Firms and the Decline in Earnings Inequality in Brazil

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We document a large decrease in earnings inequality in Brazil between 1996 and 2012. Using administrative linked employer-employee data, we fit high-dimensional worker and firm fixed effects models to understand the sources of this decrease. Firm effects account for 40 percent of the total decrease and worker effects for 29 percent. Changes in observable worker and firm characteristics contributed little to these trends. Instead, the decrease is primarily due to a compression of returns to these characteristics, particularly a declining firm productivity pay premium. Our results shed light on potential drivers of earnings inequality dynamics.

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Since the mid-1990s, Brazil has experienced a large reduction in earnings inequality resembling the experience of other Latin American economies during this period. This decrease in earnings inequality stands in stark contrast to that of the US and many developed countries, which saw inequality steadily increasing over the past two decades.[1] This paper studies the sources of this decrease.

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[1]See Lopez and Perry (2008) and Tsounta and Osueke (2014) for inequality trends in Brazil and the rest of Latin America. Kopczuk, Saez and Song (2010) and Heathcote, Perri and Violante (2010) document the evolution of earnings inequality in the US, while Atkinson and Bourguignon (2015) discuss inequality trends across other high- and middle-income countries.

To this end, we exploit a large administrative linked employer-employee dataset containing information on hundreds of millions of job spells between 1988 and 2012. By repeatedly estimating an additive worker and firm fixed effects model due to Abowd, Kramarz and Margolis (1999)—henceforth AKM—we quantify the contributions of firm and worker-specific factors towards changes in Brazilian inequality. In a second stage, we link this earnings decomposition to a rich set of worker demographics and firm financials data for Brazilian manufacturing and mining firms. The merged data allow us to study the transmission from worker and firm characteristics into pay in a large developing economy. In doing so, we distinguish between changes in the distribution of worker and firm characteristics on one hand and changing returns to these characteristics on the other hand.

We uncover three main results. First, firms played an important role in the decrease in earnings inequality in Brazil over this period, explaining 40 percent of the fall in the variance of log earnings between 1996 and 2012. Compression in worker fixed effects explains an additional 29 percent of the decrease, with the remaining part attributable to a decrease in the covariance between worker and firm fixed effects and the residual. Given that worker heterogeneity is the most important component in explaining pay levels throughout this period, the compression in firm-specific pay contributed more than proportionately towards Brazil's inequality decrease.

Second, changes in the link between firm performance and pay account for a significant fraction of the compression in the firm component of workers' earnings.[2] We first show that a substantial share of the cross-sectional variation in the firm component of pay is explained by differences in observable firm characteristics, with more productive and larger firms paying more. Moreover, more than half of the decrease in the firm component is accounted for by observable firm characteristics. All of this decrease is driven by a weakening pass-through from firm characteristics to pay, while none is due to firms becoming more similar in observable characteristics over time. Altogether, a weaker link between observable firm characteristics and worker pay explains 30 percent of the overall fall in the variance of log earnings over this period.

Third, a decrease in the return to measures of ability such as experience and education explains a sizable share of the fall in the variance of the worker component of pay. In levels, age and education explain close to 40 percent of the variance of the worker component of pay. However, we do not observe a large compression in the underlying distributions of such characteristics over time. Instead, the decrease in worker pay heterogeneity is driven by a rapid fall in the returns to observable measures of worker ability, particularly the education premia. Lower returns to worker age and education explain 14 percent of the overall fall in the variance of log earnings over the 1996–2012 period.

[2]This part of the analysis is based on the subpopulation of larger mining and manufacturing firms for which we have data. As we discuss in greater detail later, this subpopulation has experienced both a similar amount of overall compression in earnings inequality and a similar contribution of workers and firms towards it.

This decomposition of the sources of Brazil's earnings inequality decrease informs our understanding of various commonly proposed explanations of the decrease. On the worker side, our results do not support an often articulated view that changes in educational attainment accounted for the largest share of Brazil's inequality evolution over the period (Barros et al., 2010). While educational attainment increased rapidly over this period, those gains were largely offset by concurrent decreases in the high school and college education premia. We reach similar conclusions regarding the implications of changes in the age structure of the workforce. On the firm side, a reading of the existing literature would suggest that trade and other factors affecting the productivity distribution during this period could have been an important driver behind changes to the earnings distribution.[3] Yet, in line with US trends, we find that the Brazilian productivity distribution actually grew more dispersed over this period.

These findings pose a challenge to candidate explanations behind Brazil's decrease in earnings inequality over this period. Our results suggest that a theory of the inequality decrease needs to be consistent with the following three facts: (i) firm-level pay differences explain a significant share of initial inequality levels and a disproportionately large share of its decrease; (ii) lower pass-through from firm productivity to pay is a key driver behind compression in the firm component of pay; and (iii) lower returns to worker ability explain a significant share of the compression in the worker component of pay. We conclude that changes in pay policies rather than shifts in the distribution of worker and firm fundamentals played an important role in Brazil's inequality decrease during this period.

Related literature.. — We contribute to three broad strands of the literature. First, we provide a decomposition of earnings into worker and firm heterogeneity in a developing economy. With the increasing availability of large, administrative matched employer-employee datasets, a growing literature examines the role of firms in wage determination. A seminal methodological contribution that separately identifies worker and firm heterogeneity in pay is the work by AKM. They find an important role for firms in explaining observed wage dispersion in French linked employer-employee data. Similar conclusions have been reached among others for Germany (Andrews et al., 2008; Card, Heining and Kline, 2013), Italy (Iranzo, Schivardi and Tosetti, 2008), Portugal (Card, Cardoso and Kline, 2016), Brazil (Lopes de Melo, 2015), Sweden (Bonhomme, Lamadon and Manresa, 2016), Denmark (Bagger and Lentz, 2016), and the United States (Abowd, Finer and Kramarz, 1999; Abowd, Creecy and Kramarz, 2002; Woodcock, 2015; Sorkin, 2015; Engbom and Moser, 2017*b*). Some recent papers are closely related to the first stage of our empirical methodology, which applies the AKM framework in overlapping subperiods to study changes in earnings components over

[3]See for example Dunne et al. (2004) and Faggio, Salvanes and Van Reenen (2010) who conclude that parts of the increase in earnings inequality in the US can be explained by widening dispersion in the firm productivity distribution.

time. Card, Heining and Kline (2013) find that increasing dispersion in the firm-specific component of pay contributed significantly to rising earnings inequality in West Germany. Barth et al. (2016) and Song et al. (2016) show that firms were an important driver behind the increase in US labor earnings inequality since 1980, with the latter set of authors highlighting an increased assortativeness in the allocation of workers across firms through the lens of the AKM framework.

Second, we contribute to a literature studying worker pay in relation to firm outcomes by linking our decomposition results to worker and firm characteristics. In previous work, Blanchflower, Oswald and Sanfey (1996) suggest and implement a test for rent-sharing in the US manufacturing sector. Van Reenen (1996) examines pass-through from firm-level innovation to worker wages in the UK. Guiso, Pistaferri and Schivardi (2005) assess to what extent firm-level productivity shocks are passed on to workers in Italy. AKM study the link between measures of firm performance and estimated firm effects in France, but do not focus on changes over time to this relationship. Similarly, Menezes-Filho, Muendler and Ramey (2008) focus on the cross-sectional relationship between firm characteristics and wages in Brazil's manufacturing and mining sectors. Card, Devicienti and Maida (2014) focus on the relationship between rent-sharing and firm investments in Italy. Bagger, Jesper and Mortensen (2014) investigate the role of labor misallocation in driving the positive correlation between labor productivity and firm-level wages using Danish data. Card, Cardoso and Kline (2016) analyze the degree of rent-sharing in Portugal with a particular emphasis on gender differences in profit participation and the allocation of workers across firms. By differentiating between changes in the underlying distribution versus changes in the returns to worker and firm characteristics over time, we contribute toward this literature and shed light on the sources behind Brazil's large decrease in earnings inequality.

Third, we add to the literature on the drivers of inequality dynamics in Brazil by providing a comprehensive decomposition of its inequality evolution that cuts across specific explanations. Many previous papers have studied the role of isolated mechanisms in Brazil's inequality decrease over the last two decades. For example, Ulyssea (2014) and Meghir, Narita and Robin (2015) study the effects of policies on Brazil's formal and informal sector employment. Alvarez (2017) interprets empirical worker switches between sectors through the lens of a Roy model to investigate determinants of the agricultural wage gap in Brazil. Dix-Carneiro and Kovak (2017) analyze the long-lasting impact of industry-specific tariff cuts in the presence of imperfect interregional labor dynamics related to slow capital adjustment and agglomeration economies. In related work, Dix-Carneiro, Soares and Ulyssea (2016) relate Brazil's trade liberalization to income inequality and crime at the regional level, while Dix-Carneiro and Kovak (2015) examine its impact on the evolution of the skill premium. Helpman et al. (2017) show that a significant share of the rise in Brazilian wage inequality from 1986–1995 is due to between-firm differences and that these trends are consistent with the effects of trade liberalization in a heterogenous-firm model of trade and inequality. Adão (2016) finds that movements in world commodity prices explain part of the decrease in Brazilian wage inequality from 1991–2010. Medeiros, de Souza and de Castro (2014) use administrative tax return data to study the evolution of top income inequality in Brazil from 2006–2012, but they cannot distinguish between the role played by worker versus firm characteristics during that period. Using a empirical methodology similar to ours, Lopes de Melo (2015) conducts a static decomposition of earnings inequality levels in Brazil's formal sector into components due to firms and workers. de Araujo (2014) studies the role of labor adjustment costs in propagating wage inequality in the Brazilian context. Finally, using administrative linked employer-employee data and an equilibrium search model, Engbom and Moser (2017*a*) argue that the rise in the minimum wage was an important driver behind Brazil's inequality decrease from 1996–2012.

Outline.. — The rest of the paper is structured as follows: Section I provides an overview of the main institutional changes and macroeconomic trends affecting Brazilian labor markets from 1988 to 2012. Section II summarizes the administrative datasets used in our empirical analysis and discusses sample selection as well as variable definitions. Section III provides descriptive statistics on trends in earnings inequality in Brazil during this period. Section IV introduces our two-stage empirical framework, which first decomposes earnings into worker and firm components and then links this decomposition to worker and firm characteristics. Section V describes our main empirical results, presents checks on the validity of our empirical framework, and discusses implications for potential explanations behind Brazil's inequality decrease. Finally, Section VI summarizes our key findings and concludes.

I. Institutions and macroeconomic trends in Brazil

During our period of study, Brazil resumed democratic elections in 1989, ended a decade of hyperinflation in 1994, and recovered from a financial crisis in 1999. The latter came with a floating of the exchange rate and fiscal adjustment, which resulted in the government turning a deficit into a primary surplus. After a "lost decade" of economic growth leading up to 1994, real GDP per capita grew by a half percentage point a year up until 2002, by a rapid three percent per year 2002–2008, contracted by two percent in 2009, and rebounded quickly with six percent growth in 2010. In this section, we discuss some of the institutional changes that could have affected inequality during this period, including labor regulation, trade liberalization and social policy.

Brazil had a highly regulated labor market before reforms started in the late 1980s. Since 1965 a national Wage Adjustment Law mandated yearly wage increases for all workers in the economy and dismissal costs were high. After the transition to civil rule and the signing of a new constitution in 1988, flexibility in labor markets was further affected by firing penalties and the increasing power of labor unions, which gather about a quarter of employed formal workers in Brazil. The Wage Adjustment Law was finally abandoned in 1995, introducing a period of greater flexibility and less regulated wage-setting practices. Further legislation in 1997–1998 eased restrictions on temporary contracts and lowered dismissal barriers. Subsequently, formal employment increased by around five percent and unemployment fell from 10 percent in 2000 to around six percent in 2011. The overall labor force participation rate has remained roughly stable at 65–70 percent over this period (World Bank, 2016).

Hyperinflation resulted in widespread indexation of wages to the minimum wage. From 1980 to 1989, yearly inflation averaged 355 percent, which was followed by a yearly average of 1,667 percent between 1990 and 1994 (World Bank, 2016). To keep up, the minimum wage was adjusted first annually and then on a monthly basis proportionately to the previous period's realized inflation rate. In 1994, hyperinflation finally subsided with the introduction of the Plano Real. This ambitious stabilization program introduced a gradual float of the local currency, tightened monetary and fiscal policy, and lowered inflation below two-digits.

In parallel to monetary stabilization, Brazil liberalized trade during this period. Starting with initially high import tariffs that had substituted import bans from the previous decade, a series of trade liberalization bills in the late 1980s eliminated selected tariffs and eradicated quantitative import controls. Upon becoming president in 1995, social democrat Fernando Henrique Cardoso further strengthened this agenda with a reduction of tariff and non-tariff trade barriers to one tenth of their levels in 1987 (Pavcnik et al., 2004). The opening up to trade over the last 25 years has been frequently cited as a major contributor to the country's growth in total factor productivity (Ferreira and Rossi, 2003; Ferreira, Leite and Wai-Poi, 2007; Moreira, 2004; Muendler, 2004; Córdova and Moreira, 2003). In addition, Helpman et al. (2017) argue that trade reforms contributed to the rise in earnings inequality in the late 1980s and early 1990s.

Health, education and other social programs began expanding during the late 1990s. This trend further strengthened with the election of the left-wing Workers' Party in 2003, who doubled social expenditure as a fraction of GDP. Although social spending remains less than one percent of GDP, it is often portrayed as an important contributor to the reduction in household income inequality.[4] The reach of the public cash transfer program, Bolsa Famìlia, increased to cover 11 million families in 2006, which comprised nearly 25 percent of the total population (Barros et al., 2010). Education spending increased to 5.5 percent of GDP in 2009 (compared to 3.5 percent in 2000 and 5.7 percent among G20). As we discuss in Appendix A, this is reflected in a rapidly rising share of the labor force with a high school degree. Moreover, the quality of education relative to other countries, as measured by the international PISA scores, has also improved, with Brazil having the greatest increase in mathematics among 65 countries since 2003 (Organisation

[4]Using household data, Barros et al. (2010) estimate that social programs accounted for about 20 percent of the decrease in household income inequality.

for Economic Co-operation and Development, 2012).

The Worker's Party complemented social policies with accelerated minimum wage increases. Within their first year in office, they implemented a 20 percent increase of the minimum wage in 2003 and continued to implement yearly increases averaging over 10 percent during the next 10 years. As a result, the minimum to median earnings of adult male workers in Brazil increased from around 34 percent in 1996—similar to US levels—to over 60 percent, which is close to the level in France. Engbom and Moser (2017*a*) argue that this large increase in the minimum wage can explain a significant fraction of the reduction in earnings inequality in Brazil over the 1996–2012 period, while being consistent with the key facts in this paper.

II. Data

Our analysis uses two confidential administrative datasets from Brazil: the *Relação Anual de Informações Sociais (RAIS)* contains earnings and demographic characteristics of workers as reported by employers, and the *Pesquisa Industrial Anual - Empresa* (*PIA-Empresa*, or *PIA* in short) contains detailed information on revenues and costs of firms in Brazil's mining and manufacturing sectors. In the following section, we briefly discuss their collection, coverage, variable definitions, and sample selection.

A. Linked employer-employee data (RAIS)

COLLECTION AND COVERAGE.. — The RAIS data contains linked employer-employee records that are constructed from a mandatory survey filled annually by all registered firms in Brazil and administered by the Brazilian Ministry of Labor and Employment *(Ministerio do Trabalho e Emprego*, or *MTE*). Data collection was initiated in 1986 within a broad set of regions, reaching complete coverage of all employees at formal establishments of the Brazilian economy in 1994.[5] Fines are levied on late, incomplete, or inaccurate reports, and as a result many businesses hire a specialized accountant to help with the completion of the survey. In addition, MTE conducts frequent checks on establishments across the country to verify the accuracy of information reported in RAIS, particularly with regards to earnings, which are checked to adhere to the minimum wage legislation.[6]

[5]Because registration with the central tax authorities is necessary for a firm to be surveyed, the RAIS covers only workers in Brazil's formal sector. Complementing our analysis with data from the Brazilian household survey *Pesquisa Nacional por Amostra de Domicílios* (*PNAD*), we find that the formal sector employment share among male workers of age 18–49 grew from 64 to 74 percent between 1996 and 2012. Differential inequality trends between formal and informal sector workers are discussed at more length in Engbom and Moser (2017*a*).

[6]In addition to being fined, non-compliant firms are added to a "Black List of Slave Work Employers," made available publicly under law Decree No. 540/2004. Current versions of the list are disseminated by the Brazilian television news channel Repórter Brasil.

The RAIS contains an anonymized, time-invariant person identifier for each worker, which allows us to follow individuals over time. It also contains anonymized time-invariant establishment and firm identifiers that we use to link multiple workers to their employers and follow those over time. Although it would be possible to conduct part of our analysis at the establishment instead of firm level, this paper focuses on firms for three reasons. First, to the extent that there is substantial variation in pay across establishments within firms, our firm-level analysis provides a lower bound on the importance of workers' place of employment.[7] Second, we think that many of the factors that could give rise to employer-specific components of pay, including corporate culture, company leadership, etc., act at the firm level. Additionally, many regulations targeting pay policies differ as a function of firm-level employment, not establishment-level employment. Third, we will later use data on firm characteristics such as financial performance that are not available at the establishment-level.

VARIABLE DEFINITIONS.. — For each firm at which a worker was employed during the year, the RAIS contains information on the start and end date of the employment relationship, the amount the worker was paid and worker background characteristics. Reported earnings are gross and include regular salary payments, holiday bonuses, performance-based and commission bonuses, tips, and profit-sharing agreements. While this is a broad measure of earnings, it does not contain other sources of income such as capital income or in-kind transfers. To control for variation in labor supply, we divide total earnings from an employment relationship in a given year by the duration of the job spell.[8] As weekly hours only exist from 1994, our main analysis does not use per hour pay. Instead, to limit the impact of unmeasured labor supply differences, we focus on adult males. In the years for which we have hours, more than 75 percent of adult males report working 44 hours a week.[9]

We define a consistent age variable by calculating the year of birth for any observation, and then setting an individual's year of birth as the modal implied value and finally reconstructing age in each year using this imputed year of birth.[10] Because age is only reported in bins prior to 1994, we code all subsequent years into the same age bins: less than 18, 18–24, 25–29, 30–39, 40–49, and more than 49 years old.

We define a consistent measure of years of schooling by first setting it to its

[7]As we will show later, however, the explanatory power of our model incorporating firm and person effects is high, leaving little variation to be explained by separate establishment level effects. This is in line with evidence from the US in Barth et al. (2016) and Song et al. (2016) who show that most across firm dispersion drives the vast majority of cross plant variation.

[8]That is, if an employment relationship is reported as active for seven months during the year, we divide total earnings reported for that employment relationship for that year by seven.

[9]We show in Appendix D that similar inequality trends hold in hourly wage rates for full-time employed adult males for the years for which we have data on hours.

[10]We use age instead of experience throughout our analysis; results are similar using age plus six minus years of education as a measure of experience.

modal value within a year in case of multiple job spells in a year and then ensuring that the years of schooling are non-decreasing across years. Subsequently, we define four education groups based on degree completion implied by the reported number of years of schooling and the education system in Brazil: primary school (four years), middle school (seven years), high school (12 years), and college (12 or more years).

The data also contain information on detailed occupation classification of the job and detailed sector classification of the employer establishment. Both the industry and occupation classification systems underwent a significant change during the period we study. For occupations, we use the pre-2003 classification (*Classificação Brasileira de Ocupações*, or *CBO*) at the one-digit level. We also use two-digit sectoral classifications (*Classificação Nacional de Atividades Económicas*, or *CNAE*) according to the pre-2003 period. We make occupations and sectors reported for 2003–2012 consistent with the older CBO and CNAE classifications by using conversion tables provided by the Brazilian National Statistical Institute (*Instituto Brasileiro de Geografia e Estatística*, or *IBGE*). In order to increase consistency between the old and the new classification schemes we opt for one digit occupation classification and two digit sector classification, which for the purpose of this paper we think provides sufficient detail.

Our firm size measure is the number of full-time equivalent workers during the reference year. We calculate it as the total number of worker-months employed by the firm during the year divided by 12.[11]

Sample selection.. — We exclude observations with either firm or worker identifiers reported as invalid as well as data points with missing earnings, dates of employment, educational attainment or age. Together, these cleaning procedures drop less than one percent of the original population, indicative of the high quality of the data. Subsequently, to limit the computational complexity associated with estimating our model, we restrict attention to one observation per worker-year. We impose this restriction by choosing the highest-paying among all longest employment spells in any given year. As the average number of jobs held during the year is 1.2 and there is no trend in this, we believe that loosening this restriction would not meaningfully affect our results.

Finally, we restrict attention to male workers age 18–49. We make this restriction as a trade-off between on the one hand our results being comparable to a large part of the literature focusing on prime age males, and on the other to obtain as complete as possible coverage of changes in the Brazilian earnings structure over the period. The restriction to male workers has the advantage of avoiding issues with changing patterns of female labor supply over time. The restriction to age 49 and below is made to avoid issues related to early retirement, which is more common in Brazil than in the US and other developed countries.

[11] This is computed prior to making any sample restrictions so that it reflects accurately, to the extent possible, the total amount of labor used by the firm during the year.

In previous versions of the paper, we have considered a wider age range as well as both genders, leading to broadly similar findings as what we present here.

Descriptive statistics.. — Table 1 provides key summary statistics for the RAIS data for the six subperiods that we will later use in our AKM analysis, namely 1988–1992, 1992–1996, 1996–2000, 2000–2004, 2004–2008, and 2008–2012. Since our analysis focuses separately on adult males as well as adult males working for larger manufacturing and mining firms, we provide a brief comparison of these subpopulations to the overall population of formal sector employees. As we will be primarily concerned with the later four subperiods during which inequality decreased markedly and for which we have firm level data, we focus our discussion on these periods.

Table 1—: RAIS summary statistics

	# Worker-		Earnings		Age		Schooling	
	years	# Workers	Mean	St.d.	Mean	St.d.	Mean	St.d.
Panel A. All Formal Sector Workers (RAIS)								
1988–1992	165.5	41.3	1.10	0.86	31.90	11.44	7.65	4.43
1992–1996	162.1	43.0	1.18	0.86	33.17	11.29	8.09	4.40
1996–2000	174.6	46.7	1.19	0.84	33.67	11.26	8.61	4.26
2000–2004	202.7	52.6	1.00	0.80	34.01	11.32	9.50	4.05
2004–2008	254.2	62.4	0.81	0.74	34.21	11.45	10.27	3.78
2008–2012	326.5	75.7	0.71	0.71	34.46	11.62	10.81	3.51
Panel B. Adult Male Workers								
1988–1992	78.4	23.5	1.23	0.86	30.80	8.05	7.17	4.25
1992–1996	78.9	24.3	1.28	0.86	31.42	8.10	7.50	4.20
1996–2000	83.9	26.5	1.26	0.83	31.54	8.17	7.94	4.07
2000–2004	94.7	29.8	1.04	0.78	31.58	8.22	8.81	3.89
2004–2008	112.9	34.0	0.85	0.72	31.65	8.24	9.60	3.67
2008–2012	135.0	39.6	0.76	0.68	31.76	8.21	10.24	3.46
Panel C. Adult Male Workers at Large Manufacturing and Mining Firms (PIA)								
1996–2000	15.5	5.8	1.54	0.86	31.51	8.05	7.95	4.01
2000–2004	16.7	6.3	1.28	0.83	31.30	8.13	8.87	3.84
2004–2008	21.0	7.8	1.07	0.77	31.12	8.14	9.52	3.69
2008–2012	23.9	9.0	0.96	0.73	31.26	8.08	10.16	3.51

Note: The number of worker-years and number of unique workers are reported in millions. Statistics on earnings are in log multiples of the current monthly minimum wage, schooling is in years, a person's age is the average age of his age bin. Panel A includes all workers in the RAIS dataset. Panel B includes male workers that are between 18 and 49 years old. Panel C includes male workers age 18–49 working at larger manufacturing and mining firms included in the PIA firm characteristics data. Means are computed by period. The standard deviation is calculated by first demeaning variables by year and then pooling the years within a subperiod. Source: RAIS.

Panel A shows statistics for the overall formal sector work force in Brazil, while Panel B shows statistics for the subpopulation of prime age adult males. The latter group has 0.67 years of schooling less than the overall sample in the 1996–2000 subperiod; this gradually drops to 0.57 years in the last subperiod. Adult males earn 4–13 log points more than the overall population, and the variance of log earnings is slightly higher than that of the overall population.

Panel C presents statistics on the subpopulation of adult males working at larger mining and manufacturing firms. Adult males in the PIA subpopulation are about 0.03 years younger than all adult males in the 1996–2000 subperiod, which gradually increases to 0.5 years younger in the last subperiod. They are similar to all adult males in terms of education. The PIA sample of adult males earned on average 28 log points more than all adult males in the 1996–2000 subperiod; this decreased to 20 log points in the last subperiod. Finally, they display a three and five log point higher standard deviation of log earnings in the 1996–2000 and 2008–2012 period, respectively.

B. *Firm characteristics data (PIA)*

Collection and coverage.. — The PIA data contain information on firm financial characteristics from 1996–2012. The dataset is constructed by IBGE based on annual firm surveys in the manufacturing and mining sector. This survey is mandatory for all firms with either more than 30 employees or above a revenue threshold as well as for an annual random sample of smaller firms.[12] As with RAIS, completion of the survey is mandatory and non-compliance is subject to a fine by national authorities. Each firm has a unique, anonymized identifier, which we use to link firm characteristics data from PIA to worker-level outcomes in the RAIS data.

Variable definitions.. — The PIA dataset includes a breakdown of operational and non-operational revenues, costs, investment and capital sales, number of employees and payroll. All nominal values are converted to real values using the CPI index provided by the IBGE. Instead of the measure of firm size in the PIA, we prefer our measure of full-time-equivalent employees constructed from the RAIS as it accounts for workers only employed during part of the year. We define operational costs as the cost of raw materials, intermediate inputs, electricity and other utilities, and net revenues as the gross sales value due to operational and non-operational firm activities net of any returns, cancellations, and corrected for changes in inventory.[13] We construct value added as the difference between net revenues and intermediate inputs, and value added per worker as value added divided by full-time equivalent workers. This is our main measure of firm productivity. We have also constructed several alternative measures of firm productivity by cleaning value added per worker off industry-year effects and some measures of worker skill, with similar results.

Our productivity measure differs from commonly used total factor productivity (Bartelsman, Haltiwanger and Scarpetta, 2009, 2013) since it does not control for capital intensity. We opt for this measure because we do not directly observe capital stocks in the PIA data, only investment. To construct a measure of the

[12]The revenue threshold for inclusion in the deterministic survey has grown over the years, standing at USD300,000 in 2012.

[13]We have explored alternative revenue definitions such as only restricting attention to operational revenues or excluding certain types of non-operational revenues. Such robustness checks yield very similar results to what we report below.

capital stock, one would need to assume a depreciation rate to be able to impute capital using reported investment. In the absence of firm investment data prior to 1996, one would also need to impute initial capital stocks at the firm-level in 1996, as well as for any firm that (re-)enters the PIA population. We have constructed such a measure of the capital stock, but the multiple imputations required to obtain capital and fact that the investment data is incomplete for many firms lead us to prefer value added per worker as our measure of firm productivity. Instead we have constructed several variants of this labor productivity measure, making various adjustments for worker input quality that lead to very similar results to what we present below.[14]

Sample selection.. — The PIA firm survey spans the universe of larger firms (as defined above) in Brazil's manufacturing and mining sectors in addition to a random sample of smaller firms. Because parts of our analysis make use of the panel dimension on the firm side and to avoid issues with excessive sample attrition related to our later estimation procedure, we focus our analysis on the deterministic set of relatively larger firms.

Descriptive statistics.. — Table 2 shows key summary statistics on firms during the four subperiods for which we have firm financial data: 1996–2000, 2000–2004, 2004–2008, and 2008–2012. All results are weighted by the number of full-time equivalent workers employed by the firm. The number of firms in the PIA increased by 60 percent between the first and the last period. The average log firm size increased by 28 log points and average log real value added per worker grew by 15 log points. There is significant dispersion in both log firm size and log value added per worker across firms, with the standard deviation of the former being close to two and that of the latter exceeding one. Furthermore, there is no evidence of convergence in either measure: the standard deviation of firm size monotonically increases whereas the standard deviation of value added per worker first increases rapidly, then falls again in the last subperiod.

[14]Specifically, in the construction of labor productivity, we alternatively divide value added by the raw number of workers, the full-time equivalent workers, measurable human capital-augmented (i.e. accounting for education and age) workers, and also adjusting for unobserved worker characteristics captured by the worker fixed effect in pay.

Table 2—: PIA summary statistics

			Firm size		Value added p.w.	
	# Firm-years	# Unique firms	Mean	St.d.	Mean	St.d.
1996–2000	110.5	34.8	6.41	1.74	11.15	1.13
2000–2004	130.6	40.9	6.35	1.79	11.19	1.32
2004–2008	156.5	48.8	6.57	1.90	11.22	1.34
2008–2012	176.8	55.8	6.69	1.98	11.30	1.31

Note: The number of firm-years and number of unique firms are reported in thousands. Firm size is the log number of full-time equivalent employees. Value added per worker is the log of real value added per worker. Means and standard deviations are weighted by the number of full-time employees. The standard deviation is calculated by first demeaning variables by year and then pooling the years within a subperiod. Source: PIA.

III. Inequality trends in Brazil from 1988–2012

In this section, we provide a first overview of Brazil's rapid decrease in earnings inequality using our sample of prime age males.[15] We demonstrate that the decrease in inequality in Brazil occurred throughout a large part of the earnings distribution. Subsequently, we provide some suggestive evidence of firms being an important source of inequality as well as a factor behind the decrease in inequality in Brazil.

A. *The evolution of earnings inequality*

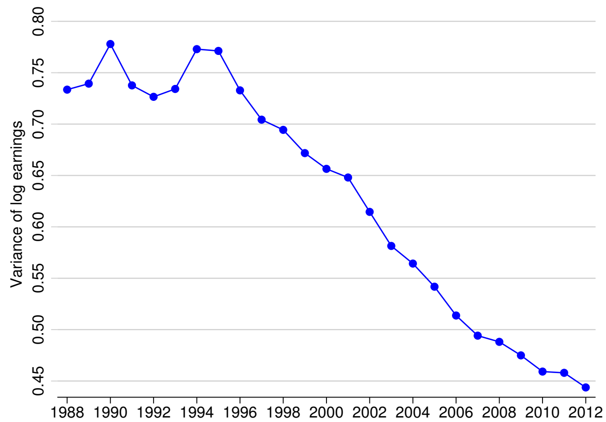
Starting from high initial levels, Brazil experienced a rapid and steady fall in earnings inequality from the mid 1990s onwards. The decrease followed years of stable or slightly increasing inequality between the late 1980s and the mid-1990s. To illustrate this, Figure 1 plots the variance of log earnings over the 1988–2012 period in the RAIS. Between 1996 and 2012, the variance of log earnings in Brazil decreased by 28 log points or 39 percent, from 0.73 to 0.44. To put this decrease into context, the US saw an increase in the variance of log annual earnings of 30 log points from 1967–2005 (Heathcote, Perri and Violante, 2010).

To depict the comprehensive nature of the decrease in inequality, Figure 2 plots the log percentile ratios of earnings, normalized to zero in 1996.[16] Two striking facts emerge: First, the compression was wide-spread throughout the earning distribution, reaching as high as the 75th percentile. Second, the amount of compression gradually decreases as one moves further up in the distribution. For instance, whereas the log 90–50 percentile ratio falls by 26 log points from 1996

[15]For clarity and consistency with our main estimation results, we present these trends using the sample of males aged 18–49 only. The trends described in this section are also present in the overall population.

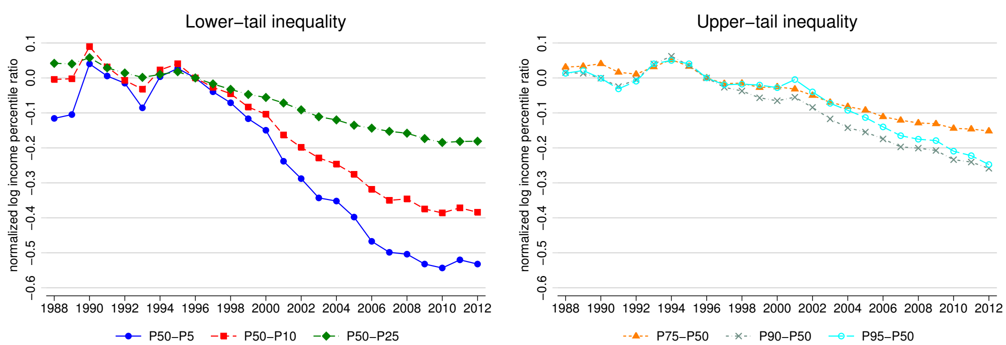
[16]Appendix B shows that there was wide-spread real earnings growth over this period.

to 2012, the log 50–10 ratio decreases by 38 log points, and the log 50–5 ratio by a remarkable 53 log points. We see less compression above the 75th percentile, and some divergence among the top 10 percent of the earnings distribution, with the log 95–50 percentile ratio falling slightly less than the log 90–50 ratio.



Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS.

Figure 1. : Variance of log earnings in Brazil, 1988–2012



Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS.

Figure 2. : Log percentile ratios of the earnings distribution in Brazil, normalized to 0 in 1996

Importantly, the inequality decrease was not driven by the rapid educational attainment expansion and demographic changes during this period. Appendix A shows within a Mincer framework that most of the decrease is in fact orthogonal to worker observables. The weak explanatory power from this worker-side analysis, along with recent evidence of firm-driven inequality trends in developed economies, motivate us to study the role of firms in the Brazilian labor market.

B. Earnings dispersion between and within firms

For a long time, economists have recognized that worker observables fail to explain a large fraction of the variance of earnings (Mincer, 1974; Heckman, Lochner and Todd, 2003). A recent literature instead highlights the role played by firms in giving rise to differences in pay. As a first step towards understanding the role of firms in the inequality decrease, we investigate the variance of earnings within and between firms. To this end, let y_{ijt} denote log earnings of worker i employed by firm j in year t, and $\bar{y}_t^j$ denote average log earnings in firm j in year t. Following Fortin, Lemieux and Firpo (2011) and Song et al. (2016) we can write[17]

$$\underbrace{Var\left(y_{ijt}\right)}_{\text{overall}} = \underbrace{Var\left(\overline{y}_t^j\right)}_{\text{between firms}} + \underbrace{\overline{Var\left(y_{ijt}\middle| i\in j\right)}}_{\text{within firms}}$$

That is, variance in overall earnings can be decomposed into the variance of average log earnings at the firm across firms (weighted by worker-years) and the variance of the difference between workers' log earnings and the average log earnings at their firm.

Based on these definitions, one could imagine two hypothetical polar extremes. First, average earnings could be identical across firms so that overall earnings inequality is completely due to variance in earnings within firms. In this case, a firm is just a microcosm of the overall economy. Second, all workers could receive the same earnings within the firm so that inequality arises entirely due to differences in earnings across firms. In reality, the question is which channel is quantitatively most important.

Figure 3 plots the decomposition of these channels over time in Brazil. We note two insights: Firstly, there is significant variability in earnings within firms, but an even greater amount of earnings inequality between firms.[18] Secondly, although

[17]To derive this expression, first use the identity

$$y_{ijt} = \underbrace{\overline{y_t}}_{\text{economy average}} + \underbrace{\left(\overline{y}_t^j - \overline{y_t}\right)}_{\text{employer deviation}} + \underbrace{\left(y_{ijt} - \overline{y}_t^j\right)}_{\text{worker deviation}}$$

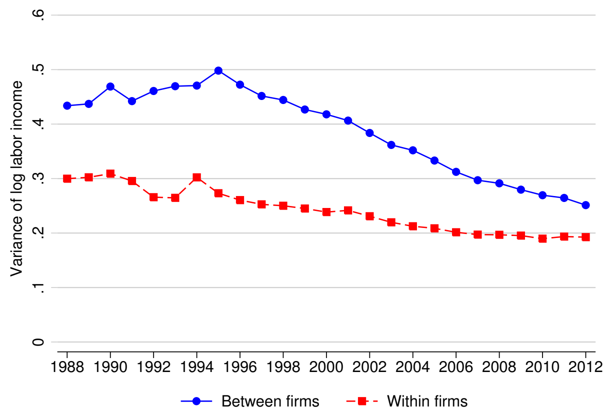
Taking variances on both sides, we get

$$Var\left(y_{ijt} - \overline{y_t}\right) = Var\left(\overline{y}_t^j - \overline{y_t}\right) + Var\left(y_{ijt} - \overline{y}_t^j\right) + \underbrace{2Cov\left(\overline{y}_t^j - \overline{y_t}, y_{ijt} - \overline{y}_t^j\right)}_{=0}$$

where the last term is zero by construction. Simplifying, we arrive at the decomposition in the text.

[18]In contrast, Song et al. (2016) document larger within relative to across firm dispersion. As will

both measures of inequality fell during this time, the decrease was particularly pronounced between firms. Inequality between firms decreased by 18 log points or 42 percent from 1988–2012, whereas within-firm inequality dropped by 11 log points or 36 percent.[19]



Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS.

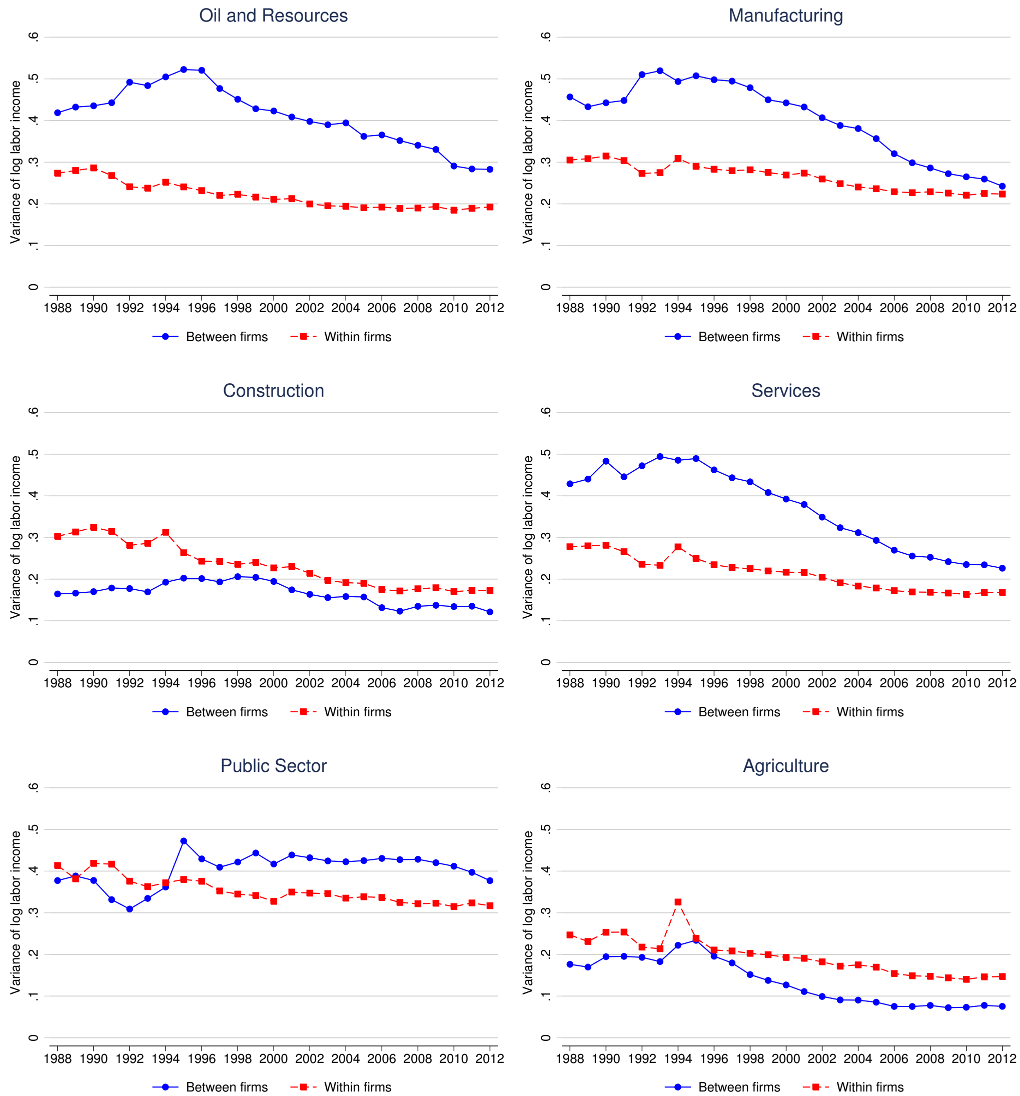
Figure 3. : Variance of log earnings between and within firms

The decrease in between-firm inequality is not due to a compression of differences between sectors. In fact, large between-firm pay compressions occurred in all Brazilian sectors except government, as shown in Figure 4. Moreover, Appendix C shows similar patterns obtain in every region of Brazil, among small and large firms, and among unproductive and productive firms—though less so at the most productive firms. Overall, the robustness of the pattern to different cuts of the data suggests that the importance of between-firm differences in explaining the inequality decrease is not due to composition along observable dimensions.

Although informative, these type of decompositions of raw earnings cannot necessarily be interpreted as firms differing fundamentally in the way they compensate their workers. The reason is that some firms could hire workers who always get paid more regardless of where they work (maybe because they are more productive, have a higher bargaining power, etc). In this case, differences in pay across firms would arise as a result of recruitment policies and not pay policies. With this in mind, the next section identifies the importance of firm pay

become clear later, this difference is driven by three factors. First, dispersion in the firm component of pay play a relatively larger role in Brazil (at least in the first periods). Second, we estimate a higher degree of assortative matching between workers and firms than in the US Finally, the remainder is due to a higher degree of segregation in Brazilian labor markets.

[19] Another way of illustrating the importance of firms is to compare earnings growth of different workers with average earnings growth at their employers. Appendix B conducts this exercise and shows how the decrease in between-firm differences was driven by a catch-up of average firm earnings among the lowest earnings groups.



Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS.

Figure 4. : Variance between and within firms, by sector

policies using the panel dimension of the data.

IV. Empirical framework

The evidence in the previous section suggests that firms might be an important determinant of earnings in Brazil. Motivated by these insights, we estimate high-dimensional fixed effects econometric models controlling for both unobserved worker and firm heterogeneity. To be able to speak to changes over time in the components of inequality, we estimate our model separately in six subperiods covering 1988–1992, 1992–1996, 1996–2000, 2000–2004, 2004–2008, and 2008–2012, respectively.[20] Subsequently, we correlate the estimated firm and worker effects with observed characteristics of firms and workers in order to investigate what may have caused changes in the firm and worker component of pay over time.

A. *Worker and firm fixed effects model*

In order to separately identify the contribution of individual and firm components in pay, one needs to observe a panel of workers linked to their employers. The RAIS, our linked employer-employee data from Brazil, satisfy these requirements. Within subperiods that we set to be five years in length, we observe a number I of workers working at J firms for a total of N worker-years. Let $J(i,t)$ denote the employer of worker i in year t (as we uniquely defined in Section II). We assume that log earnings of individual i in year t, denoed y_{it}, consist of the sum of a worker component, α_i, a firm component, $\alpha_{J(i,t)}$, a year effect, Υ_t, and an error component, ε_{it}, so we can write,[21]

$$\log y_{it} = \alpha_i + \alpha_{J(i,t)} + \Upsilon_t + \varepsilon_{it}$$

where we assume that the error satisfies the strict exogeneity condition

$$\mathbb{E}\left[\varepsilon_{it} | \alpha_i, \alpha_{J(i,t)}, \Upsilon_t\right] = 0$$

Our specification does not control in this first stage for observable worker and firm characteristics. Instead, we correlate estimated fixed effects with worker and firm observables in a second stage of our analysis. We prefer this specification to avoid identifying the time-varying effects off changes within workers and firms during the limited time frame of each subperiod.[22] Furthermore, we find this two-stage approach helpful in terms of understanding what the firm and worker effects may ultimately be standing for.[23]

As shown by AKM, worker and firm effects can only be separately identified within a set of firms and workers connected through the mobility of workers. Table F1 in Appendix F presents summary statistics on the largest set of connected workers in each subperiod—this covers 97–98 percent of all workers in each subperiod. Given the high coverage, it is not surprising that the restricted

[20]In Appendix D we show that similar results obtain in longer, nine-year subperiods.

[21]Although our current paper does not model the underlying, fundamental sources of this reduced form specification, in subsequent work we show how it can be rationalized in a frictional labor market with firm productive heterogeneity and worker ability differences (Engbom and Moser, 2017*a*).

[22]Including age effects in the above framework with individual and year effects would require a normalization, as for instance the restriction advocated by Deaton (1997).

[23]In this sense, our approach is reminiscent of that of Bertrand and Schoar (2003) in their study of the determinants of CEO pay.

Table 3—: Frequency of switches, by period

	# Unique workers	Average # of jobs	% switchers
1988–1992	23.1	1.56	0.37
1992–1996	23.7	1.48	0.33
1996–2000	25.6	1.45	0.32
2000–2004	28.8	1.46	0.32
2004–2008	33.0	1.54	0.36
2008–2012	38.6	1.66	0.42

Note: Number of unique workers in millions. A switcher is defined as a worker who is associated with two or more employers during the period. Source: RAIS.

subpopulation looks very similar to the overall population. Thus the restriction to the largest connected set seems relatively innocuous.

As identification of the model derives from workers switching between firms, Table 3 presents statistics on the fraction of switchers in each subperiod. The degree of labor mobility is high in Brazil, with more than 30 percent of the population switching firms at some point during each five-year subperiod. The average number of firms worked at during the five years in each subperiod is about 1.5. There is no strong trend in either statistic.

The assumption on the error term is referred to in the literature as that of requiring *exogenous mobility*. As explained by AKM, this rules out mobility based on the unobserved error component. Following Card, Heining and Kline (2013), we investigate the validity of this assumption in several ways. We divide estimated firm effects into quartiles and study whether the gain in the firm component of those switching between for instance the first and fourth quartile is similar to the loss of those making the reverse switch. To the extent that match effects are an important determinant of earnings and mobility, we would expect all workers to make gains from switching. Furthermore, we examine the distribution of the average residual across worker and firm effects to check for any systematic deviation from zero (which could indicate that the log linear model is misspecified).

Let a_i denote the estimated worker effect, $a_{J(i,t)}$ the estimated firm effect, Y_t the estimated year effect, and e_{it} the residual. Based on our estimated equation, we decompose the variance of log earnings within any subperiod into the variance of the worker component, the firm component, and the year trend, as well as the covariance between the worker and the firm component, the worker and year component, the firm and year component, and the variance of the residual:

$$\begin{aligned} Var\left(\log y_{it}\right) &= Var\left(a_i\right) + Var\left(a_{J(i,t)}\right) + Var\left(Y_t\right) + 2Cov\left(a_i, a_{J(i,t)}\right) \\ &\quad +2Cov\left(a_i, Y_t\right) + 2Cov\left(a_{J(i,t)}, Y_t\right) + Var\left(e_{it}\right) \end{aligned} \tag{1}$$

Note that sampling error in the estimated effects will cause us to overestimate the variance of worker and firm effects, and in general induce a negative bias in the covariance between worker and firm effects (see for instance Andrews et al., 2008). Following Card, Heining and Kline (2013), we do not attempt to correct for this, but instead assume that this error is constant over time, so that even if the level of our estimated variances is slightly overstated, the changes we document over time are still valid.[24]

B. Determinants of the estimated firm effects

In the second stage of our empirical investigation, we study how the estimated firm effects relate to observable measures of firm performance available in the PIA survey. In particular, we are interested in understanding what firm characteristics are related to pay, and whether changes in the distribution of firm effects over time can be explained by underlying changes in firm characteristics or the way the labor market translates those into pay. Since the PIA only covers larger manufacturing and mining firms,[25] we are forced to restrict attention to only these firms and workers when linking firm effects to firm characteristics. We implement this by first estimating the AKM model for the universe of firms and workers, and subsequently restricting attention to only larger manufacturing firms.

Let $\mathbf{X_j}$ denote a vector of firm characteristics—for each subperiod we regress by OLS

$$a_j = \mathbf{X_j}\boldsymbol{\beta} + \eta_j$$

All regressions are weighted by worker-years. We consider versions including average log value added per worker during the subperiod, average log firm size during the subperiod, state fixed effects, and two-digit subsector fixed effects. Additionally, we have considered versions including a range of other firm characteristics as well as higher order terms, but these add only marginally to the explanatory power of the regressions so in the interest of space we do not show them.

Based on the above regression, we compute the variance in firm effects explained by firm observables as

$$Var\left(\hat{a}\right) = \mathbf{b}'Var(\mathbf{X})\mathbf{b}$$

where $\mathbf{b}$ is the estimated coefficient vector and $\mathbf{X}$ is the design matrix. In order to isolate the importance of a compression in firm fundamentals versus a compression in the pass-through from such fundamentals to pay, we consider two counterfactuals. First, we assume that the pass-through from firm characteristics to pay, $\boldsymbol{\beta}$, remains at its initial level, while the distribution of firm characteristics, $Var(\mathbf{X})$, changes over time. Second, we assume that $Var(\mathbf{X})$ stays the same while $\boldsymbol{\beta}$ changes as in the data. A comparison of the two counterfactuals allows us to

[24] To better estimate firm effects, Bonhomme, Lamadon and Manresa (2016) suggest restricting attention to firms whose fixed effect is "well-identified" due to a high number of switchers. In practice, this procedure boils down to restricting attention to workers at firms with at least 10 switchers during the estimation period. Implementing this restriction, we get similar results as those reported below.

[25] As described in Section II, we restrict attention to the deterministic stratum of PIA containing only larger firms. We drop small firms contained in the random stratum to ensure that firms stay in the sample for multiple years for our estimation procedure below.

address whether a change in the variance of firm pay is explained by changes in underlying firm characteristics or due to a change in the degree of pass-through from such characteristics to worker pay.

C. Determinants of the estimated worker effects

We also investigate what factors influence the worker component of pay. To this end, we proceed in a similar fashion as for firms and regress the predicted worker effects on a vector of worker observables, $\mathbf{W_i}$:

$$a_i = \mathbf{W_i}\boldsymbol{\zeta} + \eta_i$$

All regressions are weighted by worker-years. We include in $\mathbf{W_i}$ a constant, a worker's age bin, four education dummies, and state fixed effects (the former two computed as the modal value during the subperiod). We have also considered versions of this regression with age and education interacted as well as including occupation or sector controls, but as neither of these alternatives changes the estimated results meaningfully we do not report the results.

Based on this regression, we predict the variance explained by worker observables as

$$Var\left(\hat{a}\right) = \mathbf{z}'Var(\mathbf{W})\mathbf{z}$$

where $\mathbf{z}$ is the estimated coefficient vector and $\mathbf{W}$ is the design matrix. Subsequently, we decompose the evolution of the variance of the explained part of the worker effect into that due to a change in the underlying distribution of such characteristics versus a change in the return to them. That is, we first keep the estimated return to the characteristic of interest constant and change only the underlying distribution to match its evolution in the data. This shows how important changes in the distribution of worker characteristics were for the overall inequality decrease. Secondly, we instead change the return to the characteristic of interest as in the data, while holding the underlying distribution constant. This evaluates how important changes in the returns to age and education were for the overall inequality decrease.

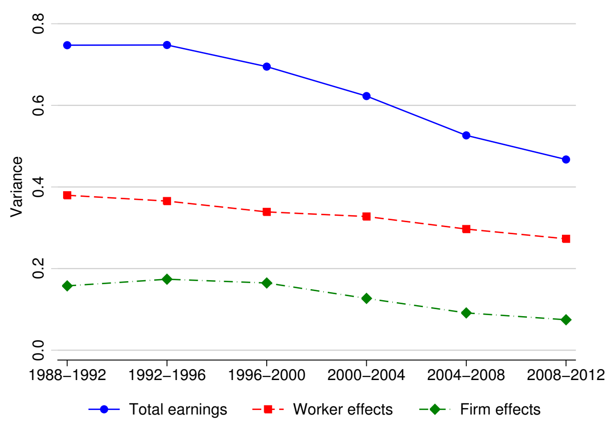
V. Results

In this section, we first present results from our first-stage two-way fixed effects model, decomposing earnings inequality into a firm and a worker component. Subsequently, we investigate the sources of the firm and worker component of pay. Finally, we provide additional results evaluating the assumptions imposed by our econometric model.

A. AKM decomposition

Table 4 presents the variance decomposition based on the estimation results of the AKM model in equation (1) for each of the six five-year subperiods between 1988 and 2012.[26] To illustrate the relative importance of the various components of this decomposition over time, Figure 5 plots the variance of raw earnings (solid blue line with circles), the variance of estimated worker effects (dashed red line with squares), and the variance of firm effects (dash-dotted green line with diamonds). The variance of year effects and covariance terms are small in magnitude and play an insignificant role in the overall inequality decrease. These terms are excluded for brevity. All results are weighted by worker-years.

Two important results emerge from our analysis. First, worker heterogeneity is the single most important determinant of earnings inequality. In the 1996–2000 subperiod, the variance of worker fixed effects makes up 49 percent of the total variance of log earnings. This increases monotonically to 58 percent by the last subperiod. The variance of firm effects makes up 24 percent of the variance of log earnings in the 1996–2000 subperiod, decreasing to 16 percent by the last subperiod. Finally, the covariance between the worker and firm effects consistently explains just under 20 percent of the overall variance.



Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS.

Figure 5. : Variance decomposition from AKM model

Second, in terms of explaining time trends, we observe a more than proportionate fall in the variance of firm effects. Between 1996–2000 and 2008–2012, the variance of firm effects falls from 16 to seven log points whereas the variance of person effects falls from 34 to 27 log points. The correlation between worker and firm effects stays fairly constant at around 0.3 throughout the period, and

[26]Appendix D shows that similar results are obtained using three longer, nine-year subperiods.

Table 4—: AKM estimation results, by period

	1988–1992	1992–1996	1996–2000	2000–2004	2004–2008	2008–2012	Change 1996–2012
Variance of log earnings	0.75 (100.0%)	0.75 (100.0%)	0.69 (100.0%)	0.62 (100.0%)	0.53 (100.0%)	0.47 (100.0%)	-0.23 (100.0%)
Variance of worker effects	0.38 (50.8%)	0.37 (48.9%)	0.34 (48.8%)	0.33 (52.6%)	0.30 (56.4%)	0.27 (58.4%)	-0.07 (29.0%)
Variance of firm effects	0.16 (21.1%)	0.17 (23.3%)	0.16 (23.7%)	0.13 (20.4%)	0.09 (17.4%)	0.07 (16.0%)	-0.09 (39.6%)
Variance of year effects	0.02 (2.2%)	0.01 (2.0%)	0.00 (0.1%)	0.00 (0.1%)	0.00 (0.1%)	0.00 (0.3%)	0.00 (-0.3%)
2×Cov. worker and firm effects	0.13 (17.3%)	0.14 (18.6%)	0.14 (20.0%)	0.12 (18.8%)	0.10 (18.6%)	0.09 (18.4%)	-0.05 (23.2%)
2×Cov. worker and year effects	-0.01 (-1.2%)	-0.01 (-1.6%)	0.00 (-0.3%)	0.00 (0.2%)	0.00 (0.1%)	0.00 (-0.6%)	0.00 (0.2%)
2×Cov. firm and year effects	0.00 (-0.5%)	-0.01 (-0.8%)	0.00 (-0.2%)	0.00 (0.1%)	0.00 (0.0%)	0.00 (0.0%)	0.00 (-0.5%)
Variance of residual	0.08 (10.1%)	0.07 (9.7%)	0.06 (7.9%)	0.05 (7.8%)	0.04 (7.4%)	0.04 (7.6%)	-0.02 (8.7%)
# worker years	77.3	77.3	81.5	91.8	110.0	132.2	
# firms	0.96	1.02	1.21	1.41	1.71	2.16	
R^2	0.90	0.90	0.92	0.92	0.93	0.92	

Note: Variance decomposition is $Var\left(y_{it}\right) = Var\left(a_i\right) + Var\left(a_j\right) + Var\left(Y_t\right) + Var\left(e_{it}\right) + 2Cov\left(a_i, Y_t\right) + 2Cov\left(a_j, Y_t\right) + 2Cov\left(a_j, Y_t\right)$. Cells contain the variance explained by each decomposition element. The share of the total variance explained by each decomposition element is given in parentheses. Weighted by worker-years. Source: RAIS.

hence the covariance term falls in line with the standard deviations of the worker and firm effects. Given the large role played by firms in the inequality decrease, understanding the drivers of more equal pay across employers over time is an important question which we address in the following section.

B. *The link between firm effects and firm characteristics*

When studying the link between firm effects and firm characteristics, we limit attention to the manufacturing and mining sector, for which we have data on firm performance and characteristics. Table 5 compares AKM estimates for this subpopulation with the estimates for the overall population. As noted earlier, we impose the restriction to the PIA subpopulation after estimating the AKM model on the entire population of adult males. This group includes a small percentage of firms in the overall economy (2.6–2.9 percent), but covers 18–19 percent of employment given the larger size of firms in the manufacturing and mining sectors. The overall variance of log earnings is five log points higher in the PIA subpopulation during the 1996–2000 subperiod and falls by 22 log points until the 2008–2012 subperiod, compared to 23 log points in the overall population. The variance of worker effects is three log points higher in the 1996–2000 subperiod and falls by two log point less. The variance of firm effects is two log points less in 1996–2000 and falls by one log point less. We conclude that inequality trends are similar in the PIA subpopulation compared to the overall population.

Why do some firms pay more than others, and what makes firms offer more equal pay over time? Table 6 reports results from regressing estimated firm effects on average log value added per worker and average log firm size by subperiod, either with or without subsector or state controls. All regressions are weighted by worker-years. Several features are worth highlighting. First, more productive and larger firms pay significantly more after controlling for sorting of workers. Our estimates suggest that a one log point more productive firm pays a given worker 0.26 log points more, or alternatively that a one standard deviation more productive firm pays over 30 percent more to a given worker. Furthermore, we find that essentially the entire return to working at a larger firm is due to a strong positive correlation between firm size and productivity—controlling for value added per worker a larger firm pays only marginally better.

Second, the amount of dispersion in firm effects explained by firm productivity is notable. Only a linear term in average log value added per worker explains around half of the variation in the firm component of pay, despite the fact that sampling error in the estimated firm effects will lead us to understate the importance of productivity for pay. Adding also controls for subsector, the R^2 is over 0.6.

Third, the pass-through from firm performance to the firm component of pay falls substantially between 1996–2000 and 2008–2012. As noted above, in the first subperiod a one log point more productive firm paid 0.26 log points more—by the last subperiod this pass-through has almost halved to 0.14. Given that

Table 5—: Comparison of AKM estimation results between workers at larger manufacturing & mining firms and largest connected set, by period

	1996–2000	2000–2004	2004–2008	2008–2012	Change 1996–2012
Variance of log earnings (% of pop. estimate)	0.74 (106.9%)	0.70 (113.0%)	0.60 (114.2%)	0.53 (112.6%)	-0.22 (95.1%)
Variance of worker effects (% of pop. estimate)	0.37 (109.8%)	0.37 (112.3%)	0.35 (116.4%)	0.32 (116.6%)	-0.05 (81.3%)
Variance of firm effects (% of pop. estimate)	0.14 (86.8%)	0.12 (92.1%)	0.08 (84.3%)	0.06 (81.4%)	-0.08 (91.2%)
Variance of year effects (% of pop. estimate)	0.00 (105.4%)	0.00 (99.4%)	0.00 (100.0%)	0.00 (99.9%)	0.00 (93.5%)
2×Cov. worker and firm effects (% of pop. estimate)	0.17 (125.9%)	0.17 (141.4%)	0.14 (137.8%)	0.11 (127.3%)	-0.07 (123.6%)
2×Cov. worker and year effects (% of pop. estimate)	0.00 (111.8%)	0.00 (122.4%)	0.00 (118.8%)	0.00 (107.4%)	0.00 (90.1%)
2×Cov. firm and year effects (% of pop. estimate)	0.00 (85.3%)	0.00 (101.4%)	0.00 (84.6%)	0.00 (-11.8%)	0.00 (96.8%)
Variance of residual (% of pop. estimate)	0.05 (95.2%)	0.05 (96.1%)	0.04 (98.1%)	0.03 (98.7%)	-0.02 (89.0%)
# worker years (% of pop. estimate)	15.5 (19.0%)	16.7 (18.2%)	21.0 (19.1%)	23.9 (18.1%)	
# firms (% of pop. estimate)	0.03 (2.9%)	0.04 (2.9%)	0.05 (2.8%)	0.06 (2.6%)	
R^2 (% of pop. estimate)	0.93 (100.9%)	0.93 (101.3%)	0.94 (101.1%)	0.93 (101.0%)	

Note: Variance decomposition of AKM model for larger manufacturing firms covered by PIA. The ratio between estimates using manufacturing firms relative to AKM estimates using all sectors is given in parentheses. Worker- and firm-years in millions. Weighted by worker-years.

Source: RAIS and PIA.

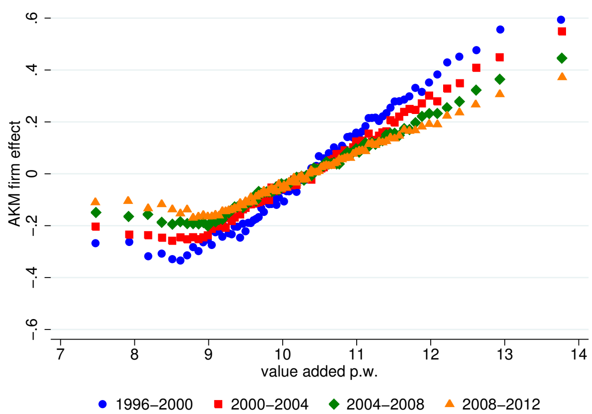
Table 6—: Results from regression of estimated firm effects on firm characteristics

	1996–2000			2000–2004			2004–2008			2008–2012		
PANEL A. NO CONTROLS												
Value added p.w.	0.256		0.136	0.198		0.099	0.158		0.090	0.140		0.078
Firm size		0.109	-0.014		0.077	-0.179		0.050	-0.120		0.045	-0.097
Value added p.w. x Firm size			0.015			0.016			0.011			0.009
Worker-years	15.5	15.5	15.5	16.7	16.7	16.7	21.0	21.0	21.0	23.9	23.9	23.9
R^2	0.582	0.247	0.601	0.558	0.160	0.571	0.527	0.117	0.537	0.464	0.130	0.474
PANEL B. SUBSECTOR CONTROLS												
Value added p.w.	0.234		0.122	0.179		0.082	0.140		0.073	0.120		0.053
Firm size		.106	-0.107		0.080	-0.139		0.056	-0.086		0.047	-0.079
Value added p.w. x Firm size			0.013			0.138			0.009			0.008
Worker-years	15.5	15.5	15.5	16.7	16.7	16.7	21.0	21.0	21.0	23.9	23.9	23.9
R^2	0.653	0.459	0.676	0.646	0.430	0.660	0.627	0.424	0.638	0.613	0.457	0.629
PANEL C. STATE CONTROLS												
Value added p.w.	0.228		0.133	0.177		0.099	0.143		0.082	0.128		0.065
Firm size		0.111	-0.059		0.083	-0.106		0.057	-0.083		0.051	-0.071
Value added p.w. x Firm size			0.009			0.011			0.008			0.007
Worker-years	15.5	15.5	15.5	16.7	16.7	16.7	21.0	21.0	21.0	23.9	23.9	23.9
R^2	0.667	0.502	0.698	0.641	0.410	0.651	0.600	0.353	0.609	0.552	0.360	0.567

Note: Dependent variable is the estimated firm effect a_j. Number of worker-years in millions. Weighted by worker-years. Source: RAIS and PIA.

the standard deviation of value added per worker remained roughly constant at just above one over this period, the variation in pay attributable to variation in firm productivity fell substantially. On the contrary, although both subsectors and states explain a non-trivial amount of the level of inequality in firm pay, compression across states or subsectors explains little of the declining dispersion in firm pay.

Figure 6 illustrates the relationship by plotting by period the average estimated AKM firm effects against 90 quantile bins of value added per worker. Over most of its support, the relationship is approximately linear, and it displays a clear flattening over time.

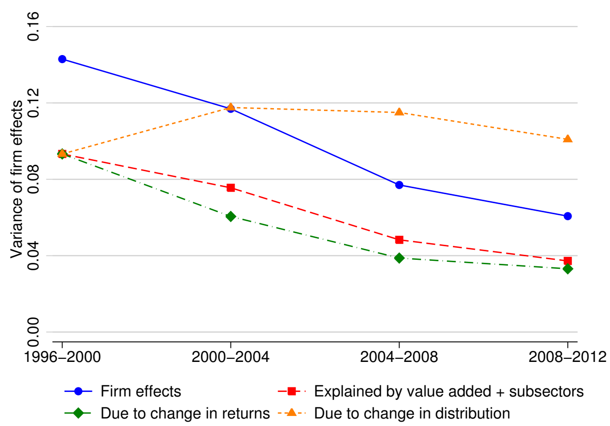


Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS and PIA.

Figure 6. : Estimated AKM firm effects versus value added per worker, by period

To illustrate the importance of the fall in the pass-through for the overall inequality decrease, Figure 7 plots the variance of firm effects (solid blue line with circles), the predicted variance due to value added per worker and subsector controls (dashed red line with squares), and the predicted variance due to only changing the passthrough from productivity to pay (dash-dotted green line with diamonds). Between 1996–2000 and 2008–2012, the variance explained by observable firm characteristics decreases by six log points, or roughly 30 percent of the overall decrease in the variance of log earnings over this period. All of this is driven by changes in the pass-through.

One possibility is that the pass-through from value added per worker to pay differs systematically by size of firm, and that changes in the firm size distribution over time has led to a fall in the measured pass-through. Table 7 investigates this by pooling all subperiods and including a time invariant interaction between value added per worker and firm size, in addition to period effects and period specific pass-throughs from value added per worker and firm size to pay. The estimated fall in pass-through from value added per worker to pay is comparable to our previous estimation results, confirming that the decrease has taken place conditional on firm size.[27] Figure 8 illustrates this by plotting the relationship between estimated AKM firm effects and value added per worker separately by firm size quartiles over time.



Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS and PIA.

Figure 7. : Variance of firm effects, variance explained by value added per worker, and counterfactual variance with constant returns

C. *The link between worker effects and worker characteristics*

We finally turn to our results regarding the link between observable worker characteristics and the worker component of pay. Table 8 shows estimates from regressing the estimated worker effects on age and education, with or without state controls. We note the following: First, more able workers, as measured by labor market experience or education level, are paid more. For instance, the oldest age group earns 44–54 log points more than the youngest age group conditional on place of work, and a college graduate earns more than twice the amount of the lowest education group. Observable worker characteristics jointly explain 37–42 percent of the variance in the worker component of pay, with most of the dispersion being observed within states.

Second, both the age gradient and the return to education decrease over time. Workers aged 40–49 experienced a decrease in pay relative to those aged 18–24 of eight log points (or 15 percent) between 1996–2000 and 2008–2012. Over the same

[27]Appendix E investigates whether opening up to trade may have mechanically reduced the pass-through by separately considering exporters and non-exporters, and finds that both groups have experienced a similar fall in the pass-through as the overall economy.

Table 7—: Results from regression of estimated firm effects on firm characteristics controlling for differential pass-through by firm size

		Baseline	State	Sector
Value added p.w.	1996–2000	0.158	0.139	0.142
	2000–2004	0.124	0.116	0.106
	2004–2008	0.082	0.075	0.062
	2008–2012	0.058	0.053	0.040
Firm size	1996–2000	-0.105	-0.063	-0.078
	2000–2004	-0.133	-0.092	-0.100
	2004–2008	-0.134	-0.092	-0.099
	2008–2012	-0.130	-0.089	-0.096
Value added p.w. x Firm size		0.012	0.009	0.010
Subsector controls		No	No	Yes
State controls		No	Yes	No
Worker-years		77.1	77.1	77.1
R^2		0.553	0.627	0.648

Note: Dependent variable is the estimated firm effect a_j. All specifications include period effects. Number of worker-years in millions. Weighted by worker-years. Source: RAIS and PIA.

time period, middle school, high-school and college graduates saw decreases of five, 19 and nine log points, respectively, relative to those with only primary school. Figure 9 illustrates these results by plotting the overall variance of worker effects (solid blue line with circles), the predicted variance due to age and education (dashed red line with squares), the counterfactual variance explained by changes only in the returns (dash-dotted green line with diamonds), and the counterfactual variance explained by changes only in the distribution. We find that education and age account for roughly 50 percent of the decline in dispersion in the worker component, and this is all due to a change in returns.[28]

D. Support for the AKM model

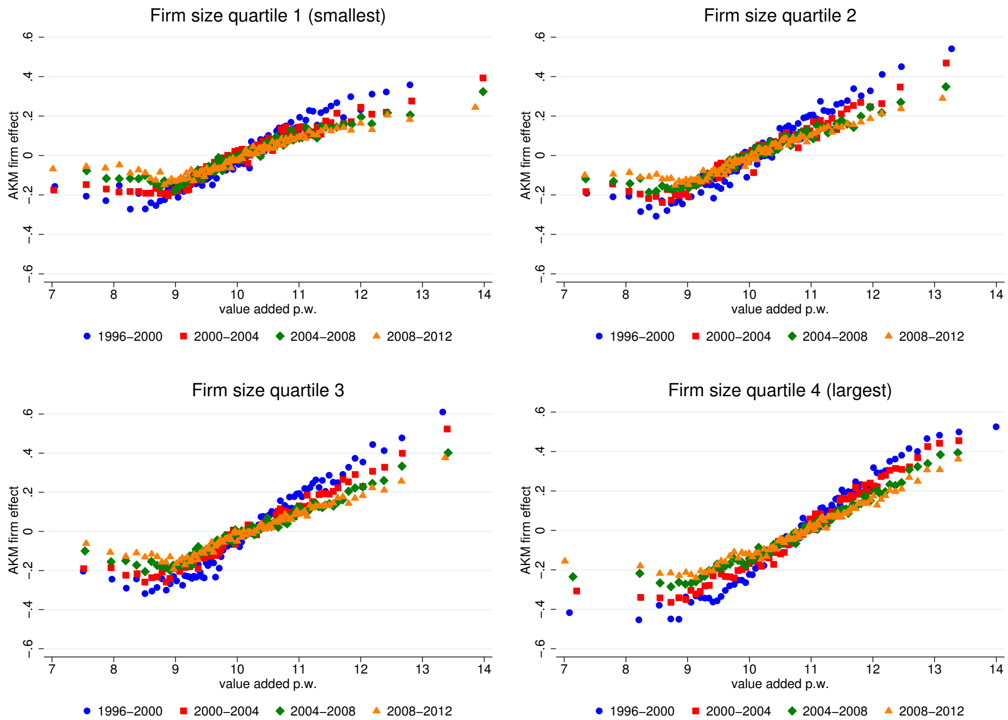
A large part of our analysis has been based on estimation results from repeated applications of the AKM framework. Although the consistently high R^2 of our model suggests that it provides a good fit to the data, our estimates can be biased if the match effect is correlated with either the firm or worker component of earnings. To investigate this possibility further, we replicate two robustness exercises proposed by Card, Heining and Kline (2013) using the Brazilian RAIS data.

[28]Of course, falling returns could result from changes in the distribution. The counterfactual of holding the distribution constant while changing returns should be interpret with this qualification in mind.

Table 8—: Results from regression of estimated worker effects on worker characteristics

	1988–1992		1992–1996		1996–2000		2000–2004		2004–2008		2008–2012	
Age groups												
25–29	0.194	0.200	0.180	0.187	0.183	0.188	0.177	0.182	0.158	0.165	0.158	0.165
30–39	0.399	0.404	0.355	0.364	0.347	0.354	0.347	0.352	0.318	0.323	0.299	0.304
40–49	0.533	0.538	0.515	0.523	0.513	0.520	0.505	0.509	0.472	0.475	0.436	0.437
Education groups												
Middle school	0.204	0.200	0.189	0.181	0.154	0.142	0.135	0.117	0.122	0.101	0.103	0.084
High school	0.617	0.623	0.572	0.576	0.463	0.459	0.380	0.363	0.320	0.296	0.269	0.246
College or more	1.235	1.228	1.192	1.178	1.152	1.128	1.176	1.146	1.125	1.088	1.066	1.030
State controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Worker-years	77.3	77.3	77.3	77.3	81.5	81.5	91.8	91.8	110.0	110.0	132.2	132.2
R^2	0.398	0.423	0.379	0.409	0.365	0.401	0.368	0.404	0.366	0.399	0.365	0.392

Note: Dependent variable is the estimated worker effect a_i. Number of worker-years in millions. Weighted by worker-years. Education estimates are relative to less than middle school ($<$ 7 years), age estimates are relative to age 18–24. Source: RAIS.



Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS and PIA.

Figure 8. : Estimated AKM firm effects versus value added per worker, by firm size quartile and period

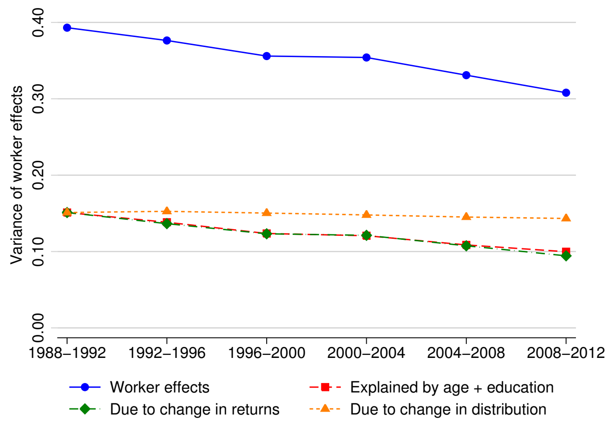
First, Figure 10 shows the average earnings of workers who switch firms up to two years prior to the switch and two years after the switch for the latest subperiod.[29] Switchers are classified by the firm effect quartile of their pre- and post-transition employers. Consistent with the AKM specification, the gains of those switching up are similar to the losses of those making the reverse switch.[30]

Second, Figure 11 shows the average estimated residual by decile of worker and firm effects for the subperiods 1996–2000 and 2008–2012.[31] There is some evidence of misspecification for the lowest decile of worker effects in the sense that they display a systematically positive residual while working at the lowest-paying firms, and vice versa for highest-paying firms. Similarly, the lowest firm effects decile shows systematic positive mean residuals for the lowest-paid workers, and vice versa for the highest-paid workers. However, the magnitude of these errors

[29]Similar results hold in other subperiods and across other quartiles.

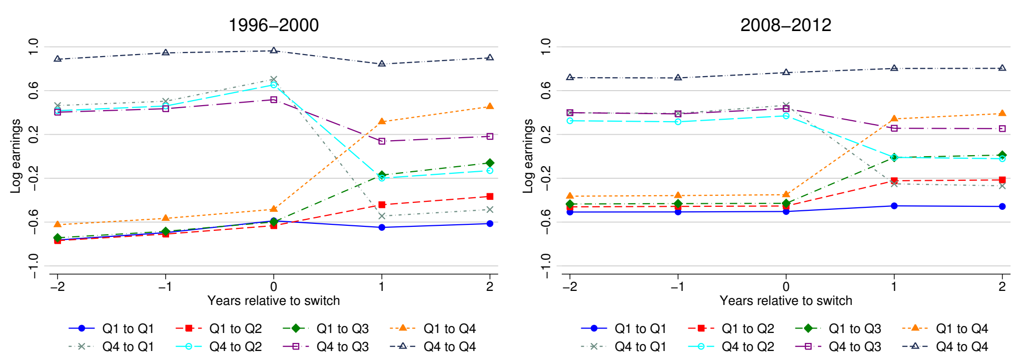
[30]Bonhomme, Lamadon and Manresa (2016) caution that models that do not feature log additivity in earnings may also satisfy this test. The results of this event study should be interpreted with this qualification in mind.

[31]Similar results hold in other subperiods.



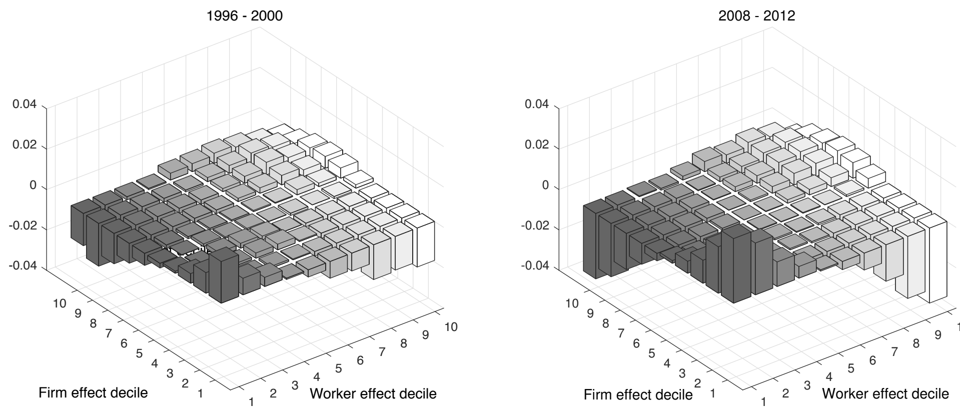
Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS.

Figure 9. : Variance of worker effects, variance explained by age and education, and variance holding the return to age and education constant



Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS.

Figure 10. : Average changes in earnings of workers switching employers



Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS.

Figure 11. : AKM residual by firm and worker fixed effect deciles

is modest and beyond the lowest deciles of worker and firm effects errors do not exhibit a strong systematic relationship.[32]

E. Potential explanations behind decreasing inequality in Brazil

A key takeaway from our analysis is that changes in the pass-through from worker and firm characteristics to pay was a major driver behind Brazil's inequality decrease from 1996 to 2012. While measures of worker ability and firm productivity are positively correlated with pay throughout this period, it is not the case that Brazil became more equal in terms of such fundamentals. Instead the pass-through from these characteristics to pay collapsed, resulting in a lower worker skill pay premium and a lower firm productivity pay premium. An important question is what might have caused this decrease in pass-through.

Although our current paper stops short of providing a complete story behind the fall in pass-through, we highlight a few explanations that we view as more or less promising based on our empirical analysis. We first note that an overwhelming majority of the inequality decrease took place within states and detailed industry classifications. Second, the pass-through from productivity to pay fell within firm size groups, for exporters and non-exporters, and for a balanced panel of surviving firms. Based on these observations, we believe that a convincing explanation goes beyond the direct effect of compositional changes.

Consistent with our empirical findings, we briefly discuss three promising explanations behind Brazil's inequality decrease. First, there was a rapid expansion in educational attainment over this period. By increasing the labor supply of higher education groups, this may have contributed towards falling education premiums.

[32]Engbom and Moser (2017*a*) argue that this pattern is consistent with a binding minimum wage.

It would be interesting to quantify this channel through an equilibrium model estimated to the microdata. However, it is worth stressing that most of Brazil's inequality decrease was due to forces on the firm side. It is less clear to us why changes in the market for education would affect firm-specific pay components.

Second, changes in bargaining between employers and employees over firm-specific surplus may directly speak to the declining dispersion in firm-level pay. Higher baseline pay and lower dependence on firm-specific (worker-specific) performance could plausibly explain our documented facts on rising real earnings and a lower pass-through from firm productivity (worker ability) to pay. Specifically, although unions have held a strong role in Brazil throughout this period, to the extent that the bargaining process became more centralized over this period, this may have made earnings less dependent on firm-specific performance and more on regional, industry or aggregate negotiation outcomes. Using detailed data on union bargaining agreements to study this further would be an interesting avenue for future research.

Third, Brazil's federal minimum wage rose by 119 percent in real terms from 1996 to 2012. Given that this legislation cuts across sectors and states, we view it as a promising candidate for explaining the decrease of inequality in Brazil over this period. Consistent with our finding that the inequality decrease is primarily due to changes in the returns to worker and firm characteristics, the minimum wage may plausibly affect the way that firm-specific surplus is split without directly affecting the distribution of worker and firm characteristics. A challenge for this story, however, is to explain why inequality fell throughout large parts of the earnings distribution. In Engbom and Moser (2017*a*), we pursue this idea further by developing an equilibrium search model and estimating spillover effects of the minimum wage.

VI. Conclusion

In this paper, we used detailed linked employer-employee dissect the evolution of inequality in Brazil between 1988 and 2012. After increasing moderately between 1988–1996, the variance of log labor earnings decreased by 28 log points between 1996–2012. To understand the sources of this decrease, we estimate high-dimensional fixed effects models of earnings controlling for worker and firm heterogeneity. Our results suggest that firms contributed more than proportionately to the decrease.

While more productive firms pay more, compression in firm productivity was not a factor behind declining inequality. Instead, we find that a declining pass-through from firm productivity to pay played an important role behind the decrease. On the worker side, higher ability workers as measured by educational attainment or experience are paid more, yet such measures of worker ability show no compression over time. Rather, a significant share of the explained decrease in worker heterogeneity is due to rapidly falling returns to such measures of worker ability. We conclude that changes in pay policies, rather than changes in firm and worker fundamentals, played a significant role in Brazil's inequality decrease.

Our findings propose a set of facts that any potential theory of the inequality decrease in Brazil should be consistent with. Such a theory must generate pay differences between firms for identical workers that are strongly positively correlated with firm productivity. Moreover, any promising explanation needs to generate a compression in firm pay differences over time not through compression in the distribution of firm productivity, but through a weaker link between productivity and pay. On the worker side, it should generate compression primarily through declining returns to ability and not through compression in the underlying ability distribution.

We think that promising candidates behind the decrease in inequality in Brazil are changes in the nature of wage setting. In follow-up work (Engbom and Moser, 2017*a*), we argue that the rapid rise in the minimum wage in Brazil during this period has had large effects on earnings inequality, while being consistent with the stylized facts presented in this paper. Our work suggests that investigating other labor market institutions represents a promising avenue for future research in the context of earnings inequality dynamics in Brazil and potentially elsewhere.

Appendix A: Mincer regressions

This section studies changes in worker observables and their returns within a Mincer framework. In contrast to a popularly held belief, Brazil's inequality decline was not driven by worker observables and the rapid increase in educational attainment that took place during this period.

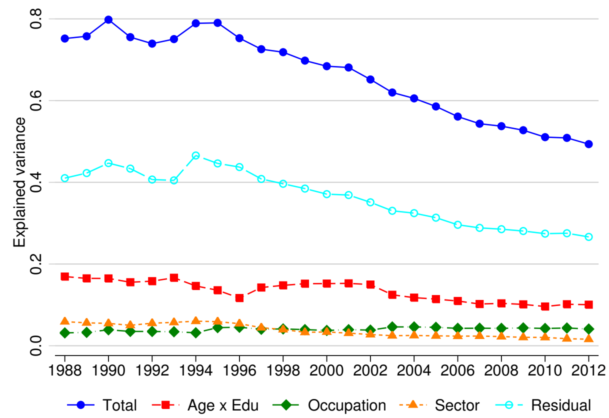
Building on the classical framework by Mincer (1974), we regress log monthly real earnings on worker observables. Specifically, we include five age group dummies interacted with nine education group dummies, one digit occupation dummies and two digit sector dummies,

$$\log(y_{it}) = age_{it} \times edu_{it} + occ_{it} + sec_{it} + \varepsilon_{it}$$

Note that all explanatory variables are allowed to vary freely by year. Based on this regression, we calculate the predicted value due to each component and report the variance of these predicted values.

Figure A1 plots the results. We draw two conclusions: First, worker observables jointly explain about 45 percent of the overall variance in log earnings. In contrast, our AKM methodology in Section IV suggests that worker observables explain 37–40 percent of the variance of *the worker component* of earnings (which constitutes 50–60 percent of the overall variance). Partly, the difference can be explained by the fact that we let observables as well as their returns vary by year in the Mincer framework while the AKM framework uses averages over the subperiod. Conceptually more important, the discrepancy suggests that part of the return to education and experience is due to a selection into better paying firms.

Second, the fraction of earnings dispersion explained by worker observables does not change much over time. Hence, worker observables and sector controls explain close to 23 percent of the fall in inequality. Decomposing this, age and education account for roughly 20 percent of the variance of log earnings and six percent of the decline. Inequality between occupations remains relatively constant around six to eight percent of total variance. The fraction of total inequality explained by differences in means across sectors falls from seven to three percent—this accounts for 15 percent of the overall decline in variance. Finally, covariances between the explanatory variables remain stable around 12–14 of total variance. We conclude that even when controlling for detailed worker characteristics, more than half of the level of inequality as well as its decline is residual in nature.



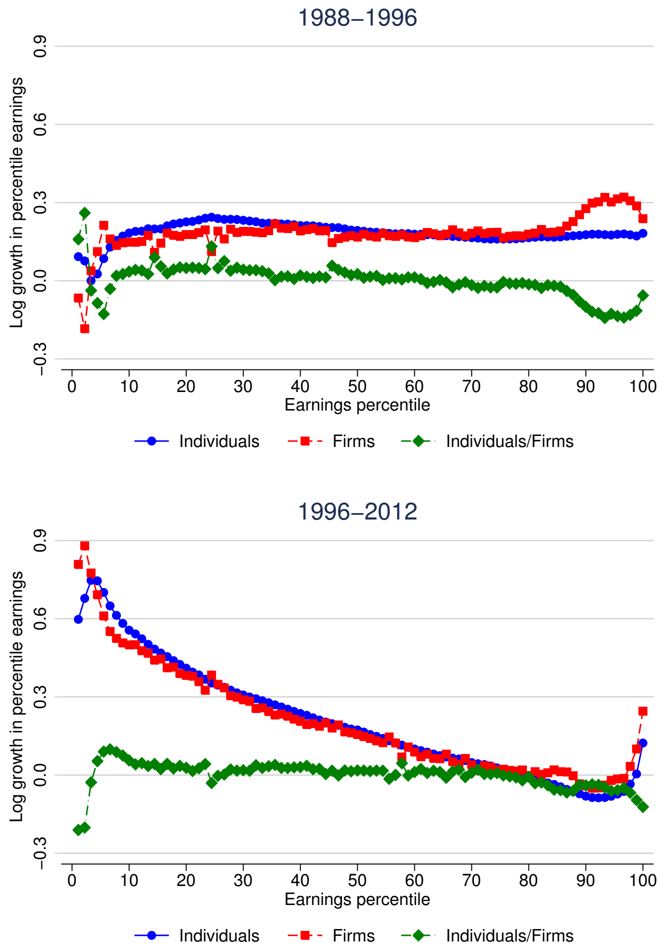
Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS.

Figure A1. : Variance decomposition from Mincer regressions

How do these results square with the common claim that a rapid increase in educational attainment contributed towards Brazil's inequality decline? To this end, it is important to note that while the Brazilian workforce saw a steep rise in high school (college) attainment from 16 (eight) percent in 1996 to 49 (ten) percent in 2012, this shift was offset by a concurrent reduction in the high school (college) premium relative to less than middle school from 0.72 (1.32) log points in 1996 to 0.22 (1.23) log points by 2012. Hence the push towards higher educational levels, particularly among initially lowest education groups, was largely offset by a decline in the returns to education. This story is consistent with our findings of a lower gradient of worker effects in worker observables, including education, which we highlight in Section V.

Appendix B: Earnings growth and firm average earnings growth by initial earnings percentiles

Following Barth et al. (2016) and Song et al. (2016), we make use of the linked employer-employee nature of the RAIS data to quantify to what extent earnings growth across income groups was mediated by changes in average pay at firms employing workers from that income group. The results of this exercise are shown in Figure B1 for the period 1988–1996, when inequality increased mildly, and for the period 1996–2012, when earnings inequality declined rapidly.



Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS.

Figure B1. : Individual real labor earnings growth between and within firms

There are three features worth noting. First, real labor earnings growth occurred at almost every percentile of the distribution throughout both periods. Second, individual earnings growth (solid blue line with circles) slopes mildly upward in initial earnings percentiles from 1988–1996 and pronouncedly slopes downward from 1996–2012, indicating that earnings inequality increased a little during the first period and decreased significantly during the second period. Third, individual earnings growth throughout the distribution is almost entirely explained by the growth of firm average earnings (dashed red line with squares) among those groups. Remarkably, there were no significant changes in within-firm earnings inequality (dash-dotted green line with diamonds).

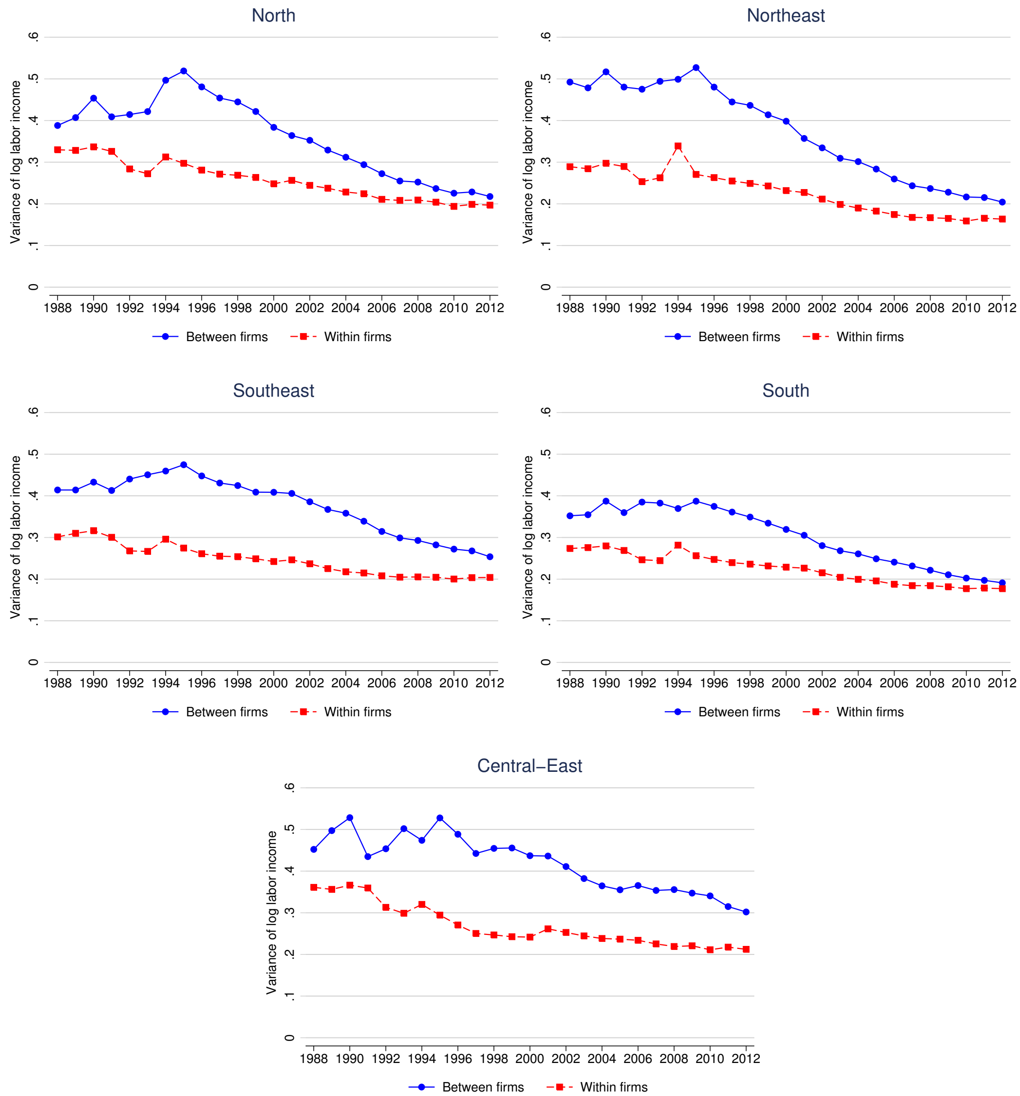
We interpret these results as suggestive evidence in favor of firms playing an important role in explaining earnings inequality dynamics during the period of increasing inequality from 1988–1996 and also during the large decrease in inequality from 1996–2012.

Appendix C: Variance between and within firms by region, firm size and productivity

We now show that the compression in pay across firms was not solely driven by a particular subset of regions or firms, nor was it driven by a compression in average differences between regions or productivity groups.

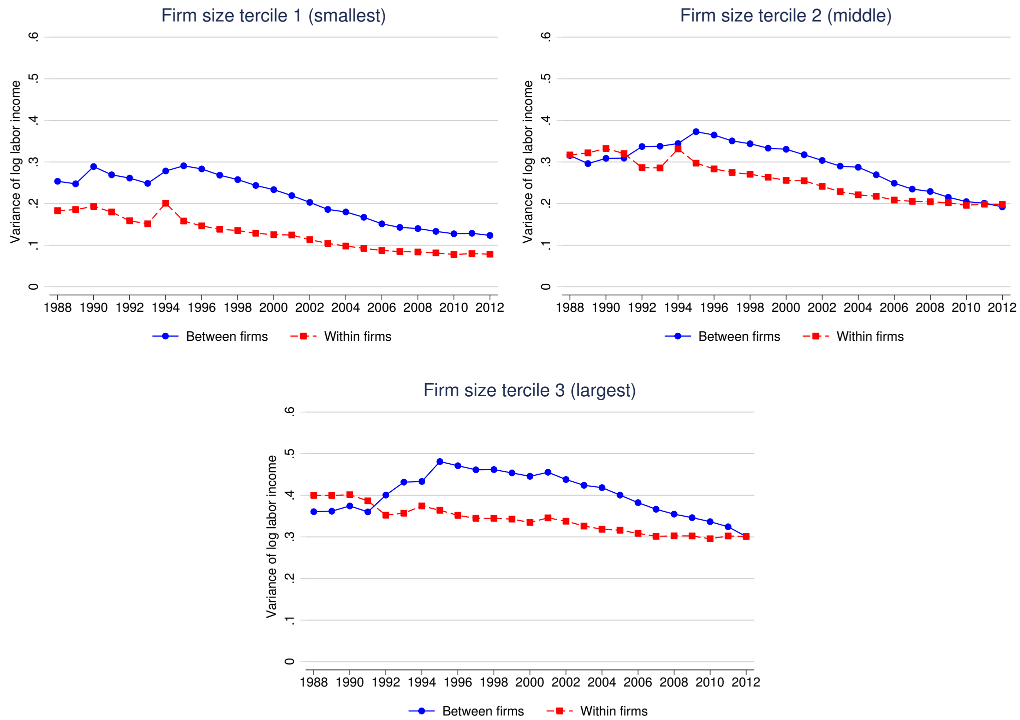
Figure C1 plots inequality across and within firms within Brazilian regions. Although there are differences in levels, all regions display substantial compression of pay over time. Moreover, the dominance of between-firm compression is present in every region.

Similarly, Figures C2 and C3 plot the same decomposition of inequality between and within firms by size of the firm and by productivity of the firm, respectively. We observe a similar pattern of substantial compression across firms within small, medium and large firms, as well as within low-productivity and medium-productivity firms. The decline is less pronounced among high productivity firms.



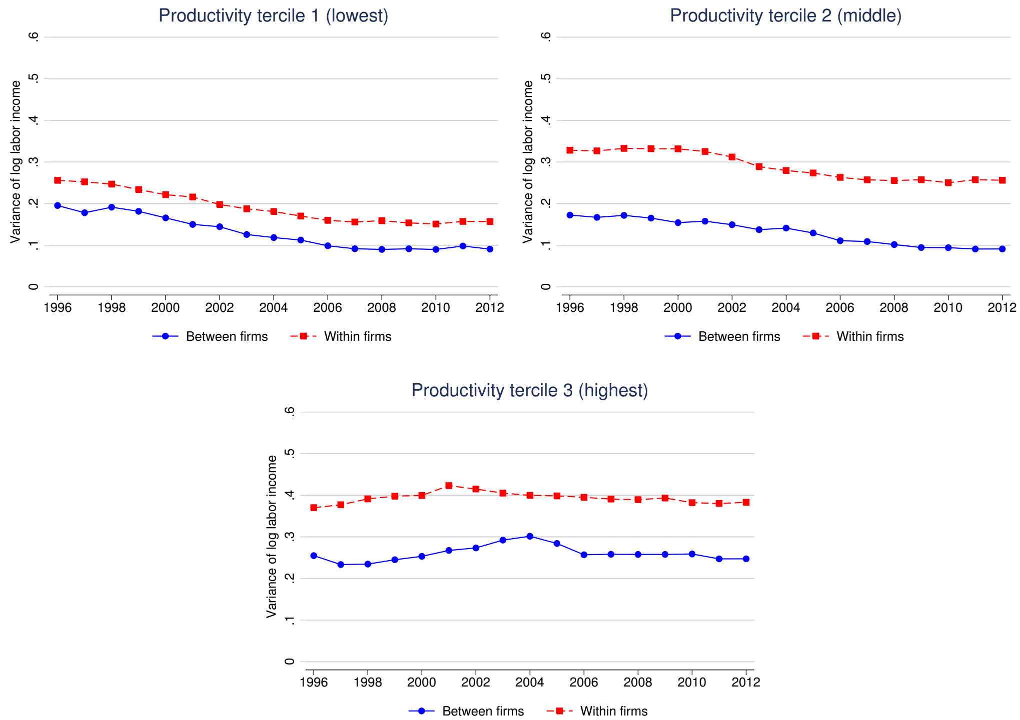
Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS.

Figure C1. : Variance between and within firms within Brazilian regions.



Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS.

Figure C2. : Variance between and within firms, by firm size terciles



Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS and PIA.

Figure C3. : Variance between and within firms, by productivity terciles

Appendix D: Robustness of AKM results

The following section presents additional robustness results to our first-stage AKM regressions. First, we show that similar results are obtained in longer, nine-year subperiods instead of our baseline five-year subperiods. Second, we present results for the last four subperiods using hourly wages.

D1. Longer subperiods

Table D1 shows results for nine-year subperiods 1988–1996, 1996–2004, and 2004–2012. As expected, worker effects explain a few percentage points less of the overall variation in earnings, which is offset by a larger variance of the residual. The share contributed by firm effects remains roughly the same. Our main conclusion that worker effects explain most of the level of inequality while firm effects explain a disproportionate share of the decline continues to hold.

Table D1—: AKM robustness results, longer subperiods

	1988–1996	1996–2004	2004–2012	Change 1996–2012
Variance of log earnings	0.77 (100.0%)	0.70 (100.0%)	0.54 (100.0%)	-0.23 (100.0%)
Variance of worker effects	0.35 (45.9%)	0.32 (46.0%)	0.29 (53.6%)	-0.06 (27.6%)
Variance of firm effects	0.170 (21.9%)	0.15 (21.7%)	0.09 (16.3%)	-0.08 (35.3%)
Variance of year effects	0.03 (3.3%)	0.00 (0.2%)	0.00 (0.2%)	-0.03 (10.9%)
2×Cov. worker and firm	0.15 (19.7%)	0.15 (21.2%)	0.11 (20.5%)	-0.04 (17.7%)
2×Cov. worker and year	-0.02 (-2.3%)	0.00 (0.5%)	0.00 (-0.2%)	0.02 (-7.3%)
2×Cov. firm and year	-0.01 (-1.4%)	0.00 (0.3%)	0.00 (0.0%)	0.01 (-4.6%)
Variance of residual	0.10 (12.8%)	0.07 (10.3%)	0.05 (9.6%)	-0.05 (20.6%)
# worker-years	155.6	175.9	249.4	
# firms	1.45	1.93	2.80	
R^2	0.87	0.90	0.90	

Note: Variance decomposition is $Var\left(y_{it}\right) = Var\left(a_i\right) + Var\left(a_j\right) + Var\left(Y_t\right) + Var\left(e_{it}\right) + 2Cov\left(a_i, Y_t\right) + 2Cov\left(a_j, Y_t\right) + 2Cov\left(a_j, Y_t\right)$. Cells contain variance explained by each decomposition element. The share of the total variance explained by each decomposition element given in parentheses. Weighted by worker-years. Source: RAIS.

D2. Hourly wages

Our data do not contain information on hours prior to 1994, but we do have data on contracted weekly hours after that year. We find relatively small variation in contracted hours for prime age males, with the top 75 percent of the distribution reporting working 44 hours a week (conditional on working). To further verify the robustness of our results to variation in labor supply, Table D2 shows results from our first stage regression for the last four subperiods using hourly wages.

Inequality in hourly wages falls by four log points more than inequality in monthly income. This is primarily accounted for by a larger fall in the variance of the worker component of pay, while the fall in the firm component is in line with our earlier findings. Yet, our main conclusion that a compression in the firm component of pay contributed the most to the overall fall remains.

Appendix E: Robustness of the relationship between productivity and pay

The following section presents additional robustness results related to our second-stage regressions of firm effects on productivity. First, we show results estimated using a balanced panel of firms. Second, we explore the relationship between exporting status and the firm component of pay.

Table D2—: AKM robustness results, hourly wage rate

	1996–2000	2000–2004	2004–2008	2008–2012	Change 1996–2012
Variance of log wages	0.73 (101.4%)	0.65 (99.2%)	0.55 (96.1%)	0.49 (93.8%)	-0.24 (120.9%)
Variance of worker effects	0.34 (94.8%)	0.33 (91.8%)	0.29 (88.4%)	0.27 (86.9%)	-0.07 (145.5%)
Variance of firm effects	0.18 (108.3%)	0.14 (110.4%)	0.11 (111.7%)	0.09 (111.0%)	-0.09 (105.9%)
Variance of Y_t	0.00 (112.4%)	0.00 (86.5%)	0.00 (88.7%)	0.00 (128.2%)	0.00 (151.8%)
2×Cov. worker and firm effects	0.16 (110.9%)	0.13 (109.0%)	0.11 (105.7%)	0.10 (101.3%)	-0.06 (132.2%)
2×Cov. worker effects and Y_t	0.00 (120.6%)	0.00 (96.6%)	0.00 (83.3%)	0.00 (128.5%)	0.00 (178.9%)
2×Cov. firm effects and Y_t	0.00 (112.9%)	0.00 (93.9%)	0.00 (103.1%)	0.00 (173.6%)	0.00 (106.9%)
Variance of residual	0.05 (99.0%)	0.05 (98.1%)	0.04 (97.0%)	0.03 (96.9%)	-0.02 (102.8%)
# worker-years	80.1	90.2	108.2	130.0	
# firms	1.20	1.40	1.70	2.15	
R^2	0.93	0.93	0.93	0.93	

Note: Variance decomposition is $Var\left(y_{it}\right) = Var\left(a_i\right) + Var\left(a_j\right) + Var\left(Y_t\right) + Var\left(e_{it}\right) + 2Cov\left(a_i, Y_t\right) + 2Cov\left(a_j, Y_t\right) +$ $+2Cov\left(a_j, Y_t\right)$. Cells contain variance explained by each decomposition element. The ratio of the variance in hourly earnings relative to monthly income is given in parentheses. Weighted by worker-years. Source: RAIS.

E1. Regressions of firm effects on firm observables in a balanced panel

We repeat our second-stage estimation for a balanced panel of firms who are present in the PIA data in all four periods from 1996 to 2012. Estimating the second stage on only surviving firms sheds light on the role of exit and entry versus changes in pay within surviving firms. We find that the results using a balanced panel are in line with those previously presented in Table 6. There is a slightly steeper relationship between value added per worker and firm effects in the balanced panel, with a similar decline in the magnitude of the coefficient over time across all specifications.

E2. Relationship between firm effects, productivity, and exporter status

Table E2 shows the results of second-stage regressions of firm effects on value added per worker using an export indicator and export intensity as additional controls.[33] All regressions include a vector of subsector dummies. The positive relationship between value added per worker and firm effects remains after controlling for exporting variables, and the coefficient declines over time. The patterns and magnitudes of the productivity-pay relationship are similar to the ones discussed in section V.

Moreover, exporting firms pay a higher premium than non-exporting firms, although the premium among exporting firms decreases with export intensity. The difference between exporting and non-exporting firms decreases from 13–25 log points to 2–7 log points once we control for differences in productivity. Also, the positive relationship between value added per worker and firm effects is present among exporting and non-exporting firms, and this has flattened among both groups. Figure E1 depicts these patterns in graphical form. The consistently positive gradient between value added per worker and firm effects among exporting and non-exporting firms, the large decline in exporting premiums after controlling for differences in value added per worker, and the finding that the firm effects gradient in value added per worker declined for both exporters and non-exporters motivate our focus on the firm productivity dimension.

[33]We define export intensity as revenues from exports divided by total revenues.

Table E1—: Regressions of estimated firm effects on firm characteristics using a balanced panel

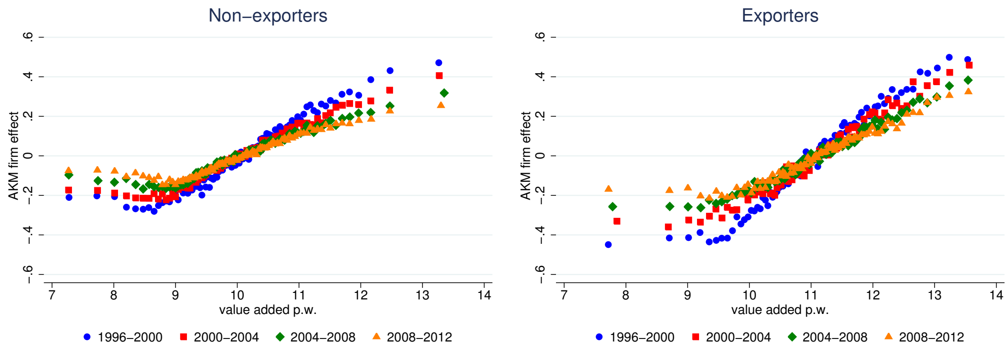
	1996–2000			2000–2004			2004–2008			2008–2012		
PANEL A. NO CONTROLS												
Value added p.w.	0.278		0.176	0.219		0.148	0.179		0.133	0.157		0.0897
Firm size		0.109	-0.116		0.0697	-0.129		0.0411	-0.0872		0.0399	-0.107
Value added p.w. x Firm size			0.012			0.011			0.007			0.009
Worker-years	9.8	9.8	9.8	11.7	11.7	11.7	14.4	14.4	14.4	15.1	15.1	15.1
R^2	0.621	0.243	0.634	0.589	0.124	0.595	0.571	0.068	0.576	0.502	0.082	0.510
PANEL B. SUBSECTOR CONTROLS												
Value added p.w.	0.258		0.152	0.200		0.125	0.158		0.113	0.136		0.0737
Firm size		0.109	-0.095		0.076	-0.099		0.052	-0.054		0.046	-0.075
Value added p.w. x Firm size			0.011			0.010			0.006			0.007
Worker-years	9.8	9.8	9.8	11.7	11.7	11.7	14.4	14.4	14.4	15.1	15.1	15.1
R^2	0.695	0.471	0.714	0.686	0.435	0.692	0.682	0.436	0.686	0.660	0.452	0.667
PANEL C. STATE CONTROLS												
Value added p.w.	0.248		0.173	0.195		0.150	0.161		0.120	0.142		0.0748
Firm size		0.110	-0.021		0.079	-0.046		0.053	-0.055		0.052	-0.076
Value added p.w. x Firm size			0.005			0.005			0.005			0.008
Worker-years	9.8	9.8	9.8	11.7	11.7	11.7	14.4	14.4	14.4	15.1	15.1	15.1
R^2	0.705	0.533	0.728	0.673	0.417	0.677	0.640	0.345	0.643	0.596	0.367	0.607

Note: Dependent variable is the estimated firm effect a_j. Number of worker-years in millions. Weighted by worker-years. Source: RAIS and PIA.

Table E2—: Regressions of estimated firm effects on exporting status

	1996–2000			2000–2004			2004–2008			2008–2012		
Exporter	0.251	0.066	-0.449	0.215	0.020	-0.471	0.168	0.020	-0.600	0.133	0.024	-0.602
Export intensity	-0.144	-0.107	0.352	-0.114	-0.144	-0.193	-0.027	-0.018	0.212	-0.003	0.014	0.450
Value added p.w.		0.226	0.204		0.182	0.154		0.137	0.105		0.116	0.088
Exporter x Value added p.w.			0.047			0.045			0.057			0.056
Export intensity x Value added p.w.			-0.040			0.004			-0.020			-0.038
Worker-years	15.5	15.5	15.5	16.7	16.7	16.7	21.0	21.0	21.0	23.9	23.9	23.9
R^2	0.353	0.657	0.660	0.360	0.653	0.658	0.382	0.628	0.637	0.410	0.615	0.626

Note: Dependent variable is the estimated firm effect a_j. All regressions include subsector controls. Number of worker-years in millions. Weighted by worker-years. Source: RAIS and PIA.



Note: Statistics computed for males of age 18–49. See text for details. Source: RAIS and PIA.

Figure E1. : Estimated AKM firm effects versus value added per worker, by exporter status and period

Appendix F: Largest connected set

Table F1 compares workers in the largest connected set to the overall population of adult males. Given that the largest connected set covers 97–98 percent of the overall population, it is not surprising that the two are very similar.

Table F1—: Summary statistics on workers in largest connected set, relative to adult males

			Earnings		Age		Schooling	
	# Worker-years	# Workers	Mean	St.d.	Mean	St.d.	Mean	St.d.
1988–1992	77.3 (98.6%)	23.1 (98.2%)	1.24 (100.9%)	0.86 (99.8%)	30.82 (100.1%)	8.04 (100.0%)	7.16 (99.9%)	4.26 (100.2%)
1992–1996	77.3 (98.0%)	23.7 (97.5%)	1.30 (101.2%)	0.86 (99.8%)	31.46 (100.1%)	8.10 (99.9%)	7.49 (99.9%)	4.21 (100.2%)
1996–2000	81.5 (97.2%)	25.6 (96.7%)	1.27 (101.3%)	0.83 (100.1%)	31.60 (100.2%)	8.16 (99.9%)	7.93 (99.9%)	4.09 (100.4%)
2000–2004	91.8 (96.9%)	28.8 (96.5%)	1.05 (101.3%)	0.78 (100.4%)	31.61 (100.1%)	8.22 (100.0%)	8.81 (100.0%)	3.91 (100.4%)
2004–2008	110.0 (97.4%)	33.0 (97.0%)	0.86 (101.2%)	0.72 (100.4%)	31.64 (100.0%)	8.23 (100.0%)	9.61 (100.0%)	3.68 (100.3%)
2008–2012	132.2 (97.9%)	38.6 (97.5%)	0.77 (101.0%)	0.68 (100.3%)	31.74 (99.9%)	8.20 (99.9%)	10.24 (100.0%)	3.47 (100.2%)

Notes: We report in parentheses the proportion of the reported statistics relative to the group of adult males described in Table 1. Earnings are in log multiples of the monthly minimum wage, schooling is years of education, age is assigned as the average of a worker's age bin. Source: RAIS.

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