for age, averages are nearly identical and the standard deviations are slightly lower in the connected sets.

3.2 Determinants of estimated fixed effects

We aggregate our estimated firm and worker effects to the sectoral and regional levels to explore how they relate to productivity, negotiated wage floors, and informality. We calculate the variance of firm and worker effects using our estimates from the largest connected set, weighting by worker-years.[12] Sectors are defined according to a custom industry classification built on the International Standard Industrial Classification (ISIC) revision 3.1. When necessary, crosswalks are used to align these sectors with the aggregation level of the explanatory variable data. Geographical units are the 23 provinces and the City of Buenos Aires, which are further aggregated into the five standard regions of Argentina: Center, West, Northwest, Northeast, and Patagonia.[13]

For an outcome variable y_{kp} (e.g., the variance of firm or worker effects) in sector k and

[12]Due to computational limitations we do not correct our estimates of the variance components of inequality at the sector-region levels.

[13]The regions are defined as follows: "Center" (City of Buenos Aires, Buenos Aires Province, 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, Corrientes), "Patagonia" (Neuquén, Rio Negro, Santa Cruz, Chubut, Tierra del Fuego).

period p, we estimate regressions of the form:

$$y_{kp} = \alpha_k + \delta_t + \beta x_{kp} + \varepsilon_{kp}$$

where x_{kp} is an explanatory variable (e.g., average sectoral productivity), and ε_{kp} is an error term. The parameter β indicates the relationship between changes in x and changes in y using within-k variation. While this analysis doesn't establish causality, it offers suggestive evidence regarding factors potentially associated to the evolution of the firm component of inequality.

3.3 Industry wage differentials

Following Card et al. (2023) we define the industry wage premium as the average firm fixed effect in the industry, weighted by the number of worker-years in each firm within the industry, according to the following equation.

$$\phi_l = \frac{\sum_{l(j)=l} N_j \psi_j}{\sum_{l(j)=l} N_j} \tag{3}$$

Where $l(j)$ is the industry of firm j and N_j is the number of worker-year observations for firm j. Then we normalize these industry premia by substracting the weighted average from each observation, thus setting the mean value to zero. This allows us to interpret the results as industry wage differentials, where a positive value indicates that an industry features salaries higher than average and *vice versa*.

4 Decomposition of the evolution of earnings inequality

This section discusses our estimates of the AKM model. We start by presenting evidence in favor of the structure of the AKM model. Then, we present the results of the estimated AKM model for the entire period and the decomposition of the evolution of earnings inequality. We present several robustness checks for our results. Finally, we compare our results with the literature.

4.1 Event study evidence

The AKM model has two important implications. First, the model imposes a symmetric structure of wage changes for workers moving across firms. To see this, consider workers moving from firm j to firm k, like in Section 3.1. We showed there that under the exogenous mobility assumption their expected wage change should be $\psi_k - \psi_j$ (up to the year fixed effects). The AKM model assumes that workers moving from k to j should experience the reverse wage change, $\psi_j - \psi_k$. Second, the exogenous mobility assumption implies that the evolution of wages before they move should evolve in parallel regardless of the origin and destination firms.

To test these implications we follow Card et al. (2013) and study the evolution of wages of workers moving across low- and high-wage firms. More specifically, we consider the set of workers that move and classify their origin and destination firms in quartiles based on their co-workers' wages. We then look at the wage changes around the time of the move, from two years before to one year after. To prevent compositional changes over time we focus on movers that are observed during 4 consecutive years around the move, and we residualize the wages by year fixed effects to adjust for the strong macroeconomic cycle in Argentina.

We find evidence that the AKM model assumptions are approximately satisfied in our data. Figure 4 shows the evolution of wages for workers moving across firms in different quartiles, for the years 1997–2001, 2006–2010, and 2013–2017. To enhance visual clarity, we show the results for workers moving to and from the first and fourth quartiles only. The first observation is that the wage changes experienced by movers are proportional to their origin and destination quartiles: going from the first to the fourth quartile is associated with a wage increase that is similar in magnitude to the wage decrease experienced by workers moving in the opposite direction. The second observation is that the evolution of wages before the move is consistent with the exogenous mobility assumption: wages evolve in parallel before the move regardless of the origin and destination firms. Appendix Figure 6 compares the wage gains for workers moving to a higher quartile with the wage losses for workers in the opposite direction. The symmetry assumption implies that the wage changes should lie on the 45-degree line, which is approximately the case for all periods and across all quartiles. The only exception is the group of workers moving between the first and fourth quartiles, where we find slightly larger wage changes for upward movers relative to the decrease experienced by downward movers. While this is an interesting finding, we consider the deviations from symmetry to be small. We then proceed to estimate the AKM model and decompose the evolution of earnings inequality.

4.2 The AKM model and the decomposition of inequality

Table 2 shows the our estimates of the variance decomposition of log earnings on the largest connected set of firms for our 5 sub-periods, which suggest an increasing importance of firms. Consider the first period, 1995–1999, displayed in column (1). Out of the total variance of 0.548 the worker component accounts for 0.266 (48.5%), the firm component for 0.212 (38.8%), and the sorting component for 0.048 (8.8%). As expected, the variance of firm wage effects is smaller than what is suggested by the raw data decomposition in between- and within-firm components discussed in Section 2.3, but it is still substantial. While in absolute levels the variance of the firm component declined relative to 1995–1999, the importance of the firm component increased as a share of the total variance. The variance decomposition for the 2015–2019 period, displayed in column (5), shows that the firm component accounts for 0.208 of a total variance of 0.438, or 47.6%. This increase of 8.8 percentage points can be almost entirely explained by a decline of 8.1 percentage points in the importance of the worker component.

Table 2 also quantifies the contribution of the different components to the evolution of earnings inequality over time. Column (6) shows a substantial reduction in the variance of log wages of 0.132 (or 24.1 percentage points) between 1995–1999 and 2005–2009. Roughly two-thirds of this change is accounted for by the worker component, while the firm component accounts for the remaining third. The covariance between worker and firm effects also declined, but the contribution of this sorting component is much smaller. These results emphasize the importance of worker factors in the reduction of inequality in this period, which is consistent with the literature's focus on the returns to education and the upskilling of the labor force (e.g., Lustig et al. 2016; Acosta et al. 2019; Messina and Silva 2019). Column (7) of Table 2 shows that the increase in inequality between 2005–2009 and 2015–2019 is driven entirely by the firm component. While the variance of log wages increased by 0.022 (or 5.3 percentage points), the variance of the firm wage effects increased twice as much. If not for decline in the variance of other components the increase in inequality would have been even larger. We also observe that the variance of worker effects remained roughly constant and the sorting component declined slightly. Figure 5 visualizes the evolution of the main components of the variance decomposition, where the sharp decline in both the worker and firm components between 1995–1999 and 2005–2009 is evident, as well as the increase in the firm component between 2005–2009 and 2015–2019.

To sum up, the variance of firm wage effects declined strongly between 1995–1999 and 2005–2009, contributing to the reduction in inequality in the 2000s, and increased between 2005–2009 and 2015–2019, contributing to the increase in inequality in the 2010s. These results beg the question of what drives the firm component of earnings inequality, which we explore in the next section. Before that, we present several robustness checks for our results.

Corrected variance decomposition. Our conclusions are robust to corrections for limited mobility bias in the variance decomposition. Appendix Figure 7 shows the corrected variance decomposition, in levels and in shares, using the correction methods of Andrews et al. (2008) and KSS. Applying these corrections significantly reduces the worker component, slightly reduces the firm component, and greatly increases the sorting component. We see, however, very similar evolutions of the components over time.

Appendix Table 1 replicates Table 2 using the leave-out-based correction of KSS. Column (6) displays our main results for the change in inequality between 1995–1999 and 2005–2009. Workers account for 60.3% and firms for 30.9% of the reduction in inequality, comparable to our baseline results (65.6% and 37.6%, respectively). As a result, the share explained by sorting is larger in the corrected decomposition (13.9% vs. 4.8% in our baseline), though its contribution remains small. Column (7) speaks to the increase in earnings inequality between 2005–2009 and 2015–2019. We find a very similar result to our baseline, with the change in the firm component being about twice as large as the change in earnings inequality (219.0% vs. 207.0% in our baseline).

Interactions. One concern with the AKM model is that it neglects the possibility of interactions between worker and firm fixed effects. To address this concern we follow Card et al. (2013) and compute the mean AKM residual in each cell of a 10 by 10 grid defined by deciles of worker and firm effects. The absence of interactions would imply that the residuals should be approximately zero in every cell. Appendix Figure 8 shows the mean residuals for the 5 sub-periods. In all cases the mean residuals are within 1.1%, and they are usually much smaller, suggesting that the AKM model is a good approximation to the data. Similar to other papers in this literature (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 fixed effects in 1995–1999 and 2000–2004, but turn negative in the subsequent periods. This may be related to the evolution of the minimum wage, which increased substantially after 2005, as discussed in Section 2.1.

Women. While our estimates for women align with those for men, they appear to suffer greater limited mobility bias. Appendix Figure 9 reveals similar trends in the variance decomposition to our baseline: a decline in worker and firm effect variances from 1995-1999 to 2005-2009 and an increase in the firm component between 2005–2009 and 2015–2019. However, we find a negative sorting component in all periods, which is mitigated by the variance corrections but remains slightly negative. Appendix Table 2 replicates the sample statistics in Table 1 for women. On average, the number of worker-years in the women connected set (Panel B) is 62.8% smaller than for men, and the share of workers with more than one firm is 17.2% smaller. Due to the significant sample size and mobility differences, we do not focus on the results for women in our primary analysis.

Geographic variation. TBD.

Varying minimum earnings cutoff. Appendix Figure 10 presents the variance decomposition for several minimum earnings cutoffs used to define the sample. Increasing the cutoff lowers the variance of log earnings, but the overall trend in inequality is very similar across cutoffs. This level reduction is entirely attributable to the firm component, whereas the worker and sorting components are largely unaffected. Consequently, the relative importance of the firm component decreases, though its time evolution mirrors our baseline results. This suggests that low-wage firms are an important driver of the firm component. Our core findings remain robust: the worker component explains most of the inequality decline between 1995–1999 and 2005–2009, while the firm component increased between 2005–2009 and 2015–2019.

Time-varying 5-year window. Appendix Figure 11 replicates our estimates using a 5-year rolling window, starting at every year from 1995 through 2015. The results are very similar to our baseline, suggesting that our results are not driven by the choice of sub-periods.

4.3 Comparison with the literature

This section compares our findings on the variance decomposition of earnings inequality in Argentina with existing literature, focusing both in the relative and absolute contribution of firm wage effects.

Our analysis reveals that the contribution of firms to earnings inequality in Argentina is substantial, exceeding estimates reported for several other countries. The left panel of Appendix Figure 13 visually presents a comparison with selected studies. The share of log earnings explained by firms in Argentina (2015–2019) is larger than estimates for other developing economies like Brazil (Alvarez et al. 2018), Mexico (Pérez Pérez and Nuño-Ledesma 2024), and South Africa (Bassier 2023), as well as advanced economies such as West Germany (Card et al. 2013) and the USA (Song et al. 2019).

However, as argued by Kline (2024, pp. 6), comparing variance levels is more appropriate than shares due to potential differences in "intrinsic noise levels" across datasets. When comparing levels, Argentina's variance of firm wage effects is still larger than advanced economies but is more comparable to other developing countries. In particular, the variance of the firm wage effects is similar to that of Mexico (Pérez Pérez and Nuño-Ledesma 2024) and smaller to that of South Africa (Bassier 2023).

5 Drivers of the components of firm inequality

TBD.

6 Conclusions

TBD.

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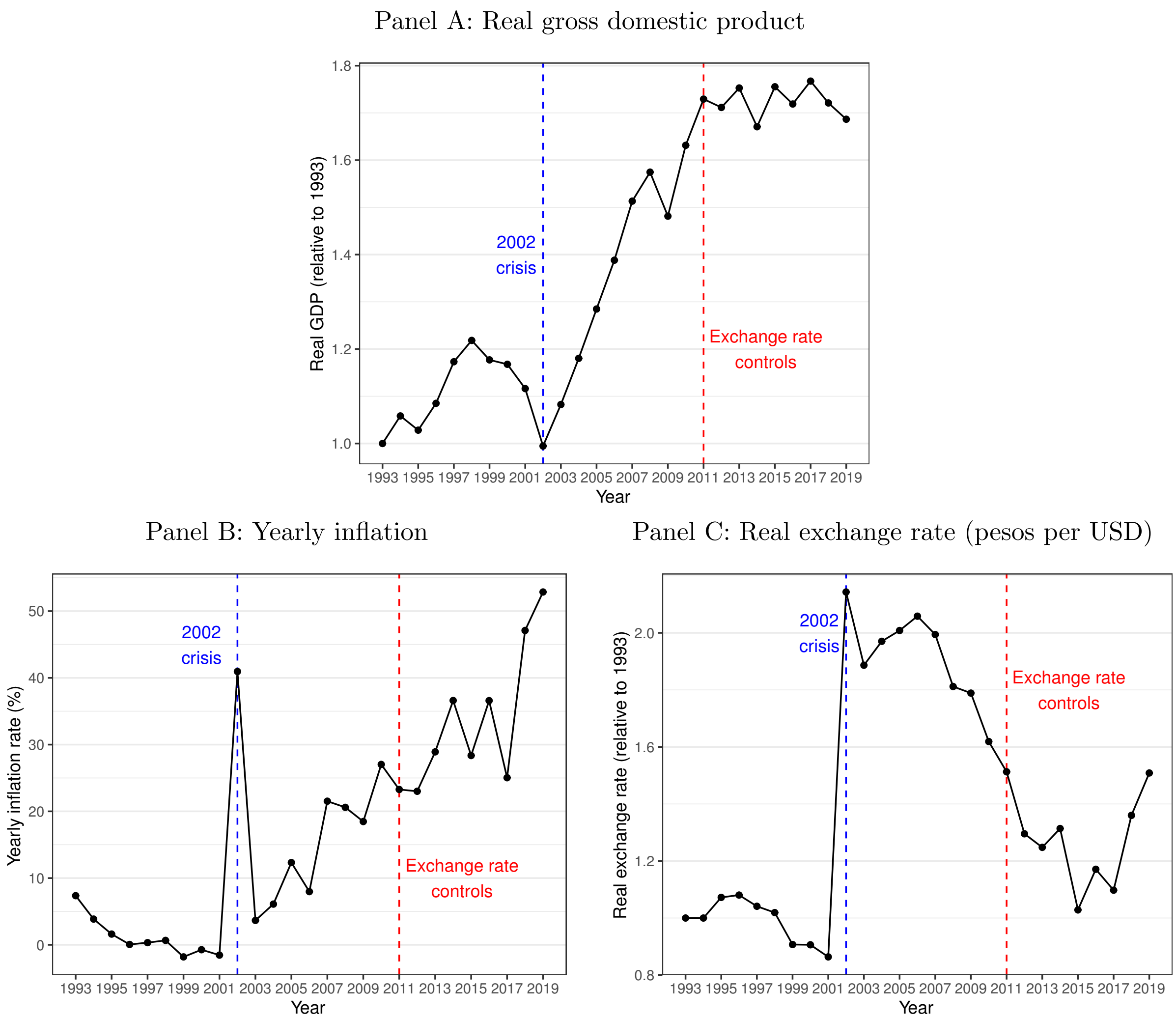
Figures and Tables

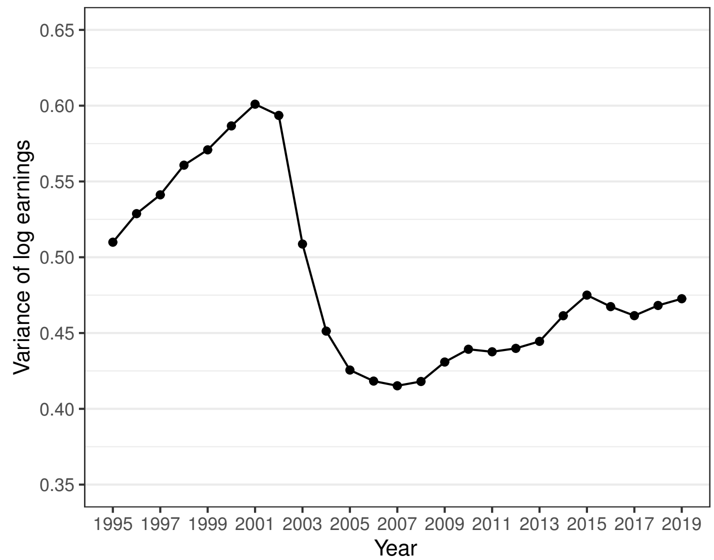
Figure 1: Macroeconomic indicators for Argentina, 1993-2019



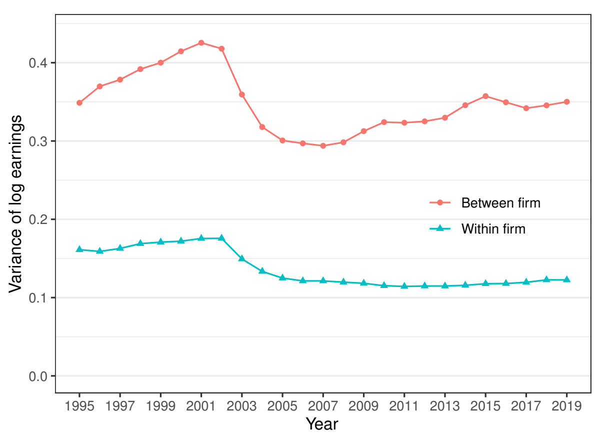
Notes: This figures shows the evolution of key macroeconomic indicators for Argentina between 1993 and 2019. Panel A shows the evolution of the real Gross Domestic Product (GDP). Panel B shows the yearly inflation rate, constructed as the percent change in the Consumer Price Index (CPI) between December of the previous year and December of the current year. Panel C shows the evolution of the real exchange rate. Data are from the National Institute of Statistics and Censuses (INDEC) and the National Accounts Office (DNCN). The inflation rate was constructed using alternative measures of the CPI index between 2007 and 2015 as the official data were reportedly manipulated.

Figure 2: Variance of log earnings in the formal labor market, prime-aged men

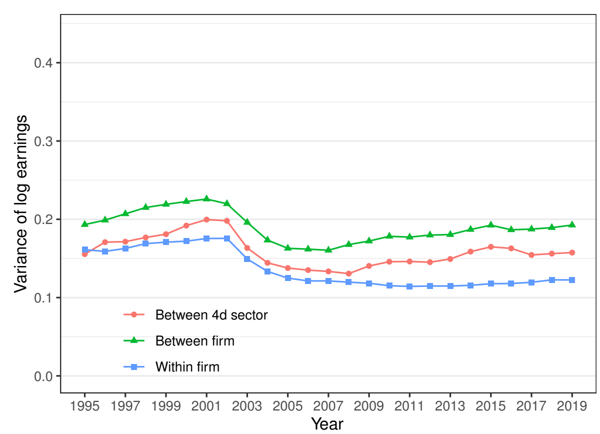
Panel A: Overall variance



Panel B: Between- and within-firm components



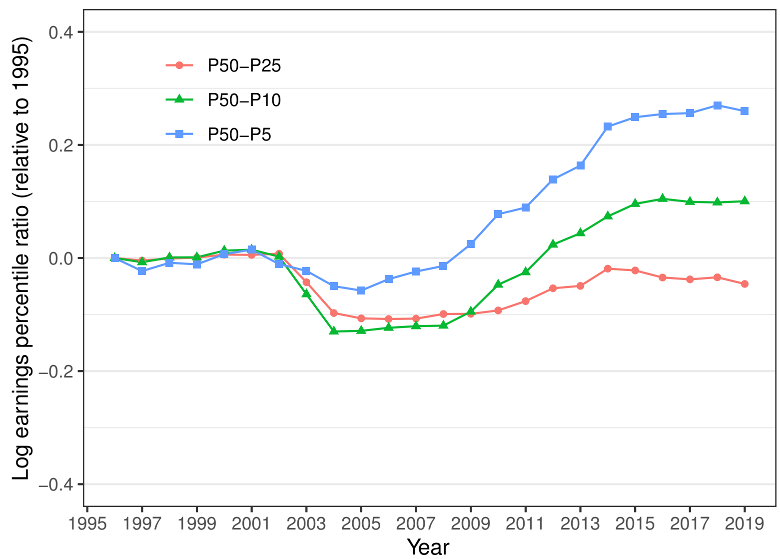
Panel C: Between-industry, within-industry between-firm, and within-firm components



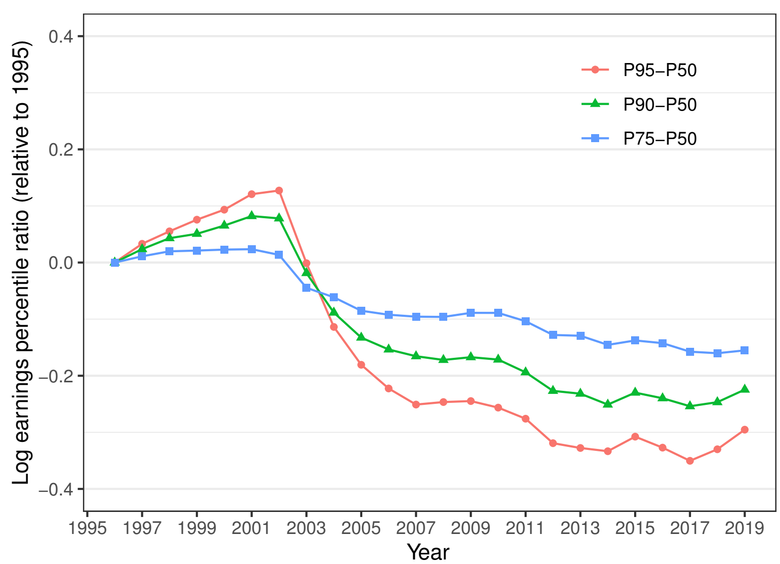
Notes: Data are from Argentina's social security system (SIPA) for individuals aged 20 to 55. This figure shows the evolution of inequality, defined as the variance of log earnings, between 1995 and 2019, for prime-aged men. Panel (a) shows the overall variance of log earnings, while Panels (b) and (c) show the decomposition of the variance into between- and within-firm components, and between-industry, within-industry between-firm, and within-firm components, respectively. Real yearly earnings are computed as the mean of monthly total real earnings. We exclude earnings above the 99.9th percentile of the distribution, and below $75 USD per month, and worker-firm-year cells that correspond to jobs shorter than 6 months and those labeled as internships.

Figure 3: Log percentile ratios of the earnings distribution in Argentina relative to 1995, prime-aged men

Panel A: Lower-tail inequality



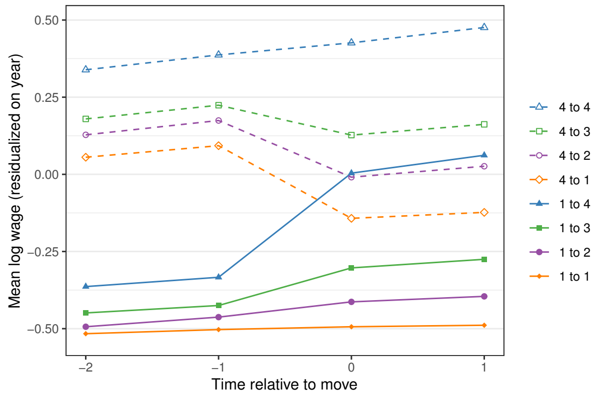
Panel B: Upper-tail inequality



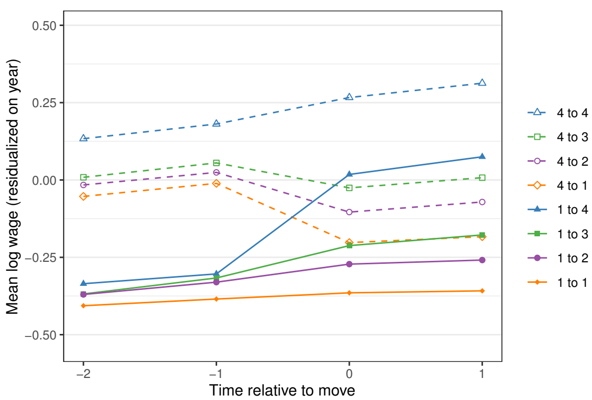
Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The figure shows the evolution of inequality as measured by the ratio of percentiles of the real earnings distribution. Real yearly earnings are computed as the mean of monthly total real earnings. We exclude earnings above the 99.9th percentile of the distribution, and below $75 USD per month, and worker-firm-year cells that correspond to jobs shorter than 6 months and those labeled as internships.

Figure 4: Evolution of wages for workers moving across firms, prime-aged men

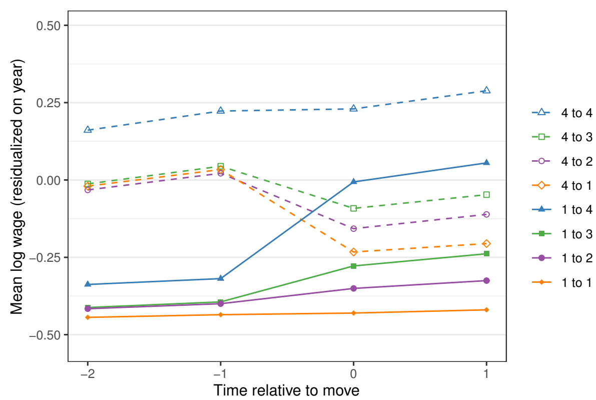
Panel A: 1997–2001



Panel B: 2006–2010

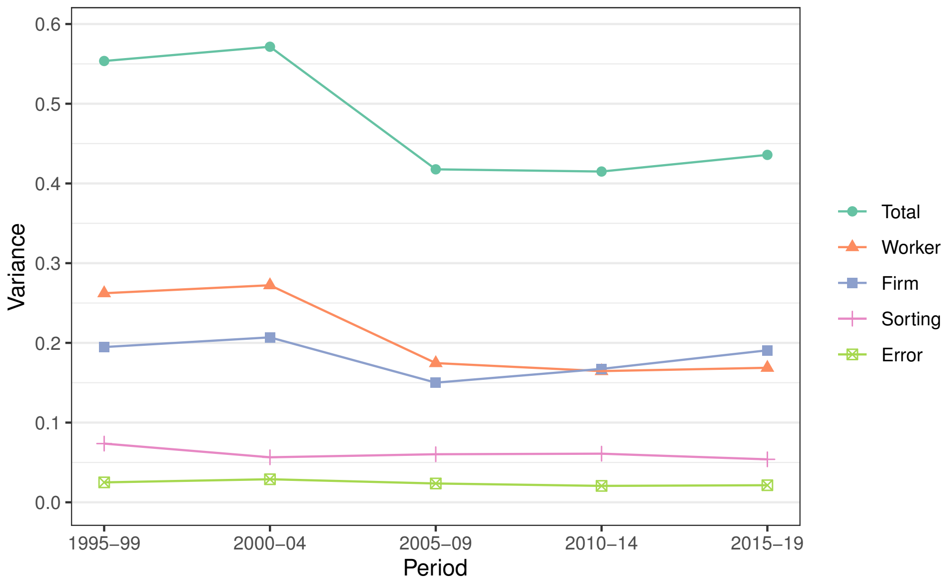


Panel C: 2013–2017



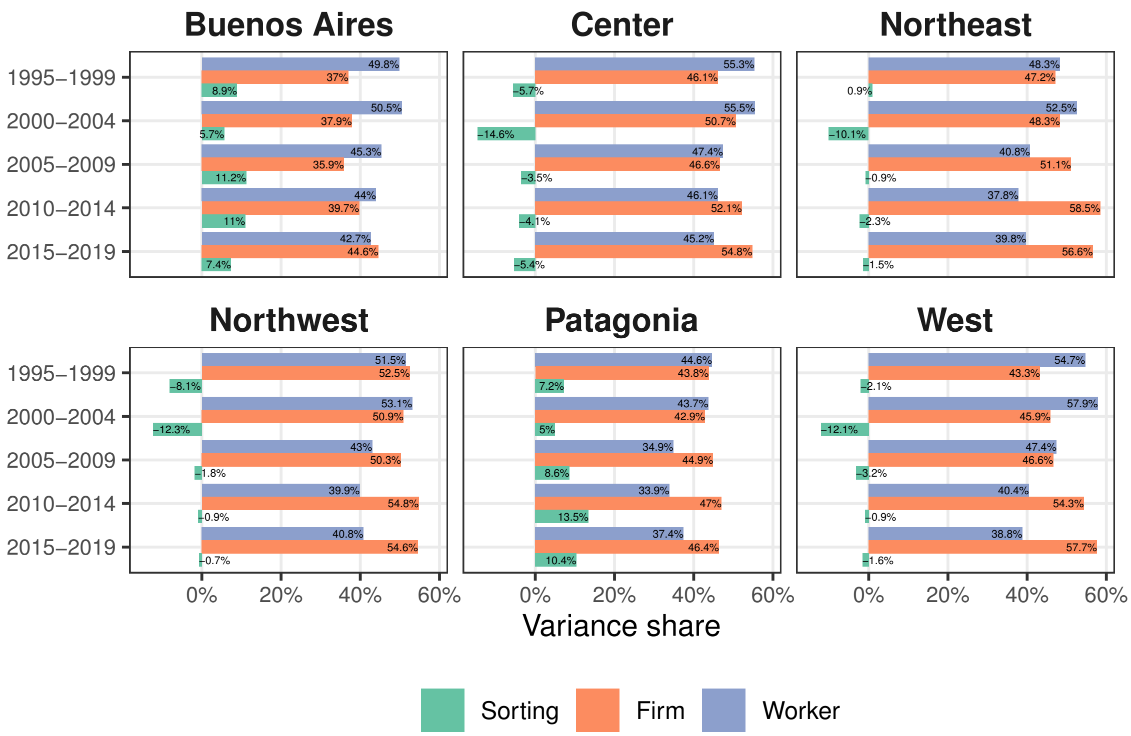
Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The figure shows the evolution of mean log wages (residualized on year dummies) for workers who move across firms around the time of move, by quartiles of co-worker's wages in the origin and destination firms. Only movers that are observed during 4 consecutive years around the move are included.

Figure 5: Variance decomposition of log earnings according to AKM model, primed-aged men



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 **?**. Panel A replicates the baseline estimates from Table 2.

Figure 6: AKM-based variance decomposition by region



Notes: The figure shows the AKM variance decomposition by geographical region. Buenos Aires includes both the city and the province, which are administratively separated in Argentina. The rest of the regions are defined according to general standards used in Argentina, both by official authorities and academic research. Center includes the provinces of Entre Ríos, Santa Fe, Córdoba, and La Pampa. Northeast includes Misiones, Corrientes, Chaco, and Formosa. Northwest includes Jujuy, Salta, Catamarca, Tucumán, and Santiago del Estero. West includes Mendoza, San Luis, La Rioja, and San Juan. Patagonia includes Río Negro, Neuquén, Chubut, Santa Cruz and Tierra del Fuego.

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

Period	Millions of: Worker years	Millions of: Workers	Millions of: Firms	Log earnings: Mean	Log earnings: SD	Age: Mean	Age: SD	Mean n. firms	Share movers
Panel A: Entire sample									
1995–1999	10.97	3.51	0.44	7.73	0.73	35.64	9.56	1.273	0.232
2000–2004	10.38	3.31	0.42	7.68	0.74	35.99	9.42	1.236	0.205
2005–2009	14.10	4.36	0.50	8.00	0.65	35.51	9.38	1.292	0.245
2010–2014	15.99	4.74	0.52	8.19	0.66	35.91	9.21	1.273	0.228
2015–2019	16.20	4.72	0.50	8.16	0.68	36.83	9.06	1.255	0.213
Panel B: Connected set									
1995–1999	8.87	2.36	0.21	7.82	0.74	35.73	9.39	1.391	0.330
2000–2004	8.20	2.13	0.18	7.78	0.75	36.01	9.24	1.349	0.301
2005–2009	12.00	3.13	0.26	8.06	0.65	35.50	9.20	1.396	0.331
2010–2014	13.67	3.44	0.27	8.25	0.65	35.90	9.02	1.366	0.305
2015–2019	13.71	3.42	0.23	8.23	0.66	36.79	8.87	1.343	0.285
Panel C: Leave-out connected set									
1995–1999	8.08	2.15	0.11	7.87	0.74	35.74	9.38	1.378	0.321
2000–2004	7.46	1.94	0.09	7.82	0.76	35.99	9.23	1.335	0.290
2005–2009	11.18	2.92	0.15	8.09	0.65	35.45	9.19	1.383	0.321
2010–2014	12.75	3.21	0.15	8.28	0.64	35.85	9.01	1.354	0.295
2015–2019	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 largest set of firms that remains connected after we leave out any worker–firm pair. 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 $75 USD 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 latest two columns show the average number of firms per worker and the share of workers with more than one firm in the period.

Table 2: Variance decomposition of AKM estimates by period, connected set

	1995–1999 (1)		2000–2004 (2)		2005–2009 (3)		2010–2014 (4)		2015–2019 (5)		Change 1995–2009 (6)		Change 2005–2019 (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 AKM. The models are estimated separately for the periods 1995–1999, 2000–2004, 2005–2009, 2010–2014, and 2015–2019, 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 1995–1999 and 2005–2009, and column (7) shows the change between 2005–2009 and 2015–2019, 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 3: Regressions of firm effects on productivity and size, 2010–2012 ENDEI sample

	Firm wage effect			Firm wage effect			Firm wage effect		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log VA per worker	0.1446		0.1028	0.1317		0.0954	0.0984		0.1190
	(0.0166)		(0.0062)	(0.0211)		(0.0137)	(0.0158)		(0.0092)
Log firm size		0.1131	0.1030		0.1089	0.1060		0.1033	0.1946
		(0.0088)	(0.0233)		(0.0093)	(0.0084)		(0.0080)	(0.0139)
Log VA pw * Log firm size			-0.0001			-0.0006			-0.0081
			(0.0015)			(0.0006)			(0.0006)
Province FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
2-digit sector 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: Firm effects are obtained from an AKM model estimated using Argentina's social security system (SIPA) data for men aged 20 to 55 in 2010–2014. Value added per worker is calculated from self-reported data collected by the *Encuesta Nacional de Dinámica de Empleo e Innovación* (ENDEI) for the 2010–2012 period. The values for those three years are averaged to obtain one value for the entire period. Data below the 1th percentile and above the 99th percentile are trimmed from the log value added distribution to prevent extreme values from driving results.

Table 4: Contribution of industry wage differentials to earnings inequality, connected set

	1995–1999 (1)	2000–2004 (2)	2005–2009 (3)	2010–2014 (4)	2015–2019 (5)	Change 1995–2009 (6)		Change 2005–2019 (7)	
Baseline variance of log earnings	0.548	0.564	0.416	0.417	0.438	-0.132	(100.0)	0.022	(100.0)
Baseline variance of firm effects	0.212	0.225	0.163	0.184	0.208	-0.050	(37.6)	0.046	(207.0)
Variance of industry wage differentials (between)	0.075	0.083	0.060	0.066	0.078	-0.015	(11.2)	0.018	(83.4)
Variance of firm effects within industries	0.138	0.142	0.103	0.118	0.130	-0.035	(26.4)	0.027	(123.6)
Share of variance in firm effects explained by industry	0.352	0.369	0.368	0.360	0.376				
Counterfactual I: 1995–1999 industry wage diff.									
Var. log earnings	0.548	0.566	0.442			-0.106	(80.1)		
Var. firm effects	0.212	0.222	0.178			-0.034	(25.8)		
Counterfactual II: 2005–2009 industry wage diff.									
Var. log earnings			0.416	0.412	0.418			0.002	(9.6)
Var. firm effects			0.163	0.178	0.191			0.028	(127.9)

Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The table shows the role of industry wage differentials in the evolution of firm wage effects and earnings inequality. The top panel shows the variance of different components of log earnings, with the first two rows replicating our baseline results in Table 2, and the next two rows showing the variance of industry wage differentials, defined as the mean firm effect within each industry, and the variance of firm effects net of industry wage differentials. The second panel the variance of firm effects explained by industry. The third panel shows the variance of log earnings and firm effects in two counterfactual scenarios. The first counterfactual keeps the industry wage differentials fixed at the 1995–1999 level, whereas the second counterfactual keeps the industry wage differentials fixed at the 2005–2009 level. Column (6) shows the change in the variance of each component between 1995–1999 and 2005–2009, and column (7) shows the change between 2005–2009 and 2015–2019, both in levels and as a percentage of the change in the variance of log earnings.

Table 5: Sectoral productivity and inequality decomposition

	Mean firm effect		Var firm effect		Mean firm log size	
	(1)	(2)	(3)	(4)	(5)	(6)
Log productivity per worker						
× Period = 1	0.2007	0.0957	-0.0234	-0.0354	0.5620	0.0178
	(0.0404)	(0.0787)	(0.0069)	(0.0221)	(0.1961)	(0.0980)
× Period = 2	0.2159	0.1106	-0.0471	-0.0573	0.5859	0.0681
	(0.0436)	(0.0817)	(0.0113)	(0.0266)	(0.2005)	(0.1068)
× Period = 3	0.2179	0.1283	-0.0468	-0.0559	0.5032	0.0623
	(0.0464)	(0.0810)	(0.0139)	(0.0273)	(0.2010)	(0.1090)
Period	Yes	Yes	Yes	Yes	Yes	Yes
Period by Sector	No	Yes	No	Yes	No	Yes
Observations	102	102	102	102	102	102
Adjusted R2	0.4329	0.9749	0.4318	0.9060	0.2516	0.9950

Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55 and from Centro de Estudios para la Producción (CEP XXI). The table shows the results of regressing the mean of AKM firm effects, the variance of AKM firm effects, and the mean of log firm size on log value added per worker, including period and sector fixed effects. The models are estimated separately for the periods 2005–2009, 2010–2014, and 2015–2019, the only ones where productivity data are available. Values in parentheses are standard errors clustered at the industry level.

Appendix for
"Firms and the Evolution of Earnings Inequality in Argentina's Volatile Economy"
(not for publication)

A Data appendix

TBD.

B Additional Tables and Figures

Appendix Table 1: Variance decomposition of AKM estimates by period, leave-out-match set

	1995–1999 (1)		2000–2004 (2)		2005–2009 (3)		2010–2014 (4)		2015–2019 (5)		Change 1995–2009 (6)		Change 2005–2019 (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 KSS. The models are estimated separately for the periods 1995–1999, 2000–2004, 2005–2009, 2010–2014, and 2015–2019, 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 1995–1999 and 2005–2009, and column (7) shows the change between 2005–2009 and 2015–2019. 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 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									
1995–1999	4.27	1.44	0.26	7.56	0.65	34.55	9.66	1.201	0.177
2000–2004	4.37	1.42	0.24	7.54	0.67	35.07	9.42	1.184	0.164
2005–2009	5.63	1.85	0.30	7.83	0.60	34.88	9.24	1.214	0.185
2010–2014	6.69	2.11	0.33	8.01	0.61	35.48	9.04	1.198	0.172
2015–2019	6.95	2.12	0.33	8.02	0.63	36.72	8.87	1.183	0.160
Panel B: Connected set									
1995–1999	3.02	0.83	0.08	7.67	0.67	34.53	9.48	1.315	0.274
2000–2004	3.14	0.81	0.07	7.64	0.69	34.96	9.22	1.290	0.256
2005–2009	4.38	1.17	0.11	7.90	0.60	34.80	9.02	1.319	0.275
2010–2014	5.23	1.34	0.12	8.09	0.60	35.42	8.83	1.291	0.251
2015–2019	5.36	1.36	0.10	8.11	0.62	36.63	8.66	1.266	0.231
Panel C: Leave-out connected set									
1995–1999	2.65	0.73	0.04	7.71	0.69	34.57	9.48	1.291	0.255
2000–2004	2.77	0.71	0.03	7.67	0.70	34.93	9.21	1.272	0.240
2005–2009	3.95	1.06	0.05	7.92	0.61	34.77	9.00	1.297	0.257
2010–2014	4.73	1.22	0.06	8.11	0.61	35.40	8.81	1.269	0.233
2015–2019	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 largest set of firms that remains connected after we leave out any worker–firm pair. 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 $75 USD 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 latest two columns show the average number of firms per worker and the share of workers with more than one firm in the period.

Appendix Table 3: Industry wage differentials across broad industries, relative to restaurant subsector

Code	Industry description	Industry wage differential			Share of worker-years		
		1995-99	2005-09	2015-09	1995-99	2005-09	2015-09
A	Agriculture, hunting and forestry	-0.091	-0.083	0.015	0.055	0.061	0.052
B	Fishing	0.664	0.639	0.510	0.003	0.004	0.003
C	Mining and quarrying	0.729	0.909	1.008	0.016	0.020	0.024
D	Manufacturing	0.341	0.363	0.493	0.322	0.283	0.264
E	Electricity, gas and water supply	0.667	0.605	0.755	0.017	0.013	0.017
F	Construction	-0.029	0.132	0.087	0.074	0.095	0.103
G	Wholesale and retail trade	0.200	0.227	0.426	0.144	0.158	0.163
H	Hotels and restaurants	0.072	0.091	0.140	0.024	0.025	0.023
I	Transport, storage and communications	0.479	0.468	0.574	0.122	0.118	0.128
J	Financial intermediation	0.604	0.523	0.754	0.036	0.024	0.022
K	Real estate and business activities	0.124	0.166	0.320	0.103	0.122	0.116
M	Education	-0.483	-0.407	-0.356	0.016	0.018	0.020
N	Health and social work	0.292	0.261	0.420	0.020	0.017	0.022
O	Other community and social service activities	0.234	0.269	0.416	0.048	0.042	0.042

Notes: The table shows the industry wage differentials aggregated at the division level for three periods, 1995-1999, 2005-2009, and 2015-2019. Divisions are defined according to ISIC Revision 3.1.

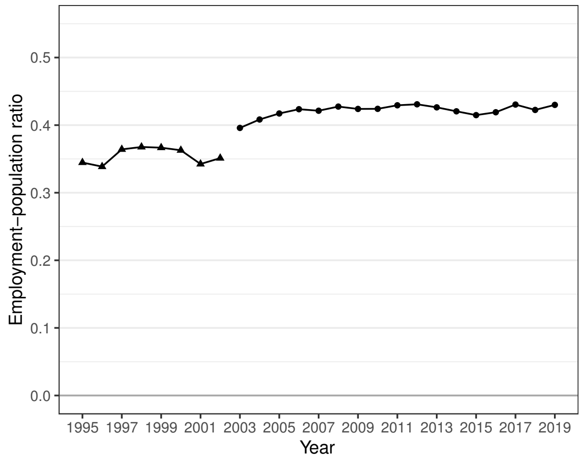
Appendix Table 4: Top and Bottom 10 Industry Wage Differentials, 2015–2019

Rank	Code	Industry	Mean log earnings	Industry premium	Mean Worker Effect	Percent of workforce
		Across industry mean	0.398	0.000	8.234	
		Across industry SD	0.280	0.148	0.391	
1	1320	Mining of non-ferrous metal ores	1.159	0.164	9.159	0.32
2	3410	Manufacture of motor vehicles	1.138	0.056	9.030	0.87
3	1120	Service activities incidental to oil and gas	1.100	0.387	9.322	1.35
4	1110	Crude Oil and Gas Extraction	1.034	0.580	9.447	0.46
5	6030	Transport via pipelines	0.992	0.403	9.229	0.05
6	4011	Production of electricity	0.959	0.471	9.266	0.29
7	4011	Services of banking financial institutions	0.948	0.286	9.069	1.08
8	2330	Processing of nuclear fuel	0.944	0.084	8.862	0.02
9	2320	Manufacture of refined petroleum products	0.926	0.267	9.032	0.16
10	2230	Reproduction of recorded media	0.918	0.320	9.073	0.00
291	0112	Vegetable Growing and Nursery	-0.248	-0.264	7.323	0.26
292	4549	Building Completion	-0.253	-0.267	7.315	0.01
293	0150	Hunting and Game Services	-0.288	0.102	7.650	0.00
294	4542	Finishing and covering of walls and floors	-0.315	-0.277	7.244	0.03
295	0502	Fish farms and other aquatic products	-0.318	-0.100	7.422	0.00
296	0503	Fishing services	-0.324	0.085	7.595	0.00
297	8000	Education	-0.356	0.144	7.623	1.96
298	4511	Building demolition	-0.362	-0.203	7.270	0.01
299	4544	Painting and decorating work	-0.422	-0.236	7.178	0.05
300	5242	Retail sale of used books	-0.431	-0.011	7.406	0.00

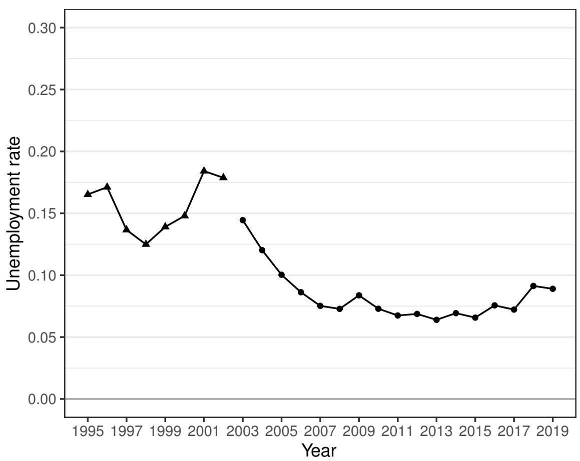
Notes: XXXXX. Names were shortened for display purposes.

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

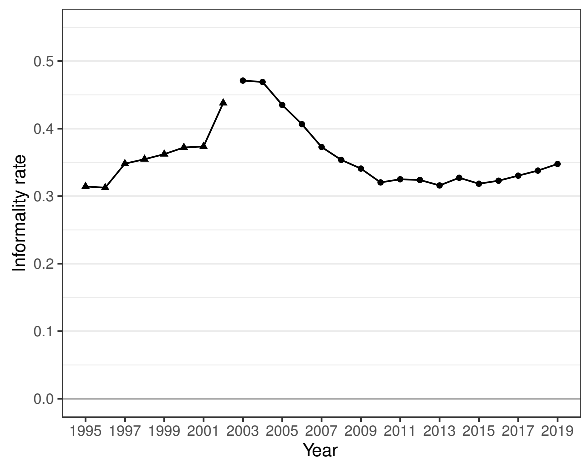
Panel A: Employment to population ratio



Panel B: Unemployment rate

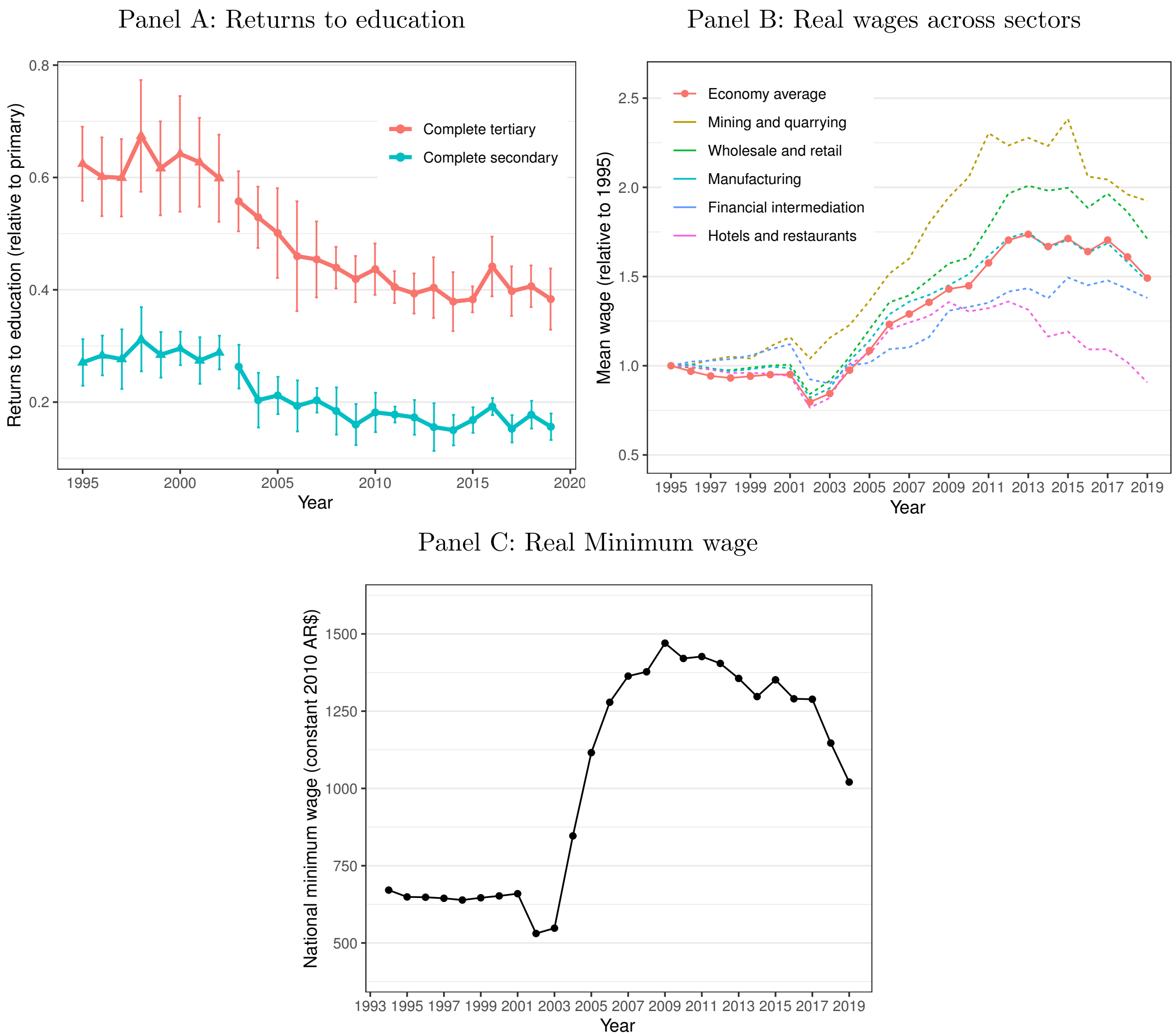


Panel C: Informality rate



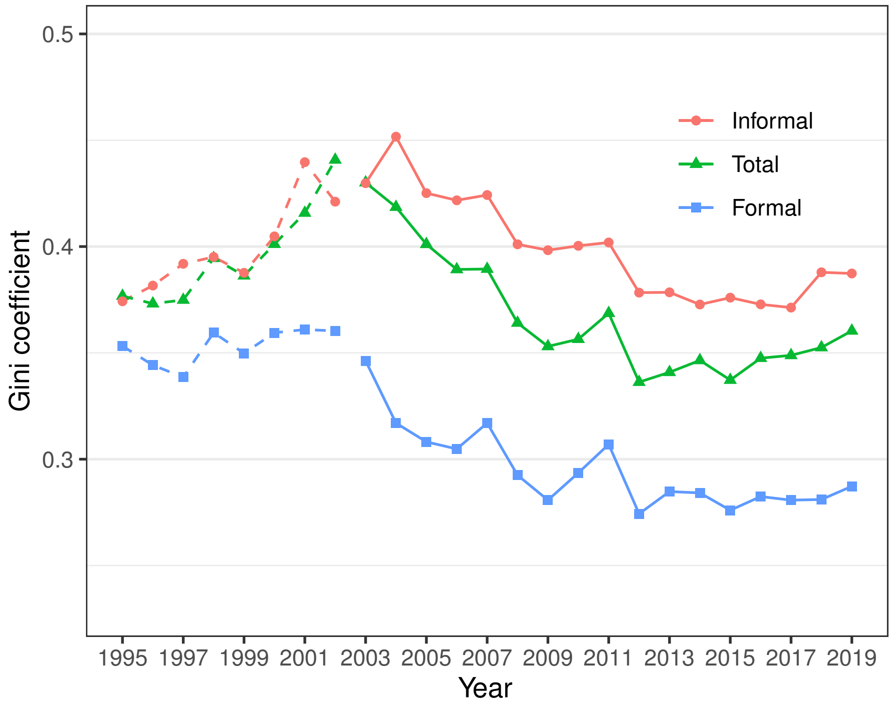
Notes: This figure shows the evolution of key labor market indicators for Argentina between 1995 and 2019. Panel A shows the employment to population ratio, Panel B the unemployment rate (as a percentage of the economically active population), and Panel C the informality rate among salaried workers (as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

Appendix Figure 2: Correlates of wage inequality in Argentina, 1993-2019



Notes: This figure shows the evolution of correlates of wage inequality in Argentina between 1993 and 2019. Panel A shows the returns to education, Panel B the real minimum wage, and Panel C the evolution of real wages across a few selected sectors. The returns to education are 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 (less than 12 years of education), "Complete secondary" corresponds to complete secondary and incomplete tertiary education (typically 12 to 18 years of education), "Complete tertiary" corresponds to complete tertiary education (typically more than 18 years of education). 95% confidence intervals are computed using robust standard errors clustered at the region level. Data are from the Permanent Household Survey (EPH) of the National Institute of Statistics and Censuses (INDEC). The format of the EPH survey changed in 2003, which is indicated by different shape markers in the graph. The nominal minimum wage and the average wage across sectors are obtained from the Ministry of Labor, Employment, and Social Security, and was adjusted by the CPI to obtain real values.

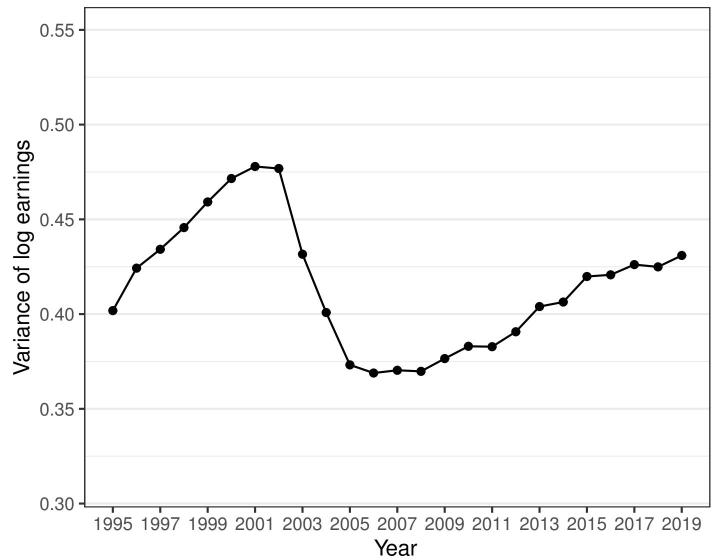
Appendix Figure 3: Gini coefficient of earnings between 1995 and 2019, household survey data



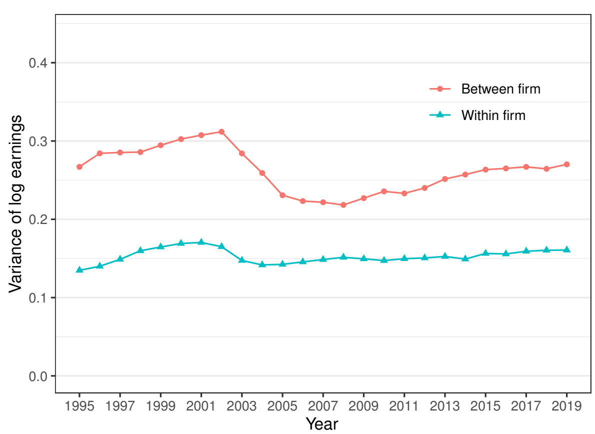
Notes: Data are from the Permanent Household Survey (EPH) for individuals aged 20 to 55. This figure shows the evolution of the Gini coefficient of real earnings in Argentina between 1995 and 2019, separately for formal, informal, and total workers. We include earnings in the primary job of the worker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

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

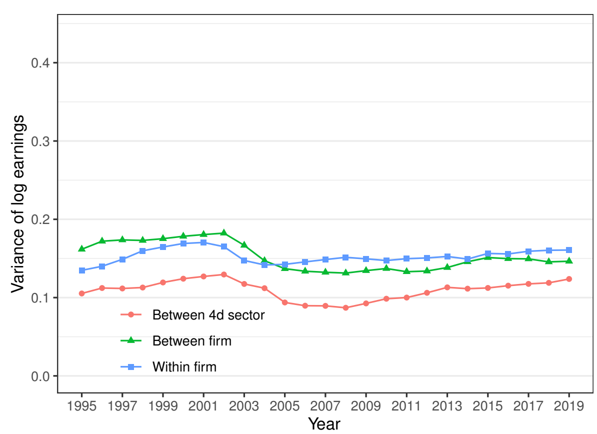
Panel A: Overall variance



Panel B: Between- and within-firm components



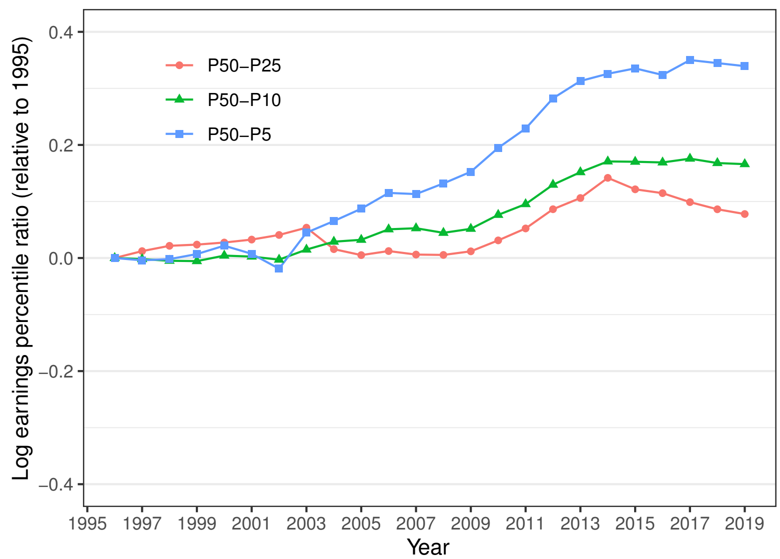
Panel C: Between-industry, within-industry between-firm, and within-firm components



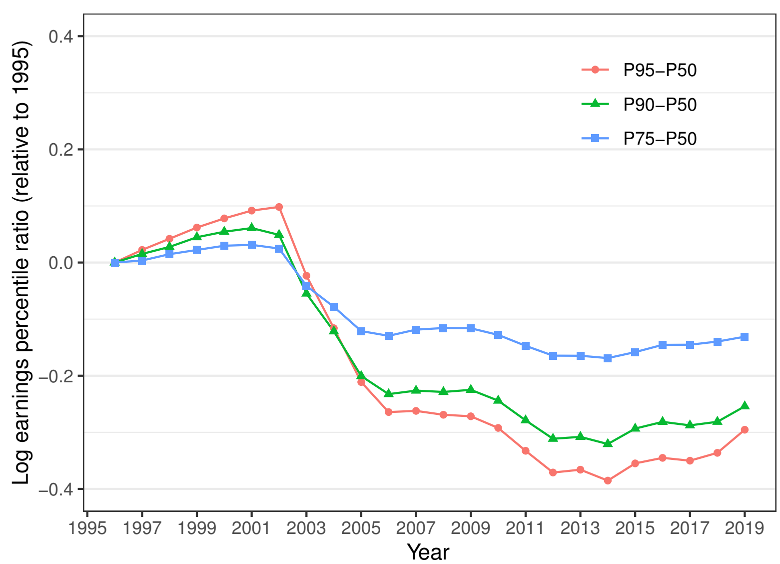
Notes: Data are from Argentina's social security system (SIPA) for individuals aged 20 to 55. This figure shows the evolution of inequality, defined as the variance of log earnings, between 1995 and 2019, for prime-aged women. Panel (a) shows the overall variance of log earnings, while Panels (b) and (c) show the decomposition of the variance into between- and within-firm components, and between-industry, within-industry between-firm, and within-firm components, respectively. Real yearly earnings are computed as the mean of monthly total real earnings. We exclude earnings above the 99.9th percentile of the distribution, and below $75 USD per month, and worker-firm-year cells that correspond to jobs shorter than 6 months and those labeled as internships.

Appendix Figure 5: Log percentile ratios of the earnings distribution in Argentina, normalized to 1995 for women

Panel A: Lower-tail inequality

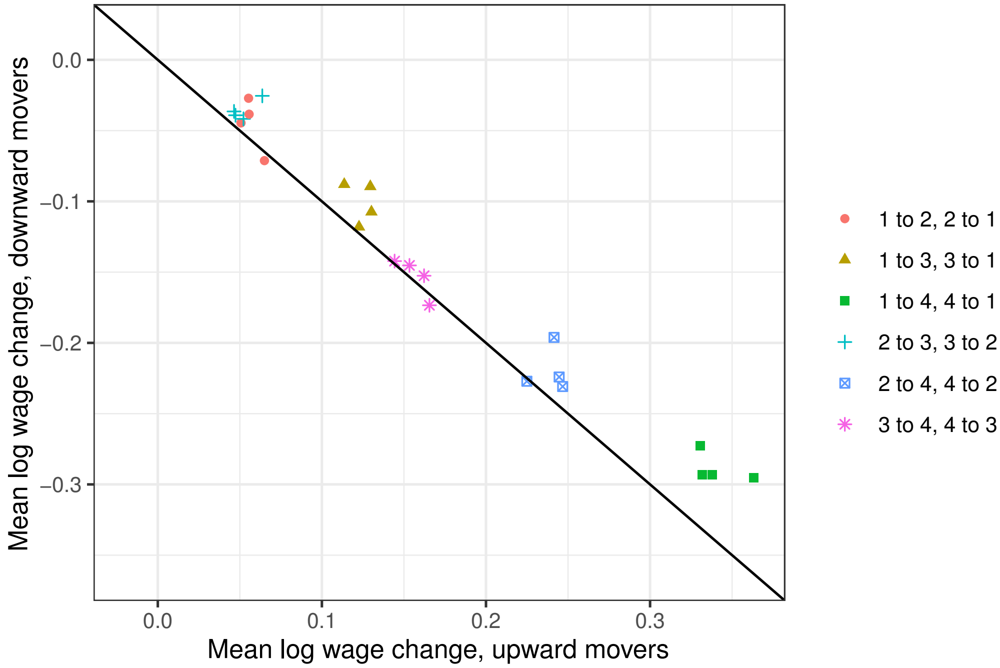


Panel B: Upper-tail inequality



Notes: Data are from Argentina's social security system (SIPA) for women aged 20 to 55. The figure shows the evolution of inequality as measured by the ratio of percentiles of the real earnings distribution. Real yearly earnings are computed as the mean of monthly total real earnings. We exclude earnings above the 99.9th percentile of the distribution, and below $75 USD per month, and worker-firm-year cells that correspond to jobs shorter than 6 months and those labeled as internships.

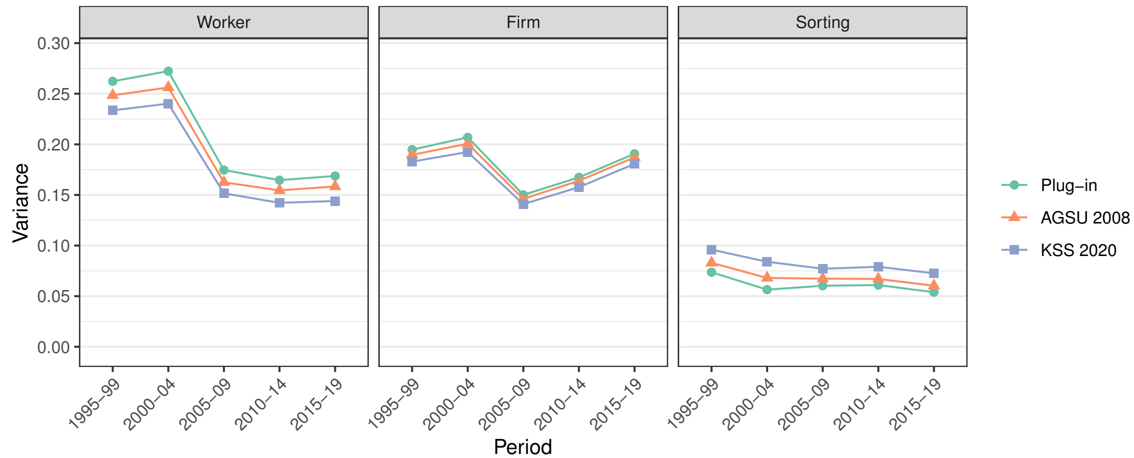
Appendix Figure 6: Evolution of wages for workers moving across firms, prime-aged men



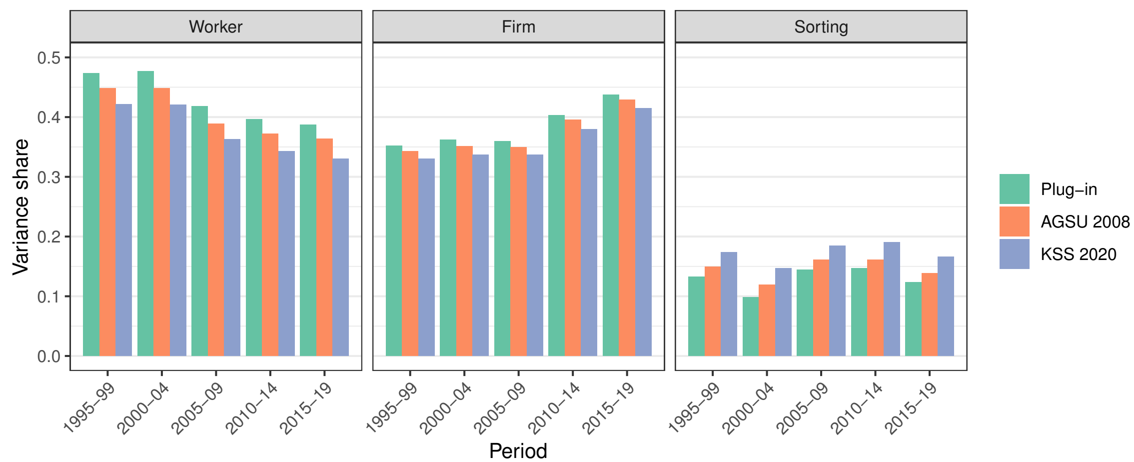
Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. Each point indicates the mean log wage change of workers who move from a firm located in a given wage quartile to another firm located in another wage quartile and for those who move in the opposite direction (in both cases firms are classified in quartiles based on co-workers' wages). The black line, representing an inverted 45-degree line, is shown for reference.

Appendix Figure 7: Corrected variance decomposition of AKM estimates on leave-out-match connected set, prime-aged men

Panel A: Variance levels



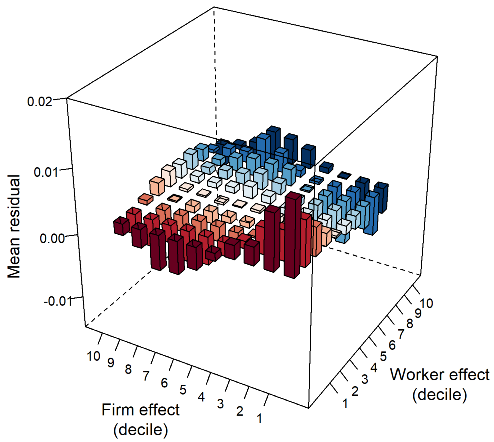
Panel B: Variance shares



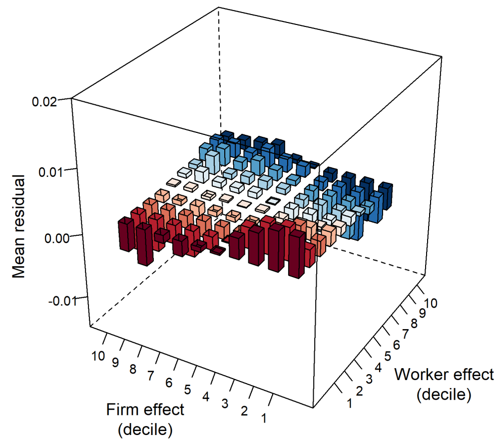
Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The figure shows the contribution of each component of the AKM decomposition to the variance of log earnings, correcting the estimates of the variance terms, on the leave-out-match largest connected set of firms. "Plug-in" refers to the computation of the variance components directly using the AKM estimates. "AGSU 2008" refers to the variance decomposition proposed by Andrews et al. (2008), which assumes that the error term is homoskedastic. "KSS 2020" refers to the variance decomposition proposed by Kline et al. (2020), which allows for heteroskedasticity in the error term.

Appendix Figure 8: AKM residuals across deciles of worker and firm fixed effects, prime-aged men

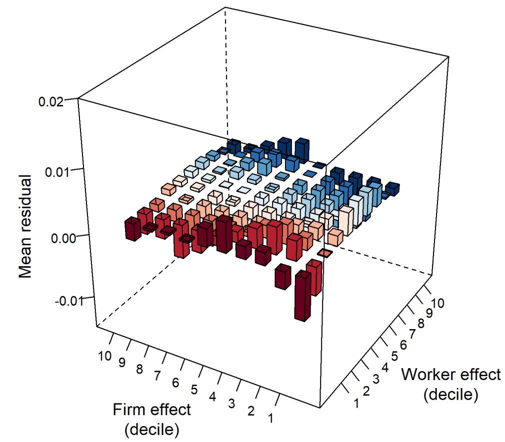
Panel A: 1995–1999



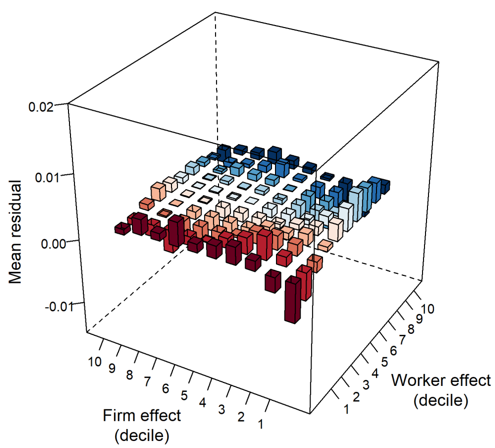
Panel B: 2000–2004



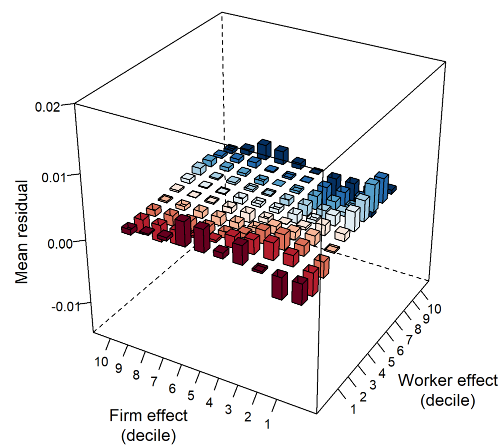
Panel C: 2005–2009



Panel D: 2010–2014



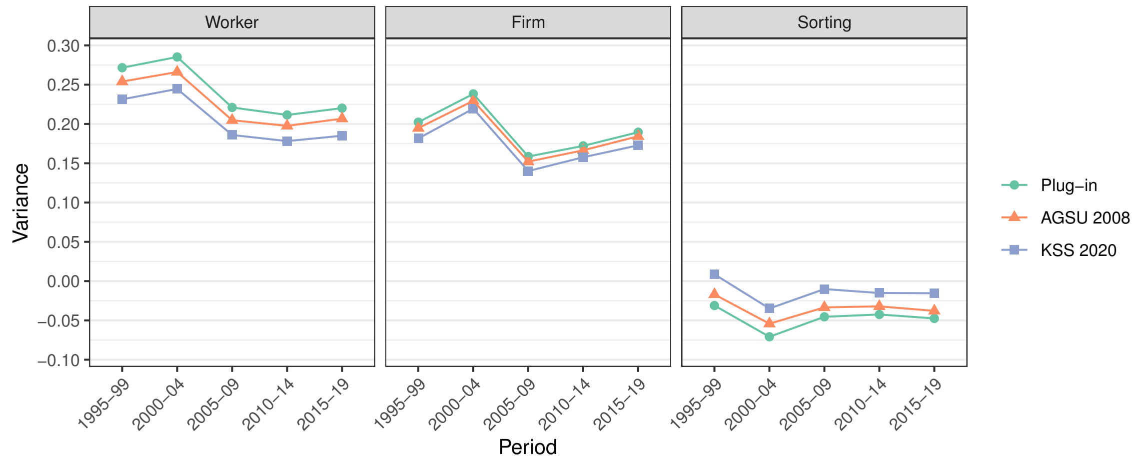
Panel E: 2015–2019



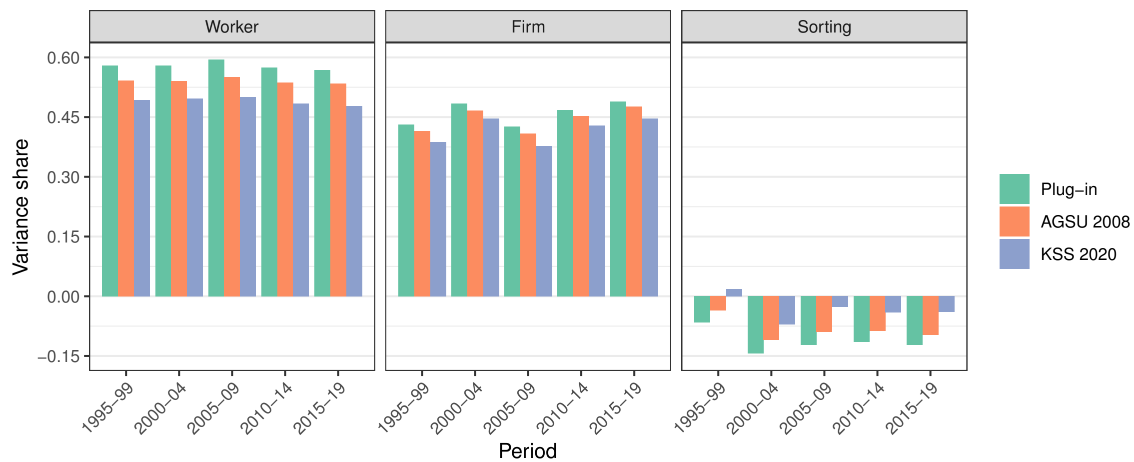
Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The figure shows the mean residual of the estimated AKM models by deciles of the worker and firm fixed effects. The models are estimated separately for the periods 1995–1999, 2000–2004, 2005–2009, 2010–2014, and 2015–2019, using the largest connected set of firms in each period.

Appendix Figure 9: Corrected variance decomposition of AKM estimates on leave-out-match connected set, prime-aged women

Panel A: Variance levels

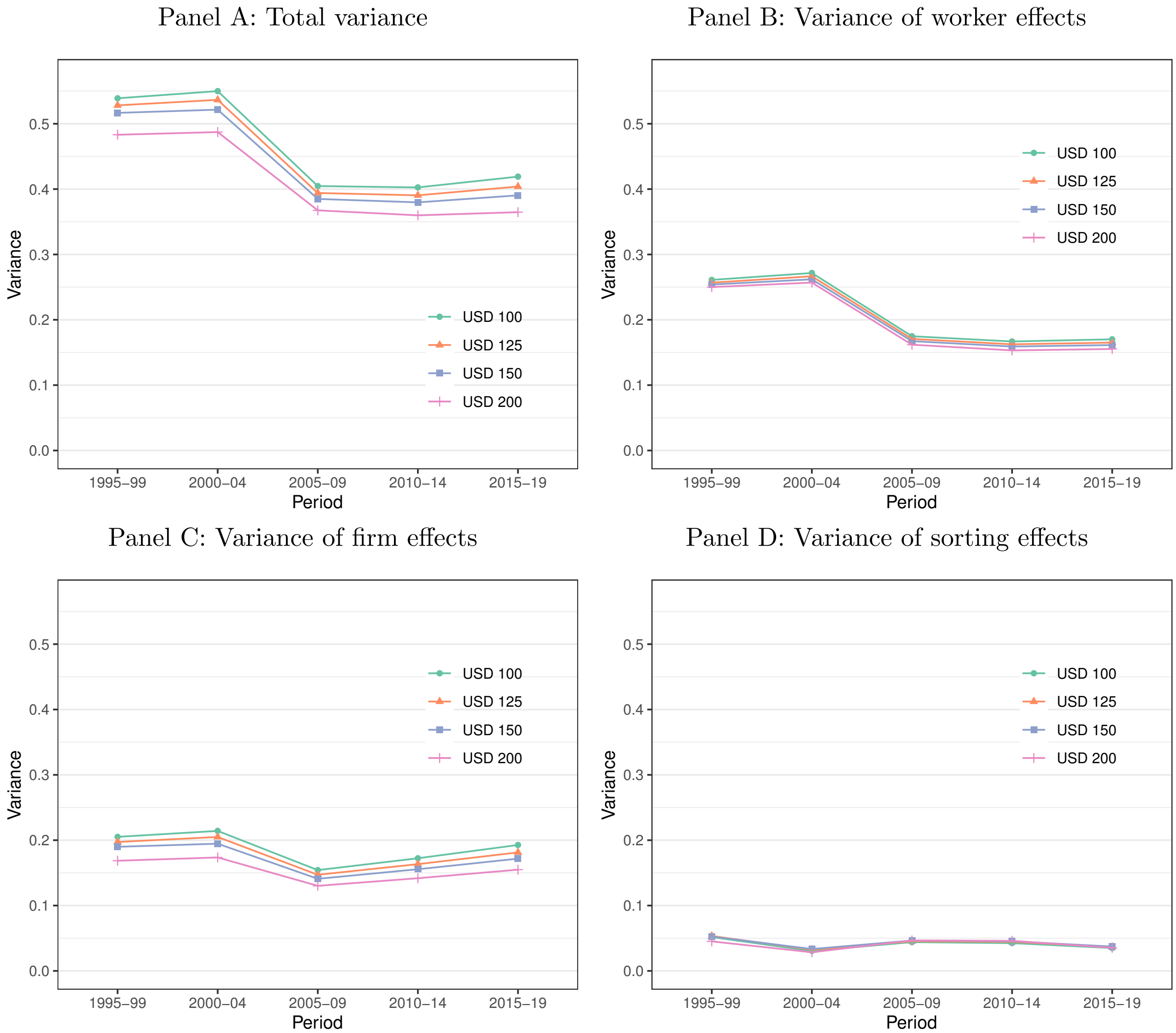


Panel B: Variance shares



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 AKM decomposition to the variance of log earnings, correcting the estimates of the variance terms, on the leave-out-match largest connected set of firms. "Plug-in" refers to the computation of the variance components directly using the AKM estimates. "AGSU 2008" refers to the variance decomposition proposed by Andrews et al. (2008), which assumes that the error term is homoskedastic. "KSS 2020" refers to the variance decomposition proposed by Kline et al. (2020), which allows for heteroskedasticity in the error term.

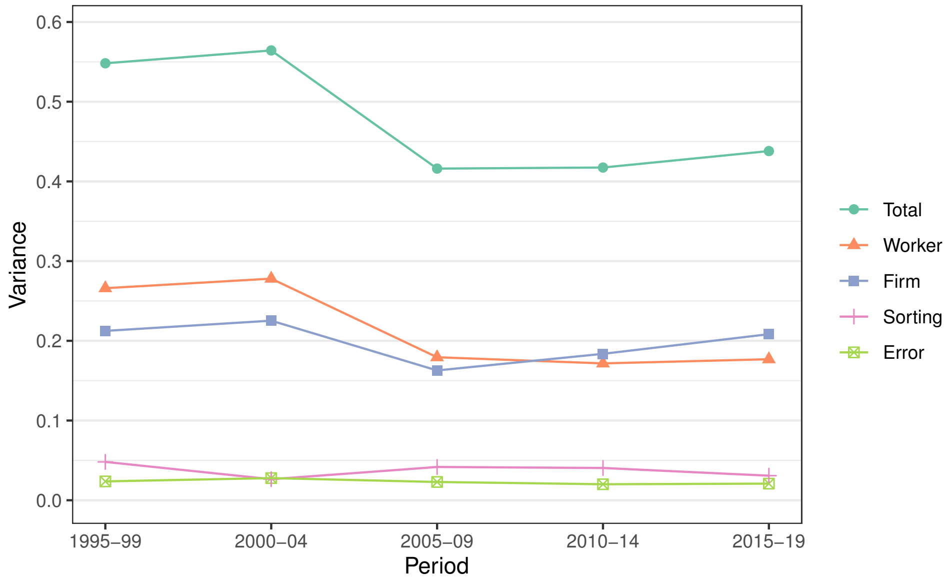
Appendix Figure 10: Variance decomposition of log earnings according to AKM model by minimum earnings cutoff, prime-aged men



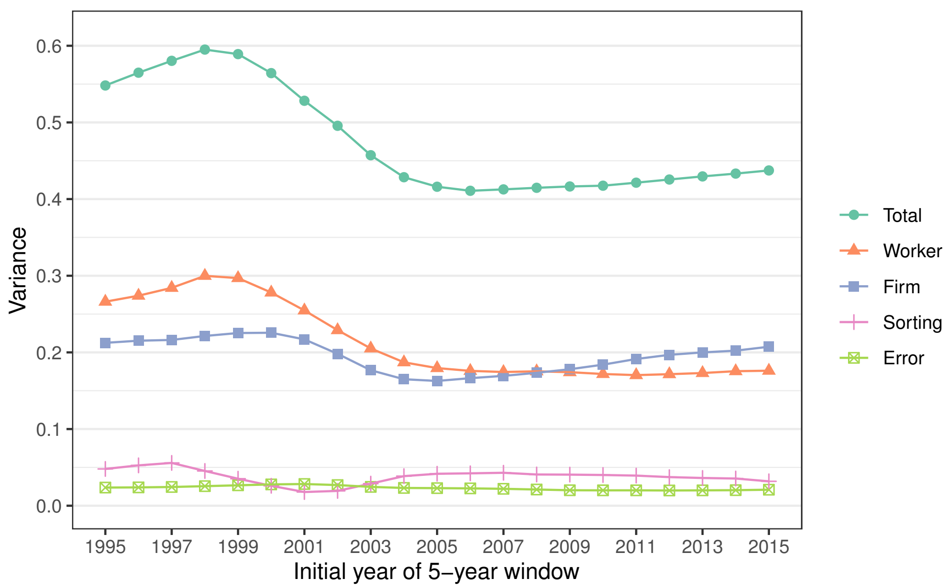
Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The figure shows estimates of the variance decomposition of a model of log earnings on worker fixed effects, firm fixed effects, and year fixed effects following **?**, for different values of the level of minimum earnings to be included in the sample. 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 variance of sorting effects. We show plug-in variance estimates on the largest connected set of firms.

Appendix Figure 11: Variance decomposition of log earnings with a time-varying window, prime-aged men

Panel A: Baseline estimates

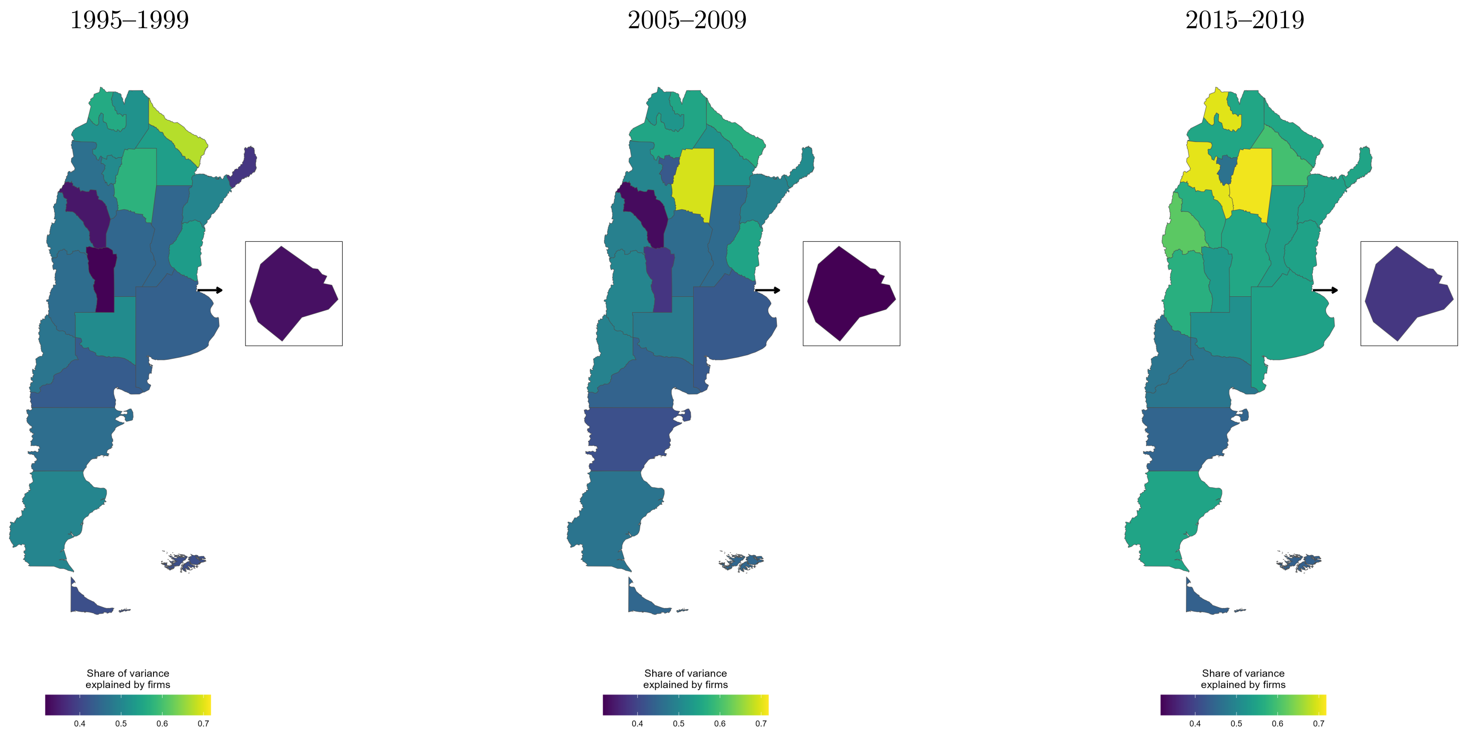


Panel B: Varying-window estimates



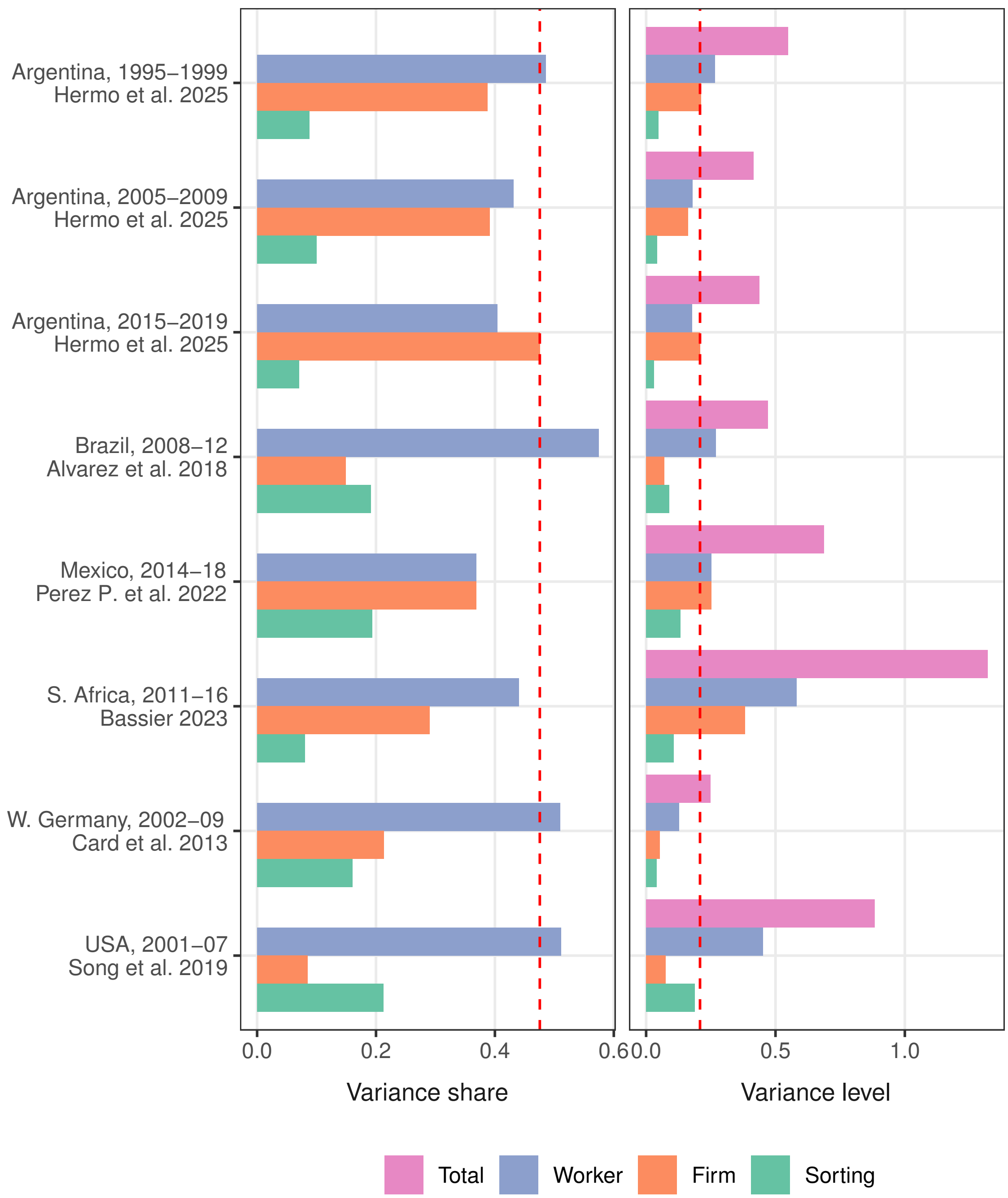
Notes: Data are from Argentina's social security system (SIPA) for men aged 20 to 55. The figure shows estimates of the variance decomposition of a model of log earnings on worker fixed effects, firm fixed effects, and year fixed effects following AKM. Panel A replicates the baseline estimates from Table 2. Panel B shows results of models estimated separately for five-year periods with initial year ranging from 1995 through 2014.

Appendix Figure 12: Share of variance explained by firms



Notes:

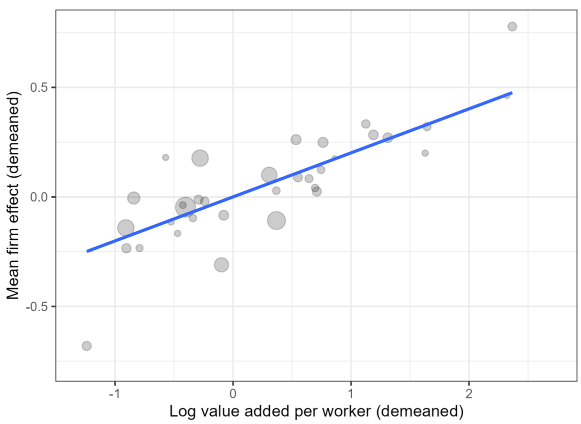
Appendix Figure 13: Comparing AKM-based variance decomposition across countries



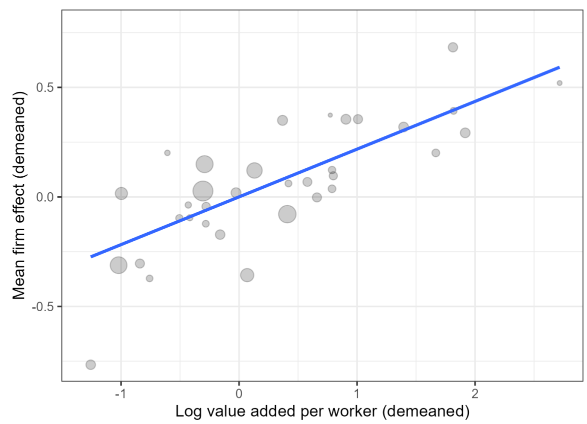
Notes: The figure shows a comparison across selected studies of the contribution of each component of the AKM-based variance decomposition. The left panel shows the share of the worker, firm, and sorting components out of the total variance. The right panel shows the levels of the variances, including the total variance of log wages. The red line signals the variance level or variance share for Argentina in 2015–2019. We use plug-in estimates for the variance components for all countries to ensure comparability. All reported estimations shown include year fixed effects as controls. With the exception of Alvarez et al. (2018), they also include worker age. Card et al. (2013) also includes education. All studies focus on men, with the exception of Bassier (2023), which includes both men and women in the estimation.

Appendix Figure 14: Firm effects and sectoral productivity in Argentina, 2005–2009 vs 2015–2019

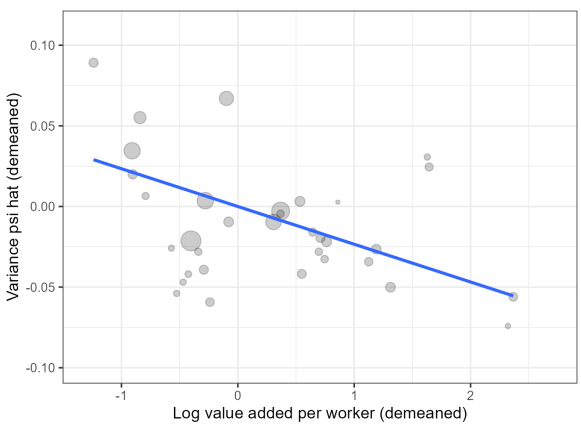
Panel A: Mean firm effect and sectoral productivity in 2005–2009



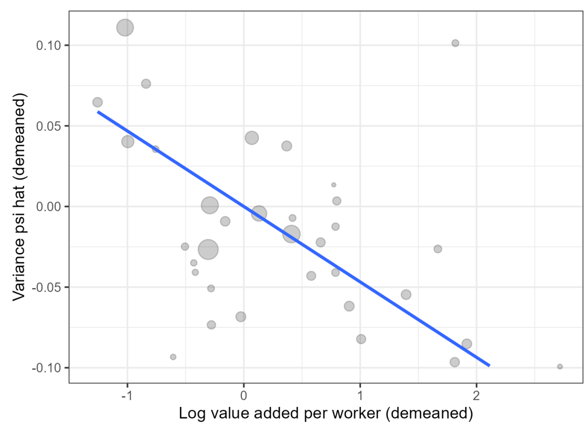
Panel B: Mean firm effect and sectoral productivity in 2015–2019



Panel C: Variance of firm effects and sectoral productivity in 2005–2009



Panel D: Variance of firm effects and sectoral productivity in 2015–2019



Notes: This figure shows the relationship between firm effects and sectoral productivity in Argentina for the periods 2005–2009 and 2015–2019. Panels A and C show the association between the mean of firm effects and productivity, while Panels B and D show its correlation to the variance of firm effects. Data are from Argentina's social security system (SIPA) for men aged 20 to 55 and from Centro de Estudios para la Producción (CEP XXI). Sectors are defined at the 2-digit level of the Argentinean Classification of Economic Activities (CLAE).