Earnings Inequality and Dynamics in the Presence of Informality: The Case of Brazil*

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Abstract

Using rich administrative and household survey data, we document a series of new facts on earnings inequality and dynamics in a developing country with a large informal sector: Brazil. Since the mid-1990s, both inequality and volatility of earnings have declined significantly in Brazil's formal sector. Higher-order moments of the distribution of earnings innovations show cyclical movements in Brazil that are similar to those in developed countries like the US. Earnings mobility is comparatively high, especially at the bottom of the distribution. Compared with those in the formal sector, earnings in the informal sector are more volatile. Workers who switch between sectors experience earnings innovations that have a positive mean and are positively skewed when moving to the formal sector but have a negative mean and are negatively skewed when moving to the informal sector. Since the early 2000s, a secular shift of employment toward the less volatile formal sector has contributed to a decline in the economy-wide volatility of earnings.

Keywords: Earnings Inequality, Earnings Volatility, Earnings Mobility, Informality

JEL Classification: J31, J46, J62, D31, D33, E24, E26

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1 Introduction

A salient feature of many developing and even some developed countries is a large informal sector, in which jobs evade government oversight in the labor market. The informal sector can be thought of as serving a dual role in labor market dynamics. On one hand, it offers workers readily available employment in case a worker is laid off or decides to quit owing to unfavorable pay or business conditions in his or her previous job. Through this channel, the informal sector provides insurance against labor income risk. On the other hand, it allows workers and firms to avoid costly labor regulations and income taxes, thereby enhancing the efficiency of hiring, firing, and production. This increased efficiency also means that workers are not covered by labor regulations such as employment protection laws, the minimum wage, social security contributions, and other benefits offered by formal jobs. Through this channel, the informal sector increases labor income risk.

As part of the Global Income Dynamics Project, we study earnings inequality, volatility, and mobility in a developing country with a large informal sector: Brazil. We find that among Brazilian metropolitan regions in 2004, 42 percent of all jobs were informal (i.e., without a formal work permit). At the same time, earnings inequality and informality rates significantly declined between the early 2000s and the late 2010s. This makes Brazil a particularly interesting setting to study for our purposes.

To dissect the distribution of earnings levels and earnings innovations, we use a combination of rich administrative and household survey data from Brazil covering the period from 1985 to 2017. The administrative records cover nearly the entire universe of formal sector workers in Brazil over those years. We complement these administrative records with detailed household survey data that follow individuals within households in Brazil's six largest metropolitan regions in a rotating panel structure from 2002 to 2015. The advantage of the household survey data is twofold. First, the data let us validate our findings on labor market outcomes in Brazil's formal sector, based on the administrative records. Second, they allow us to compare earnings levels and earnings innovations between workers in Brazil's formal and informal sectors as well as for workers switching sectors between survey waves. In this way, we uncover a set of new facts for workers within and between the formal and informal sectors of Brazil.

In the first part of the paper, we compute a set of standardized statistics on earnings inequality, volatility, and mobility in Brazil's formal sector based on administrative data covering the period from 1985 to 2017. We start by documenting a remarkable decrease in earnings inequality for both men and women, which starts around 1995 and lasts until the end of our sample.[1] The decrease in overall earnings inequality is associated with relatively greater compression in the left tail of the distribution, which in

[1] See Barros et al. (2010) for an overview of recent inequality trends in Brazil.

turn is due to rapid real earnings growth among bottom earnings percentiles. The decrease in inequality is also widespread among the lower 95 percent of the distribution. In contrast, the top five earnings percentiles have fanned out because of growth rates in real earnings that were increasing in ranks between the 95th and the 99.99th percentiles of the distribution. Earnings inequality across cohorts entering the labor market also fell over this period, but more so in the upper than in the lower tail of the distribution.

We then turn to earnings dynamics among formal sector workers in Brazil. Overall dispersion in one-year earnings innovations, conditional on gender-specific controls for worker age and educational attainment, rose rapidly during a volatile economic period in Brazil in the late 1980s and early 1990s, which included several inflation stabilization plans and a hyperinflationary period. This rise in dispersion of earnings innovations is driven almost entirely by increasing lower-tail dispersion – that is, greater downside earnings risk. Following the macroeconomic stabilization after 1994, the dispersion of earnings innovations decreased markedly, first driven by a decrease in the lower tail and later followed by a decrease in the upper tail of the distribution. We also find that the skewness of earnings innovations is strongly procyclical (i.e.,it is lower during recessions) but without much of a trend, while the kurtosis increased secularly from 1985 onward.

Although inequality in current earnings in Brazil has fallen dramatically over our period of study, this does not mean that inequality in more permanent earnings has followed the same trend. The relation between current and more permanent inequality is commonly summarized through measures of earnings mobility (Shorrocks, 1978). We find high levels of earnings mobility in Brazil, compared with those in concurrent studies for the US (McKinney and Abowd, 2021) and Canada (Bowlus et al., 2021), especially at the bottom of the distribution. Moreover, the extent of earnings mobility has not changed much over time, despite the fact that the volatility of earnings innovations has declined. That is, individuals now move across the earnings distribution to the same extent as in the past. The magnitude of the earnings change associated with a move between two particular rungs of the earnings distribution is, however, smaller now, since the underlying earnings distribution is more compressed.

In the second part of the paper, we complement our analysis of Brazil's formal sector based on administrative records with longitudinal household survey data for 2002–2015 for the six largest metropolitan regions. We make the two data sets as comparable as possible and use them to validate our findings on earnings inequality and volatility across data sets. Although there remain important differences between the two data sets, the evolution of earnings inequality lines up quite closely between administrative and household survey data. Earnings volatility shows somewhat more diverging trends across the two data sources: the volatility of earnings changes is flat in the administrative records but decreasing in the household survey data over the 2002–2015 period. These differences are plausibly due to discrepancies

in the coverages, income definitions, and the response rates across data sources.[2]

We proceed to exploit the longitudinal household survey data to study earnings inequality and dynamics within and between the formal and informal sectors. We draw four conclusions. First, mean one-year residual earnings innovations are similar in formal and informal jobs, but informal innovations are significantly more dispersed, with greater probability mass in both tails of the distribution. Second, workers who switch between sectors have highly asymmetric earnings innovations: workers transitioning from the informal to the formal sector tend to make earnings gains, whereas workers making the opposite transition on average lose earnings. Third, there was a pronounced decrease in the dispersion of earnings innovations in the overall economy (the formal sector pooled with the informal sector) during the early 2000s, which was followed by a period of stabilization from 2006 onwards. Fourth and finally, holding everything else fixed, the large employment shift toward the less volatile formal sector on its own results in a fall in the volatility of earnings; the fall corresponds to 50 percent of the total decline since 2002. In other words, the process of labor market formalization appears to have played an important role in the decline in earnings volatility over this period. Together, these facts paint a rich picture of earnings volatility in Brazil, which is shown to be a developing country with a large informal sector.

Related literature. Our work combines two separate strands of the literature on informality and income dynamics. The first strand of the literature is concerned with labor market informality—see Ulyssea (2020) for an excellent review. Meghir et al. (2015) use a subperiod of the same household survey data that we use for the second part of our analysis. They show that both the distribution of wages and that of firm productivity substantially overlap between Brazil's formal and informal sectors. Ulyssea (2018) uses linked employer-employee survey of informal establishments to document facts about the distribution of (in-)formal employment across the firm size distribution. Among the drivers behind high levels of informality in developing countries are high labor regulation costs (Almeida and Carneiro, 2012), weak enforcement (Seminario-Amez, 2021), payroll taxes (Haanwinckel and Soares, 2020), and the incidence of social policies like the minimum wage and conditional cash transfer programs such as Bolsa Família in Brazil (Fairris and Jonasson, 2020). We complement this body of research by studying earnings dynamics within and between the two sectors, highlighting the importance of the informal sector in particular.

Related work by Dix-Carneiro and Kovak (2019), Ponczek and Ulyssea (2020), and Dix-Carneiro et

[2]In this manner, we contribute to an emerging literature that compares administrative and household survey data in other lower-income countries, such as Argentina (Blanco et al., 2021) and Mexico (Calderón et al., 2021).

al. (2021) also highlights the role of the informal sector as an insurance mechanism against negative shocks to Brazilian local labor markets in the context of international trade. Building on their insights, we characterize earnings inequality and dynamics within and between the formal and informal sectors.

We also contribute to a growing literature on the causes of the pronounced decrease in earnings inequality in Brazil since the mid-1990s. Firpo and Portella (2019) provide an excellent survey of recent studies that quantify the importance of falling returns to education and experience (Ferreira et al., 2017), falling returns to firm productivity (Alvarez et al., 2018), trade liberalization (Gonzaga et al., 2006; Ferreira et al., 2007; Dix-Carneiro and Kovak, 2015), and the rapid rise of the minimum wage (Engbom and Moser, 2021)—among other factors—toward this decrease in earnings inequality.

The second strand of the literature is concerned with income dynamics. Earnings dynamics have been studied in administrative and household survey data in many developed countries (see, for example, Moffitt and Gottschalk, 1995 and Sabelhaus and Song, 2010). A seminal contribution in this area is that by Guvenen et al. (2014), who use 34 years of social security records to document new facts on the cyclical properties of higher-order moments of earnings innovations in the US. Recent work has shed further light on the nature of earnings dynamics over the life cycle (Guvenen et al., 2019) and over time (Bloom et al., 2017) in the US context. Hoffmann and Malacrino (2019) show that unemployment insurance reduces some of the cyclicality in skewness of earnings innovations in Italy. We contribute to this literature a set of new empirical facts on earnings dynamics in a developing country with a large informal sector.

A recent study by Gomes et al. (2020) also studies earnings dynamics in Brazil's formal and informal sectors. Their analysis is based on different survey data that are nationally representative over the period from 2012 to 2018. We find that our data confirm their finding of greater dispersion in earnings innovations in Brazil's informal sector and complement their work in several ways. For instance, by using a longer panel from 2002 to 2015 in our household survey data and from 1985 to 2017 in our administrative data, we are able to document secular and cyclical movements over time of higher-order moments of the distribution of earnings innovations. We also provide a holistic picture of Brazil's formal and informal sectors by jointly studying earnings inequality, volatility, and mobility by using a combination of administrative and household survey data.

Outline. The rest of the paper is structured as follows. Section 2 describes Brazil's relevant institutional background from 1985 to 2017. Section 3 introduces the administrative and household survey data on which we base our analysis. Section 4 presents a set of standardized statistics pertaining to earnings inequality, volatility, and mobility. Section 6 validates findings between the administrative and household

data and also dissects the role of (in-)formality in Brazil's labor market. Finally, Section 7 concludes.

2 Brazil's macroeconomy from 1985 to 2017

Between 1985 and 2017, Brazil underwent a transformative yet volatile macroeconomic period. The period was characterized by rapid growth spurts interlaced with severe economic recessions, with negative GDP per capita growth recorded during the high-inflation period of the late 1980s and early 1990s, the financial crisis of the late 1990s, the global financial crisis around 2008, and the commodity price bust and political turmoil from 2014 to 2016—see panel (a) of Figure 1.

With rapid growth came other fundamental economic changes for Brazil. Over the period from 1985 to 2017, the services sector grew from 47 percent to 74 percent of total GDP, while the industrial sector shrank from 42 percent to 21 percent and the agricultural sector shrank from 11 percent to 5 percent, as illustrated by panel (b).

Although this statistic does not fully reflect labor market slack in the presence of a large informal sector, Brazil's unemployment rate fluctuated between 3 percent in the late 1980s and 13 percent in the early 2000s—see panel (c).

A particularly scarring event in Brazil's recent macroeconomic history was a prolonged episode of high inflation in the first part of our sample period, from 1985 to 1994. Our preferred measure of inflation is based on the Broad Consumer Price Index *Índice Nacional de Preços ao Consumidor Amplo* (IPCA) used by the country's central bank since an inflation-target system was implemented. After fast-rising inflation during the early 1980s, Brazil eventually suffered from hyperinflation, with annual inflation rates above 6,500 percent and several different national currencies. After several stabilization attempts, inflation was eventually brought under control with the implementation of the Plano Real in 1994 and was relatively stable thereafter (Ayres et al., 2019)—see panel (d).

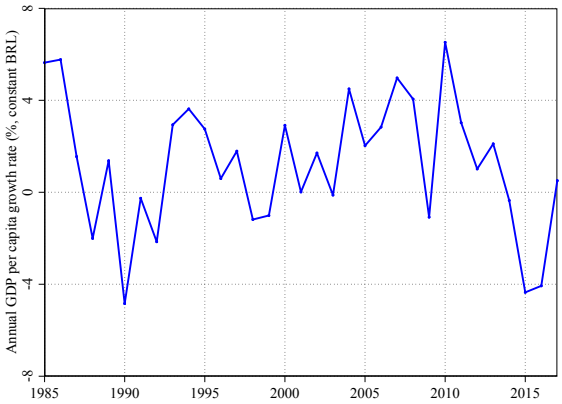
Over the same period, Brazil's currency fluctuated significantly in value, first depreciating heavily from the early 1990s until 2002, then appreciating quickly for a decade, and eventually depreciating again in the wake of a commodity supercycle (Benguria et al., 2021)—see panel (e).

Finally, Brazil implemented several economic policy changes between 1985 and 2017. Among the most salient changes is the rapid rise of the minimum wage starting in the early 2000s; its increase coincided with the election of the left-leaning Workers' Party. Over the subsequent decade and a half, Brazil's minimum wage increased by over 100 percent in real terms—see panel (f).[3]

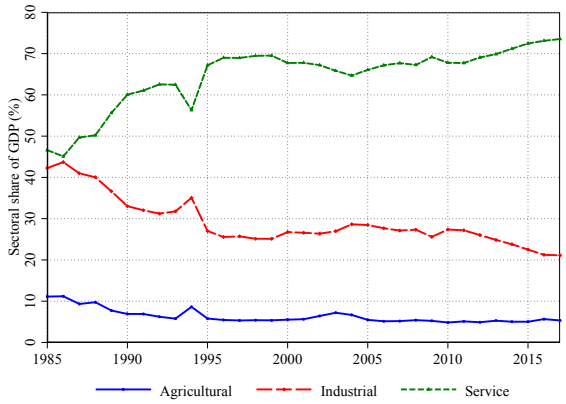
[3] Engbom and Moser (2021) and Haanwinckel (2020) show that the rise of the minimum wage had a pronounced effect on the earnings distribution over this period.

FIGURE 1. MACROECONOMIC INDICATORS FOR BRAZIL, 1985–2017

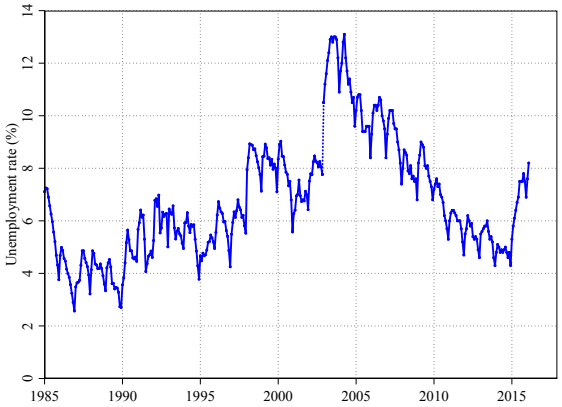
(A) ANNUAL GDP PER CAPITA GROWTH RATE



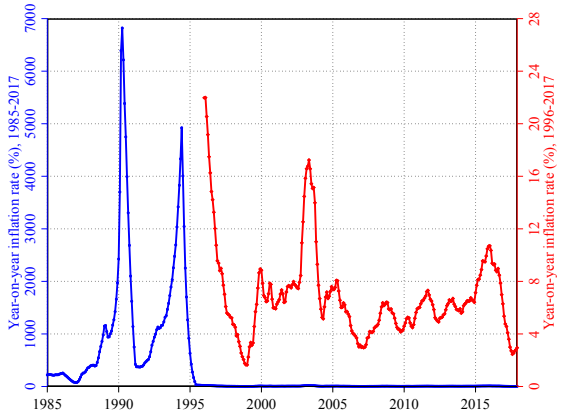
(B) SECTORAL COMPOSITION OF GDP



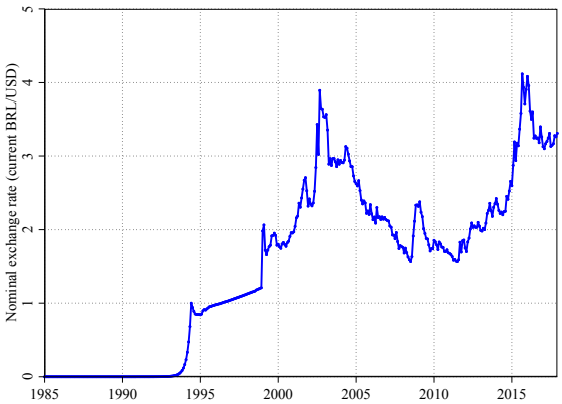
(C) UNEMPLOYMENT RATE



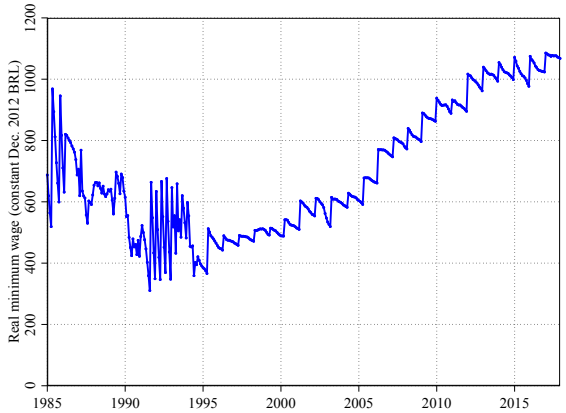
(D) YEAR-ON-YEAR INFLATION RATE



(E) NOMINAL EXCHANGE RATE



(F) REAL MINIMUM WAGE



Note: Panel (c) is based on data from the PME Antiga survey (January 1985–November 2002) and the PME survey (December 2002–February 2016), which cover Brazil's six largest metropolitan areas: Recife, Salvador, Belo Horizonte, Rio de Janeiro, São Paulo e Porto Alegre. The dotted line between November and December 2002 indicates a structural break at the point where the two surveys are pasted together—see also footnote 7. *Source:* Panel (a) plots data from World Bank. Panels (b), (c), (d), and (f) plot data from IPEA. Panel (e) plots data from FRED.

3 Data

In this section, we describe the two data sets used in our empirical analysis and our sample selection criteria. Our administrative data source is the *Relação Anual de Informações Sociais* (RAIS), a linked employer-employee longitudinal data set that covers nearly all formal jobs in Brazil. We complement our empirical analysis with microdata from the Brazilian monthly labor force survey *Pesquisa Mensal de Emprego* (PME) to validate our findings based on administrative data and to investigate whether income dynamics differ between formal and informal workers.

3.1 Administrative data (RAIS)

Data description. Our main data source is RAIS, which contains administrative records from Brazil's Labor Statistics Dissemination Program (*Programa de Disseminação das Estatísticas do Trabalho*) within the Brazilian Ministry of the Economy (*Ministério da Economia*), formerly the Ministry of Labor (*Ministério do Trabalho*). RAIS covers nearly the entire universe of workers in tax-registered firms. Every year, firms must report information to RAIS on all employees who were on the payroll in the previous year.

Compliance with filling in RAIS is high because of large penalties for late, incomplete, or inaccurate data. Since the main purpose of RAIS is to administer a federal wage bonus to formal employees, there are incentives for truthful reporting. RAIS is also used by ministries for administrating an array of social programs related to the monitoring of formal jobs.

Each observation in RAIS is a worker-establishment match, or job, in a given year. For each job, the data set includes worker-related variables (e.g., gender, age, education, and unique worker identifier), firm-related variables (e.g., sector of activity, establishment size, municipality, and unique establishment and firm identifiers), and job-related variables (e.g., mean monthly earnings during the current year, contractual weekly hours, tenure, occupation, months of hiring and separation, and reason for separation).

Each worker has a unique identification number in RAIS, which allows us to recover the full formal work history of all individuals in the database. We use data from 1985 to 2017. RAIS is very large, with an average of around 40 million observations per year, which sums to approximately 1.2 billion job records for the 1985–2017 period.

Sample selection. We apply some standard filters to the administrative data. First, we drop all workers without valid identification numbers or with zero earnings. We then restrict the data to workers in the 25–55 age range. Earnings data in RAIS are censored above 120 times the national minimum wage. A Pareto tail imputation exercise suggests that censored observations correspond to a very small pro-

portion, approximately 0.01 percent of the sample. To focus on workers with a meaningful attachment to the labor market, we drop those with total annual nominal earnings (defined in the next paragraph) below the equivalent of part-time earnings from three months of employment at the minimum wage.[4]

Variable construction. Since the period from 1985 to 1994 was characterized by high inflation and mutliple national currencies, we use as our numeraire information on mean earnings in terms of multiples of the prevailing minimum wage. To obtain total annual real earnings, we multiply this multiple by the mean nominal minimum wage in current Brazilian Reais during the month's of a given year's job spell. We then construct total annual nominal earnings for each individual by summing over all their jobs in RAIS in a given calendar year. Finally, we obtain total annual real earnings by deflating total annual nominal earnings by the annual mean IPCA. By measuring earnings in this way, we minimize measurement error related to very volatile nominal variables.

Using the administrative data, we construct the following five variables for an individual i of gender $G(i) \in \{\text{male}, \text{female}\}$ and age group $A(i,t) \in \{25, 26, \ldots, 55\}$ in year $t \in \{1985, 1986, \ldots, 2017\}$:

1. Log total annual real earnings, or "log earnings," $\ln y_{it}$;

2. Residual log earnings conditional on gender-year-specific age dummies, or "residual earnings,"

$$\varepsilon_{it} = \ln y_{it} - \sum_{G',t',A'} \alpha_{G't'A'} \mathbb{1}[G(i) = G', t = t', A(i,t) = A'], \tag{1}$$

   where $\alpha_{G't'A'}$ is a gender-year-age-specific coefficient on $\mathbb{1}[G(i) = G', t = t', A(i,t) = A']$, which denotes an indicator for the combination of gender G', year t', and age A';[5]

3. One-year-forward change in residual earnings based on equation (1), or "one-year earnings innovations,"

$$g^1_{it} = \varepsilon_{i,t+1} - \varepsilon_{i,t};$$

4. Five-years-forward change in residual earnings based on equation (1), or "five-year earnings inno-

[4] We drop any observation of an individual i in year t with total annual nominal earnings y_{it} if $y_{it} < \frac{1}{2} \times 40 \frac{\text{hours}}{\text{week}} \times 4 \frac{\text{weeks}}{\text{month}} \times 3 \text{ months} \times \overline{\text{MW}}_t$, where $\overline{\text{MW}}_t$ is the mean prevailing minimum wage over the individual i's period of employment in year t.

[5] In Appendix A.2, we present results of an alternative definition of residual earnings that also conditions on the education group $E(i) \in \{\text{primary}, \text{middle}, \text{high school}, \text{college}\}$,

$$\varepsilon_{it} = \ln y_{it} - \sum_{G',t',A'} \alpha_{G't'A'} \mathbb{1}[G(i) = G', t = t', A(i,t) = A'] - \sum_{G',t',E'} \beta_{G't'E'} \mathbb{1}[G(i) = G', t = t', E(i) = E'].$$

vations,"

$$g_{it}^{5} = \varepsilon_{i,t+5} - \varepsilon_{i,t};$$

5. Residual log mean earnings over the previous three years, conditional on gender-year-specific age dummies, or "permanent earnings,"

$$P_{i,t} = \ln\left(\frac{y_{i,t-2} + y_{i,t-1} + y_{i,t}}{3}\right) - \sum_{G',A'} \gamma_{G't'A'} \mathbb{1}[G(i) = G', t = t', A(i,t) = A'],$$

where $\gamma_{G't'A'}$ is a gender-year-age-specific coefficient on $\mathbb{1}[G(i) = G', t = t', A(i,t) = A']$, which denotes an indicator for the combination of gender G', year t', and age A'.

Table 1 presents basic summary statistics for selected years between 1985 and 2017 on the gender and age composition, the earnings distribution, and sample sizes, based on our sample from RAIS data.[6] Among the noteworthy features of Brazil's formal sector over this period are the pronounced increases in female labor force participation, high school completion, and overall employment, with a concurrent decline in the standard deviation of log earnings.

3.2 Household survey data (PME)

Data description. To study earnings inequality dynamics for both formal and informal workers in Brazil, we use microdata from PME. The survey was conducted by the Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística*, or IBGE) in Brazil's six largest metropolitan areas: São Paulo, Rio de Janeiro, Belo Horizonte, Porto Alegre, Salvador, and Recife. It was administered from the early 1980s until 2016, when it was terminated and replaced with a different survey. While it was active, the survey was used to compute official unemployment statistics for Brazil.

The rotating panel design of PME is such that the surveys are representative at the metropolitan-area level in each month. We use data from 2002 to 2015, the so-called *PME-Nova* (new PME).[7] By the end of the period, the sample covered around 34,000 households and 95,000 individuals in each month. The pooled data for the 2002–15 period feature approximately 7.3 million observations, or around 500,000 per

[6] Table 4 in Appendix A.1 presents more detailed summary statistics on the distribution of earnings for each year between 1985 and 2017. Appendix Tables 5 and 6 show the same statistics separately for men and for women.

[7] PME underwent a major change in 2002, with a significantly larger questionnaire with more checks on actual labor market participation and other variables. The old PME (*PME-Antiga*), which started in 1982, was then replaced by the new PME. *PME-Nova* was discontinued in February 2016, because in 2012, IGBE introduced a new national household survey with five-quarter longitudinal information, the *PNAD-Contínua*. The old PME does not have enough information on employment and income to be of adequate use for our paper.

TABLE 1. SUMMARY STATISTICS FOR ADMINISTRATIVE DATA (RAIS)

	1985		1995		2005		2017	
	Men	Women	Men	Women	Men	Women	Men	Women
Share	0.69	0.31	0.64	0.36	0.60	0.40	0.56	0.44
Age:								
Mean	35.30	34.90	36.50	36.50	36.80	37.10	37.90	38.00
Std. dev.	7.70	7.40	8.10	7.90	8.30	8.40	8.40	8.40
Education shares:								
Middle school	0.18	0.16	0.21	0.18	0.23	0.16	0.20	0.13
High school	0.17	0.30	0.22	0.34	0.35	0.45	0.52	0.58
College	0.10	0.21	0.10	0.21	0.10	0.23	0.10	0.21
Earnings:								
Mean	30,423	21,574	29,099	22,736	26,575	22,788	33,809	29,549
Std. dev.	41,489	25,621	41,774	31,820	42,463	33,887	47,391	38,678
Log earnings:								
Mean	9.74	9.50	9.61	9.41	9.59	9.47	9.95	9.84
Std. dev.	1.11	1.01	1.19	1.14	1.07	1.04	0.96	0.94
Observations	10.86	4.83	13.97	7.87	18.40	12.06	23.57	18.71

Note: Table shows summary statistics for select years separately by gender. The omitted education category is primary school. Observations are in millions. *Source:* RAIS 1985–2017.

year on average. The main variables we use are the worker ID, gender, age, schooling, monthly earnings, labor market status (employed, self-employed, unemployed, or out of the labor force), and information on whether the individual holds a formal work permit (explained below). Monthly earnings include wage, salary, and bonus payments in gross amounts.

Formal employees in Brazil are hired under the Brazilian labor codes *Consolidação das Leis do Trabalho*, CLT. CLT states that each employer has to fill in and sign the employee's working card (*Carteira de Trabalho*) when formally hiring a worker in Brazil. [8] After asking if he or she is employed, PME elicits whether the worker possesses a signed working card. Since RAIS covers only workers hired under CLT, workers with a working card correspond to those in the administrative data.

It is important to note that all household surveys run by IBGE are anonymous. IBGE has long had reputation of never granting outsiders access to any personally identifiable information of respondents.

PME surveys have a rotating panel structure similar to that of the Current Population Survey (CPS) in the US. Households are surveyed for two spells of four consecutive months; the spells are eight months apart from each other. This means that households complete four monthly interviews, followed by an eight-month pause, and then by another four monthly interviews. This rotating panel structure means

[8] The working card is a booklet with information on an individual's complete formal labor market history, including all details of each job held by a worker - date of hiring or firing, paid vacation periods, leaves of absence, etc.

that the months the individual is interviewed are the same in any two consecutive years. Interviews are spread evenly within a month and households are always interviewed in the same week of the month.

Households are correctly identified throughout all eight interviews. However, PME does not assign the same identification number to each individual in the household across interviews. To reduce attrition, we use an algorithm developed by Ribas and Soares (2008), which identifies the same individual in each household across interviews using a fuzzy merge based on the combination of reported dates of birth and genders.[9]

Sample selection. We make several choices to make the information in the two data sets—RAIS and PME—as comparable as possible for formal workers. First, we use only data for workers in the 25–55 age range. For the cross-sectional exercises, we construct comparable measures of annual earnings, y_{it}. Since the panel structure of PME allows us to follow workers for only one year, we also compute one-year-forward residualized log annual earnings changes.

For comparability reasons, we drop all business owners who contribute to social security and domestic employees in PME, since they are not measured in the administrative data. The final sample is thus composed of formal workers (i.e., employees with a valid working card) and informal workers (i.e., employees without a valid working card and self-employed individuals who do not contribute to social security). Note that this sample includes workers employed in the public sector. Our main analysis focuses on characteristics of individuals' primary job, although in Section 6, we discuss workers with multiple jobs, who make up less than 3 percent of all workers.

We apply the following selection criteria. We drop individuals with year-on-year survey attrition or without positive earnings from any (formal or informal) employment during any of the survey waves during a year. For the longitudinal statistics, we restrict ourselves to individuals to who have a full eight months of nonmissing responses in the two consecutive years. To mimic the top-coding in RAIS, we drop monthly earnings above 120 times the minimum wage. Finally, we trim observations with annualized incomes below the equivalent of 1.5 months of full time work at the prevailing minimum wage, which is the equivalent of the bottom threshold we used in our baseline analysis of RAIS.

In the sectoral analysis, we consider as formal (informal) workers only those individuals who showed up as formal (informal) employees in all monthly observations within a calendar year. Therefore, when comparing the earnings dynamics of formal and informal workers, we drop individuals who worked in the two sectors within the same year. This worker group accounts for around 10 percent of the total

[9]Standardized cleaning procedures and the panel linkage method are available from Data Zoom by PUC-Rio at http://www.econ.puc-rio.br/datazoom/english/index.html.

sample, and we analyze them separately in Section 6.

Variable construction. We construct variables in PME to be analogous to those in the administrative data whenever possible. Since the household survey follows a rotating panel format, we create seasonal dummy variables that identify each four-month period in the calendar year in which the individual is interviewed (which we refer to as a survey wave).[10] Using the household survey data, we construct the following three variables for an individual i of gender $G(i) \in \{\text{male}, \text{female}\}$, age group $A(i,t) \in \{25, 26, \ldots, 55\}$, and season group $S(i,t) \in \{(\text{Jan-Apr}), (\text{Feb-May}), \ldots, (\text{Jan-Mar; Dec})\}$ in year $t \in \{2002, 2003, \ldots, 2015\}$:

1. Log total annual real earnings, or "log earnings," $\ln y_{it}$;

2. Residual log earnings conditional on gender-year-specific age dummies and gender-year-specific season dummies, or "residual earnings,"

$$\varepsilon_{it} = \ln y_{it} - \sum_{G',t',A'} \delta_{G't'A'} \mathbb{1}[G(i) = G', t = t', A(i,t) = A'] - \sum_{G',t',S'} \eta_{G't'S'} \mathbb{1}[G(i) = G', t = t', S(i,t) = S'], \tag{2}$$

   where $\delta_{G't'A'}$ is a gender-year-age-specific coefficient on $\mathbb{1}[G(i) = G', t = t', A(i,t) = A']$, which denotes an indicator for the combination of gender G', year t', and age A', and $\eta_{G't'S'}$ is a gender-year-season-specific coefficient on $\mathbb{1}[G(i) = G', t = t', S(i,t) = S']$, which denotes an indicator for the combination of gender G', year t', and season S';

3. One-year-forward change in residual earnings based on equation (2), or "one-year earnings innovations,"

$$g^1_{it} = \varepsilon_{i,t+1} - \varepsilon_{i,t}.$$

4 Earnings inequality and dynamics in Brazil's formal sector

This section documents patterns of earnings inequality and earnings dynamics in the formal sector in Brazil using the administrative RAIS matched employer-employee data. In the next section, we turn to

[10] There are twelve seasonal dummies for the cross-section statistics, based on the 4-8-4 panel system: (Jan-Apr), (Feb-May), (Mar-Jun), (Apr-Jul), (May-Aug), (Jun-Sep), (Jul-Oct), (Aug-Nov), (Sep-Dec), (Jan; Oct-Dec), (Jan-Feb; Nov-Dec), (Jan-Mar; Dec). For the longitudinal exercises, only a subset consisting of nine seasons is relevant: (Jan-Apr), (Feb-May), (Mar-Jun), (Apr-Jul), (May-Aug), (Jun-Sep), (Jul-Oct), (Aug-Nov), and (Sep-Dec).

the informal sector and compare administrative and survey data.

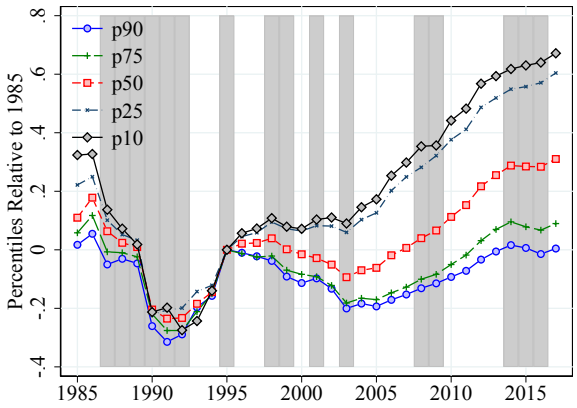
4.1 Earnings inequality

All percentiles of the earnings distribution in Brazil experienced significant cumulative real wage growth over the past 30 years, as illustrated by Figure 3. Wage growth was not, however, monotone. In particular, real wages fell consistently during the high inflationary years of the late 1980s and early 1990s. Since the extensive macroeconomic reforms undertaken in the early 1990s, however, workers across the earnings spectrum have seen real wage growth. The patterns are quite similar for men and women.

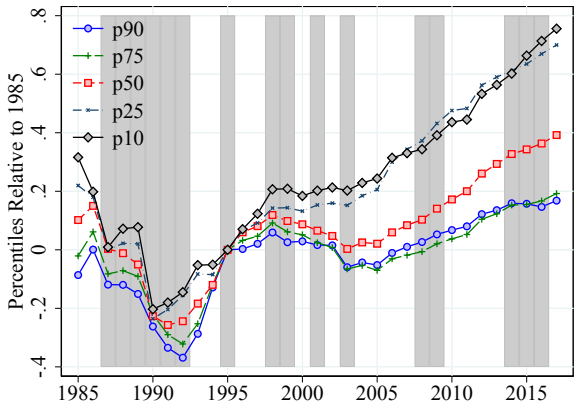
While all parts of the earnings distribution experienced significant real wage growth since the early 1990s, there is also important heterogeneity across the earnings distribution. In particular, since the early 1990s, earnings have grown disproportionately at the bottom of the earnings distribution. For instance, since 1995, earnings at the 75th percentile grew by about 10 log points, while at the 25th percentile, they rose by 60 log points. This pattern is reversed at the very top of the earnings distribution, which experienced widening inequality similar to that of many developed countries. For instance, earnings at the 99th percentile rose by more than at the 90th percentile.

FIGURE 2. EVOLUTION OF EARNINGS PERCENTILES, BY GENDER

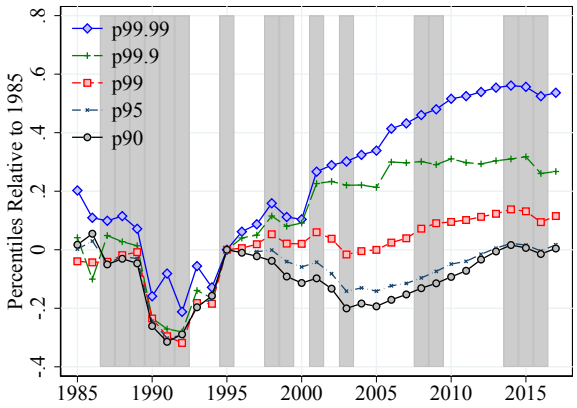
(A) OVERALL, MEN



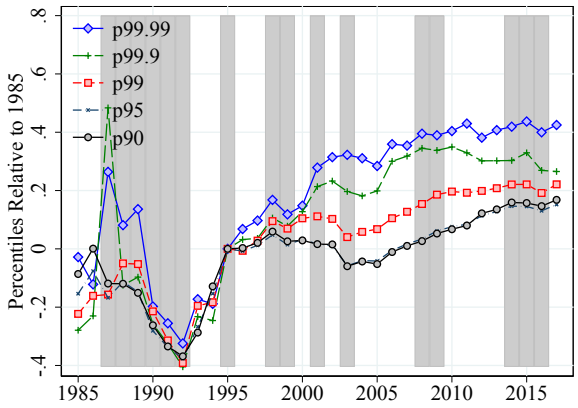
(B) OVERALL, WOMEN



(C) TOP PERCENTILES, MEN



(D) TOP PERCENTILES, WOMEN

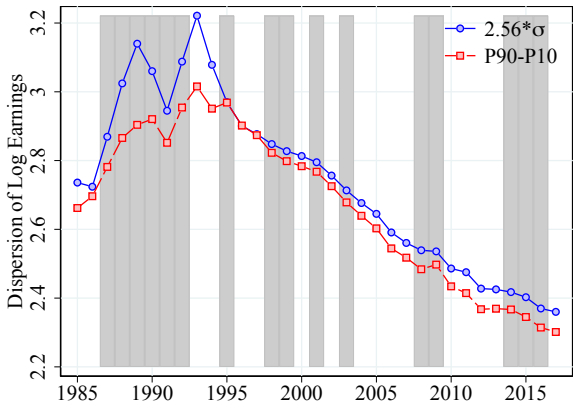


Note: Workers aged 25–55. Percentiles of the distribution of log real annual earnings, normalized to 1995. *Source:* RAIS 1985–2017.

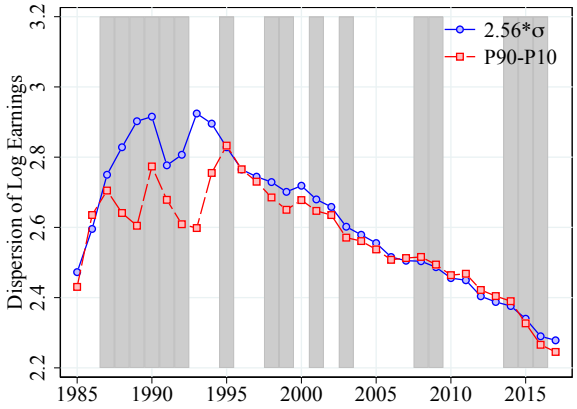
As expected given the faster real wage growth at the bottom of the distribution, inequality fell dramatically in Brazil starting in the early 1990s, as shown in Figure 3. The 90-10 percentile ratio declined from 3 to 2.3. The patterns are again quite similar among men and women. Moreover, the fall in inequality was particularly pronounced at the bottom of the earnings distribution, as evidenced by the larger fall in the 50-10 ratio compared with that of the 90-50 percentile ratio. Nevertheless, the 90-50 percentile ratio also fell by a significant amount, driven by fast real median wage growth. This large decrease in inequality is particularly remarkable given that many countries experienced increases in inequality over the same period. That said, Brazil continues to have high levels of inequality.

FIGURE 3. EARNINGS INEQUALITY, BY GENDER

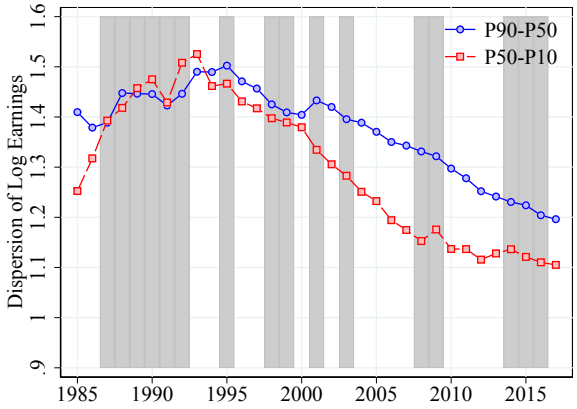
(A) OVERALL, MEN



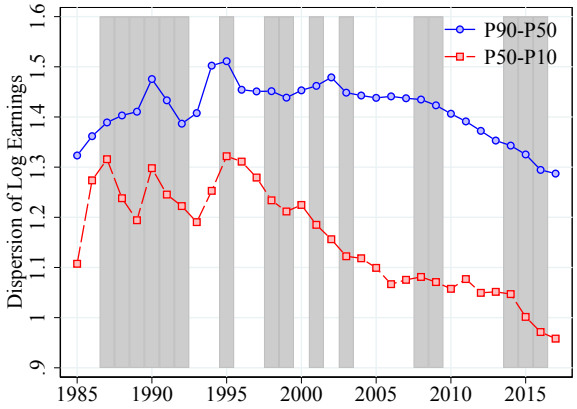
(B) OVERALL, WOMEN



(C) RIGHT AND LEFT TAILS, MEN



(D) RIGHT AND LEFT TAILS, WOMEN

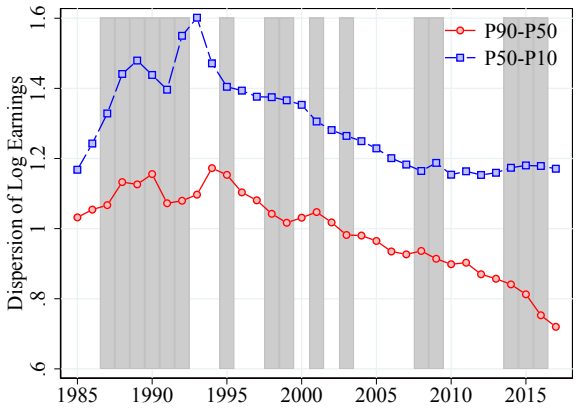


Note: Workers aged 25–55. σ denotes the standard deviation of log real annual earnings. *Source:* RAIS 1985–2017.

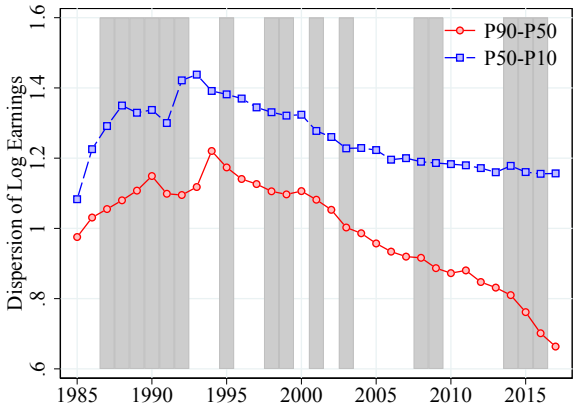
The role of entry conditions. Figure 4 plots lower and upper tail inequality among 25-year-olds by gender over time. As for the aggregate trends, from the early 1990s onwards, young workers experienced a large decline in inequality. In other words, the large overall decline in inequality was not solely the result of changes in earnings dynamics after labor market entry. Instead, inequality is lower also among labor market entrants. The compression in the earnings distribution among young workers was again particularly pronounced at the bottom of the earnings distribution, as evidenced by the larger fall in the 50-10 percentile ratio relative to that of the 90-50 ratio. Patterns are similar among men and women.

FIGURE 4. EARNINGS INEQUALITY AMONG 25-YEAR-OLDS, BY GENDER

(A) MEN



(B) WOMEN

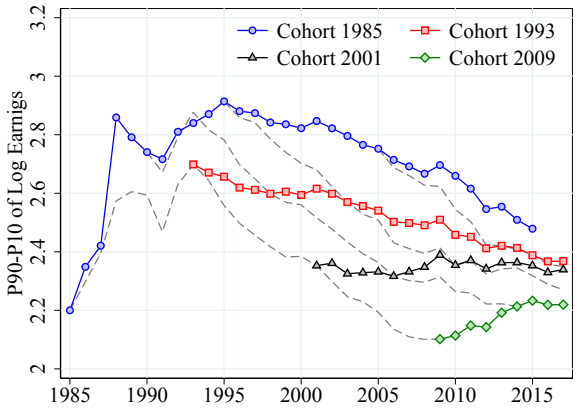


Note: Workers aged 25. *Source:* RAIS 1985–2017.

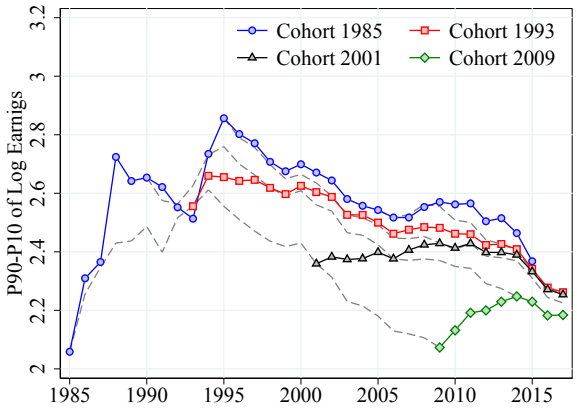
To further investigate the role of changes in initial conditions versus that of changes in post-entry life-cycle dynamics, in Figure 5 we follow cohorts over time as they age. The earliest cohort to turn 25—those who did so in 1985—saw an initial increase in inequality during the first 10 years, followed by a subsequent decline. This initial increase, however, may be the result of a time effect associated with the period of high inflation experienced by Brazil over this period. Subsequent cohorts of men and women have seen a gradual flattening and eventual reversal of the profile of within-cohort inequality with age. One possible factor behind this interesting pattern is the rapid increase in the minimum wage over this period. It is well known that a minimum wage tends to disproportionately affect young workers, and it may have contributed to a particular compression in inequality at labor market entry. As older workers are less affected by the minimum wage, inequality has fallen by less at older ages, which by itself has contributed toward a steepening of life-cycle inequality profiles.

FIGURE 5. LIFE-CYCLE INEQUALITY ACROSS COHORTS, BY GENDER

(A) MEN



(B) WOMEN



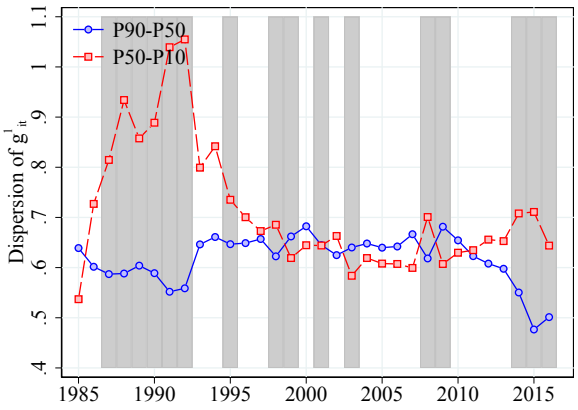
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

4.2 Earnings dynamics

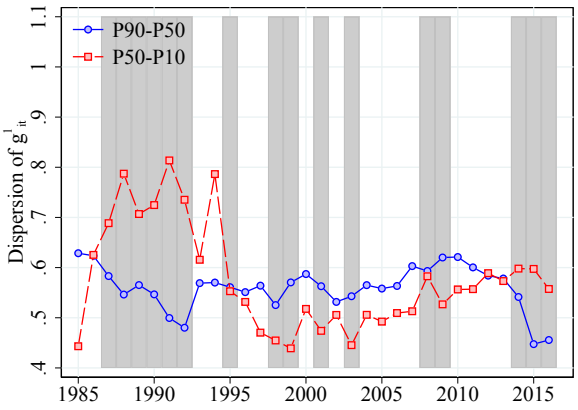
We now turn to trends in earnings dynamics. Figure 6 plots percentile ratios of one-year residual log earnings changes by gender. Men have somewhat more volatile earnings, although the gender differences are not particularly pronounced. Negative (positive) earnings shocks became more (less) pronounced during the years of high inflation in the late 1980s and early 1990s. Since then, earnings have gradually become less volatile. The magnitude of negative shocks is counter-cyclical—meaning such shocks become more pronounced in recessions—while the magnitude of positive shocks is pro-cyclical.

FIGURE 6. DISPERSION OF ONE-YEAR LOG EARNINGS CHANGES, BY GENDER

(A) MEN



(B) WOMEN



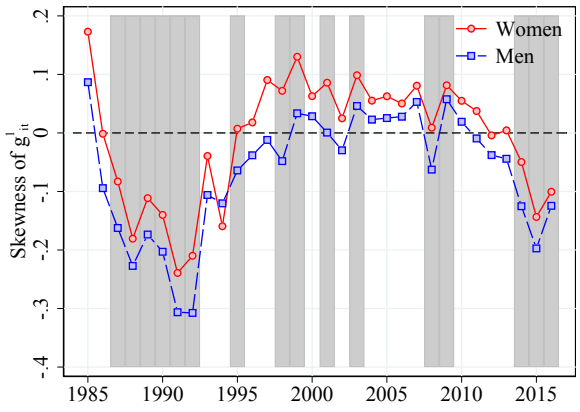
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

Figure 7 plots the skewness and kurtosis of one-year residual earnings changes. As suggested by

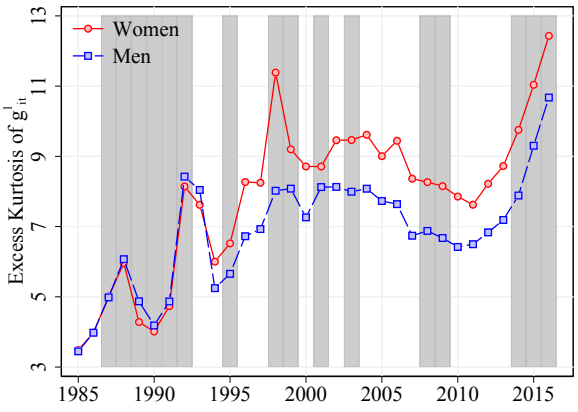
Figure 6, the skewness of earnings innovations is pro-cyclical: negative shocks become more pronounced in recessions. In contrast, it is difficult to reach a definitive conclusion about the cyclicality of the kurtosis. The skewness displays little secular trend over the past 30 years, while the kurtosis has gradually risen. In other words, the likelihood of very large negative and positive shocks has risen over time. One possible factor behind this pattern is the decline in informality. It may be that workers 20 years ago were more likely to leave the formal sector in response to large negative shocks, whereas today they tend to remain formally employed, though at lower earnings. If earnings were to later revert, this would account for an increase in kurtosis. A further assessment of this intriguing pattern is, however, beyond the scope of this paper.

FIGURE 7. SKEWNESS AND KURTOSIS OF ONE-YEAR LOG EARNINGS CHANGES

(A) KELLEY SKEWNESS



(B) EXCESS CROW-SIDDIQUI KURTOSIS

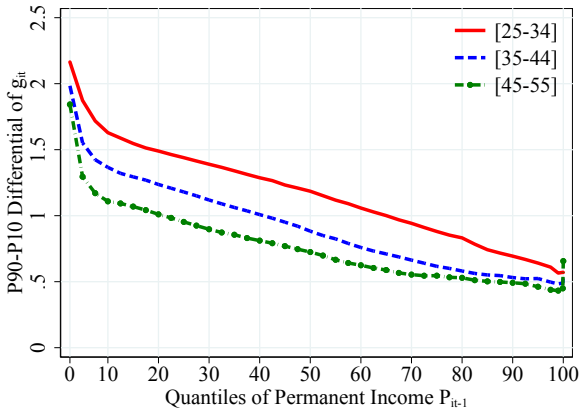


Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

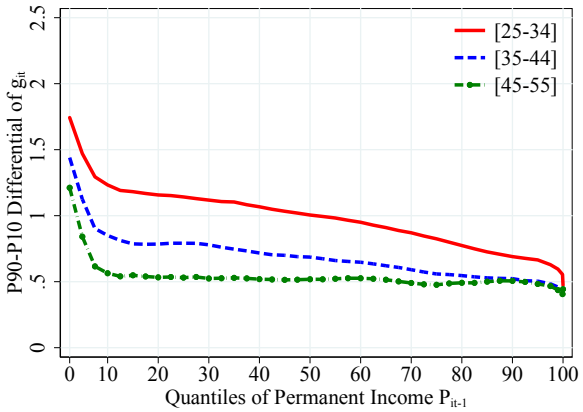
Life-cycle dynamics. Instead of providing a time series view, Figure 8 studies earnings innovations from a life-cycle perspective. In particular, it plots the 90-10 percentile ratio, the skewness and kurtosis of one-year log earnings changes by age group as a function of permanent earnings. Young workers have more volatile earnings as measured by the 90-10 percentile ratio, as do lower-permanent-earnings workers within all age groups. There is no pronounced systematic pattern for the skewness. Interestingly, the pattern for the kurtosis of earnings changes is partly inverted relative to that for the 90-10 percentile ratio. While low-permanent-earnings workers also have the highest kurtosis within all age groups, older workers have higher kurtosis than their younger counterparts. Young workers are subject to more volatile but less extreme shocks compared with the ones faced by their older counterparts. Women are less likely than men to experience negative earnings shocks as measured by the skewness, possibly because they are more likely to drop out of the formal sector in response to such shocks.

FIGURE 8. MOMENTS OF THE DISTRIBUTION OF ONE-YEAR EARNINGS INNOVATIONS, BY GENDER

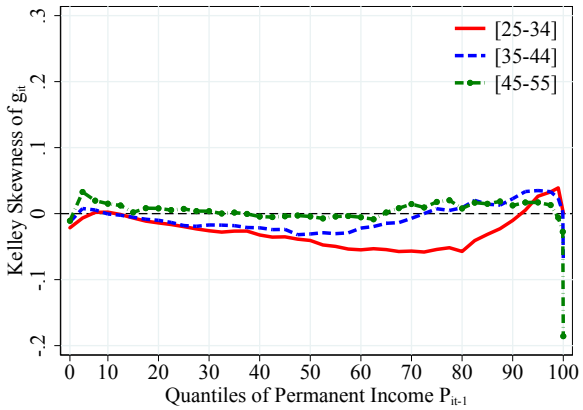
(A) P90-P10, MEN



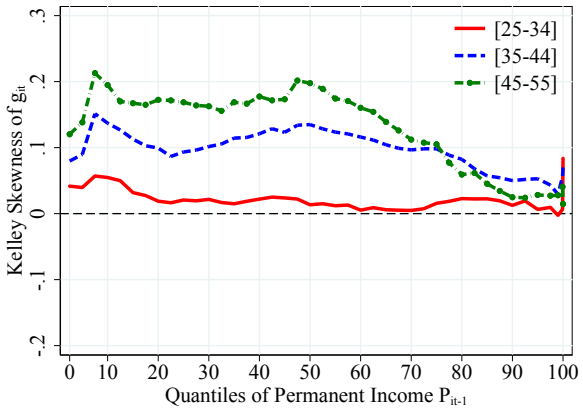
(B) P90-P10, WOMEN



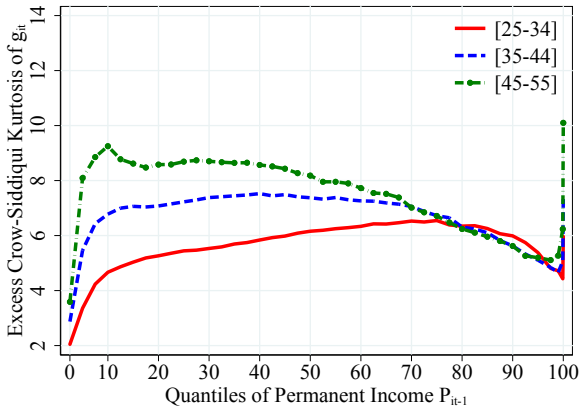
(C) KELLEY SKEWNESS, MEN



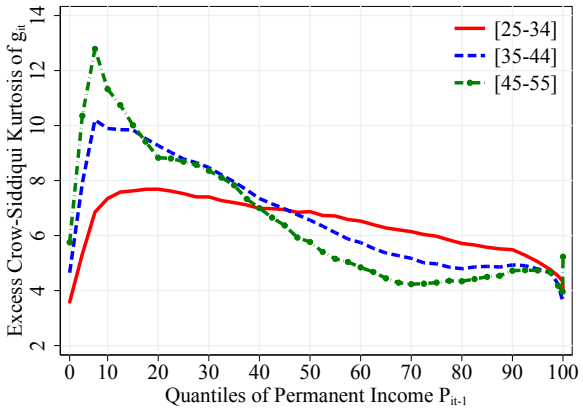
(D) KELLEY SKEWNESS, WOMEN



(E) EXCESS CROW-SIDDIQUI KURTOSIS, MEN



(F) EXCESS CROW-SIDDIQUI KURTOSIS, WOMEN

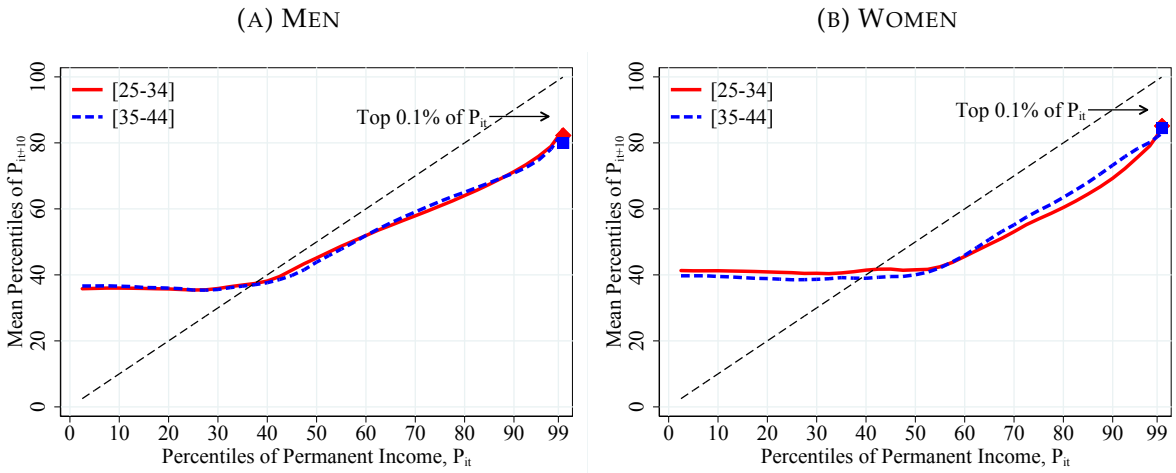


Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

Earnings mobility. Figure 9 investigates earnings mobility. In particular, it plots a worker's average rank in the earnings distribution 10 years later as a function of his or her rank in the distribution today,

separately by age and gender (the Appendix contains similar plots for outcomes five years later, with a similar conclusion). The distribution is ergodic, in the sense that individuals currently at the bottom of the distribution tend to move up the distribution over time and vice versa. In the top 60 percent of the earnings distribution (top 50 for women), individuals on average lose a fraction of their current rank. Thus, if an individual currently is in percentile p of the earnings distribution, 10 years later he or she is expected to be in percentile xp, where $x \in (0,1)$. This pattern is quite different in the lower part of the distribution (lower 40 percent for men, lower 50 percent for women). There, the average rank of individuals 10 years later is essentially unrelated to their current rank.[11] There are no pronounced life-cycle differences in this pattern.

FIGURE 9. EVOLUTION OF 10-YEAR MOBILITY OVER THE LIFE CYCLE, BY GENDER



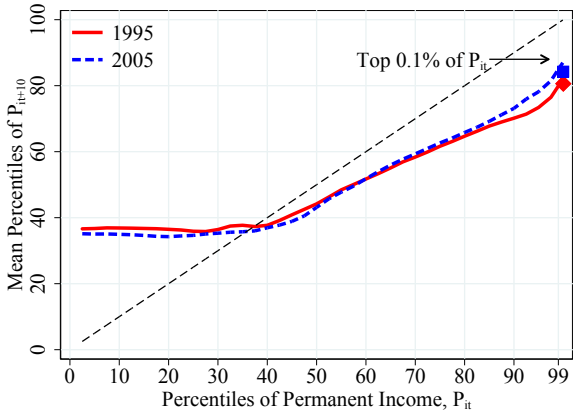
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

Figure 10 conducts the same analysis instead over time: it plots the average rank of workers 10 years later as a function of their rank in the earnings distribution today, separately by year and gender. The same pattern that holds by age also holds over time. There is no pronounced change in mobility patterns over time in Brazil. This pattern is particularly interesting in light of the gradual decline in earnings volatility over this period in Figure 6. Individuals move across the earnings distribution to the same extent now as in the past. Since the underlying earnings distribution is more compressed now than in the past, however, the earnings change associated with a move between two particular rungs of the earnings distribution is smaller.

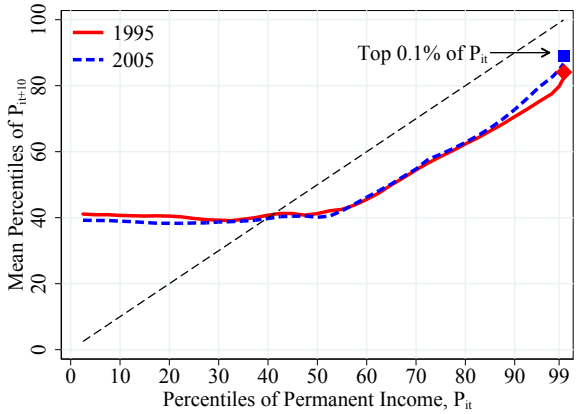
[11] We think the reason for this is that a significant share of the lower tail of the earnings distribution (lower 40 percent for men and lower 50 percent for women) at any date earns zero earnings today but has positive earnings 10 years later.

FIGURE 10. EVOLUTION OF 10-YEAR MOBILITY OVER TIME, BY GENDER

(A) MEN



(B) WOMEN



Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

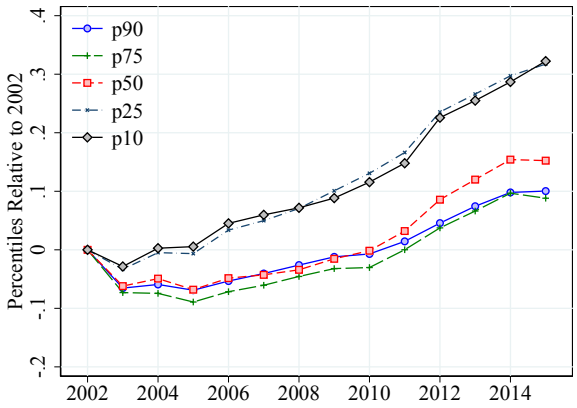
5 Comparing administrative and household survey data

To what extent do the patterns in administrative data correspond with what households self-report in surveys? To address this question, we compare our results for the formal sector from the RAIS administrative data with the PME household survey. We replicate our exercises for the formal sector from the previous section for the formal sector in the PME. To that end, we restrict the RAIS sample to the subset of the six metropolitan areas covered by the PME and to 2002–2015 to align with the available data from the PME. Since trends for men and women are quite similar, in the interest of space, we pool both genders. We also abstract from an analysis of the very top of the earnings distribution and limit our discussion of higher-order moments of earnings changes, as we believe that the modest sample size of the PME prevents a reliable analysis of these outcomes.

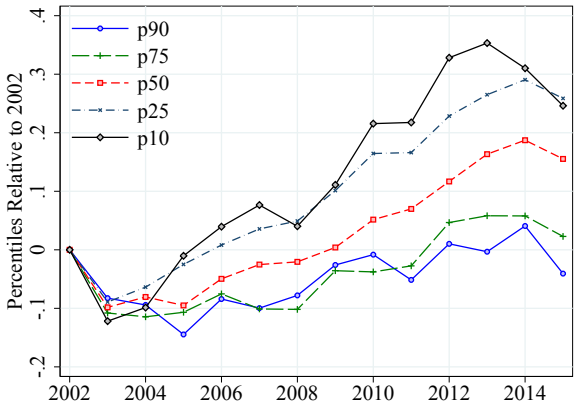
Figure 11 plots percentiles of the log earnings distribution, normalized to 2002. Note that, in general, the results based on the RAIS in the left panel differ from those in the previous section, since we now restrict attention to the subset of the six metropolitan areas covered by the PME. In practice, however, the time trends closely correspond to the trends for the full country in the previous section. Reassuringly, the percentile ratios evolve similarly in the administrative and in the household survey data.

FIGURE 11. PERCENTILES OF THE LOG REAL EARNINGS DISTRIBUTION, RAIS AND PME

(A) RAIS



(B) PME

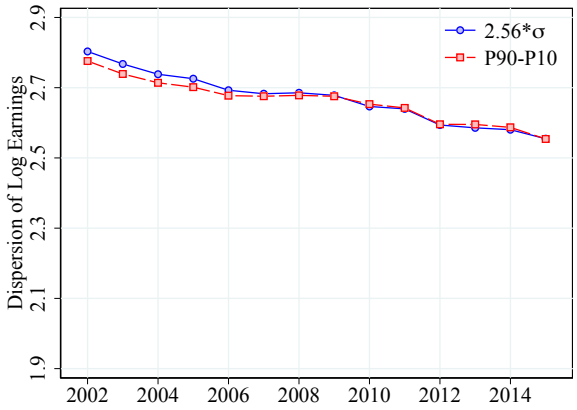


Note: Workers aged 25–55. *Source:* PME and RAIS 2002–2015.

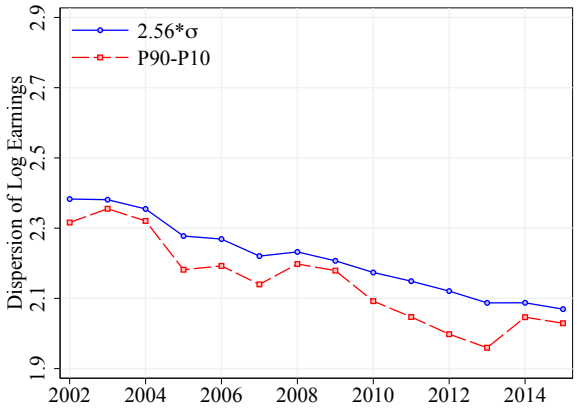
Not surprisingly, given that the percentiles line up closely across the two data sets, Figure 12 finds that measures of inequality follow similar trends in the RAIS and in the PME. That said, the household survey data understate the level of inequality in the administrative data; for instance, the 90-10 percentile ratio is higher by almost 30 log points in the RAIS.

FIGURE 12. EARNINGS INEQUALITY, RAIS AND PME

(A) RAIS



(B) PME

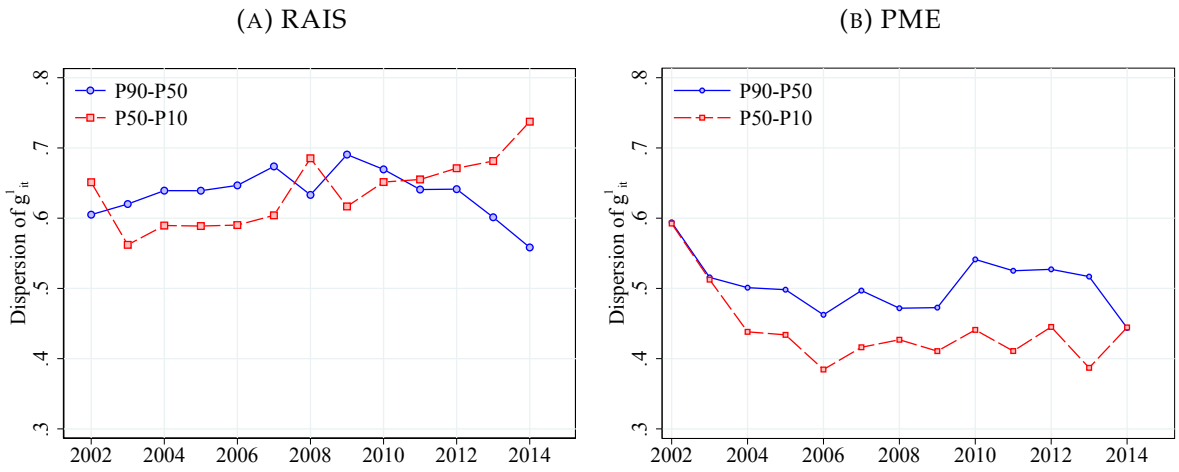


Note: Workers aged 25–55. *Source:* PME and RAIS 2002–2015.

We next turn to a comparison of earnings dynamics in the administrative and survey data. Figure 13 plots dispersion in one-year earnings innovations in the RAIS and the PME. The two data sets show broadly similar patterns, although with some important differences, especially during the 2002–2006 period. For instance, according to PME, dispersion in both the top and the bottom of the earnings innovation distribution fell sharply from 2002 to 2004, whereas it was fairly stable in RAIS. One possibility is

that the modest sample size of the PME results in a noisy estimate of the underlying population variance of earnings innovations. That said, the two surveys give broadly similar results for the period from 2006, showing a pattern of relative stability.

FIGURE 13. DISPERSION OF ONE-YEAR LOG EARNINGS CHANGES, RAIS AND PME



Note: Workers aged 25–55. *Source:* PME and RAIS 2002–2015.

6 The role of (in-)formality in Brazil

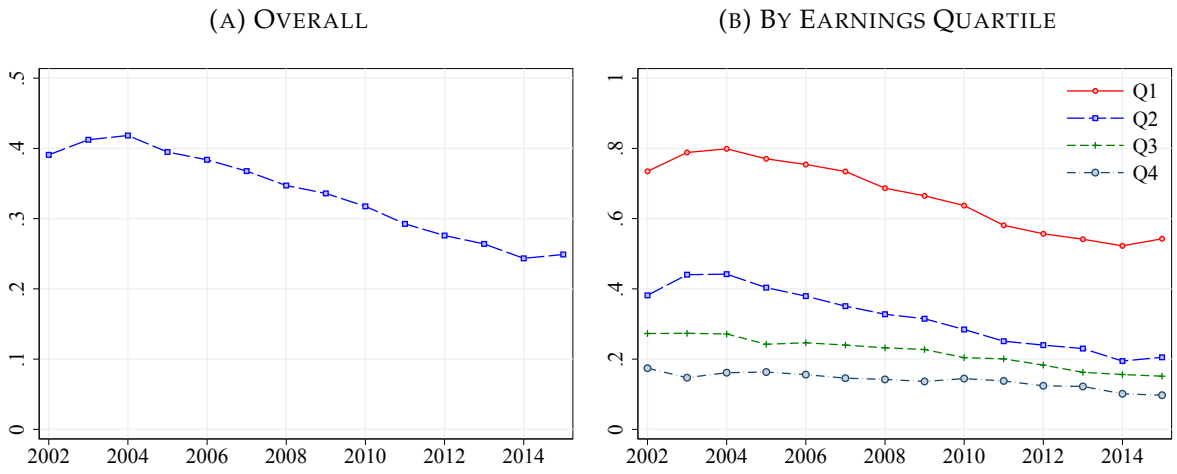
How different are the distributions of earnings levels and earnings innovations in the informal sector relative to those in the formal sector in Brazil? And how has economy-wide earnings inequality and volatility, pooling Brazil's formal and informal workers, evolved since 2002? To answer these questions, we extend our empirical analysis to Brazil's informal sector, exploiting the joint power of our administrative and survey data. We proceed in three steps. First, we dissect the process of labor market formalization in Brazil over the period from 2002 to 2015. Second, we compare earnings inequality and dynamics in Brazil's informal sector to those in the formal sector. Finally, we quantify the sources of a decline in earnings volatility in the overall Brazilian economy, pooling the formal and informal sectors.

6.1 The process of labor market formalization

An analysis of the informal sector is highly relevant in a developing country like Brazil, which is characterized by a large share of informal sector employment, as illustrated by Figure 14. The left panel shows that the informal share has declined over the past 10–15 years, dropping from 39 percent in 2002 to 25 percent in 2015. The right panel dissects the decline across the earnings distribution. In the bottom quartile of the earnings distribution, almost three-quarters of workers were in the informal sector in 2002,

while the corresponding figure in the top quartile was 17 percent. Over time, the decline in informality was particularly pronounced at the bottom of the distribution—the share of the first quartile working in the informal sector fell by 19 percentage points from 2002 to 2015. Yet, the process of labor market formalization was widespread throughout the earnings distribution, with the share of the top quartile working in the informal sector also declining by seven percentage points. Despite the decline in informality, however, the informal sector continues to account for over half of employment among workers in the bottom quartile of the earnings distribution, highlighting its continued importance.

FIGURE 14. SHARE OF INFORMAL EMPLOYMENT



Note: Workers aged 25–55. *Source:* PME 2002–2015.

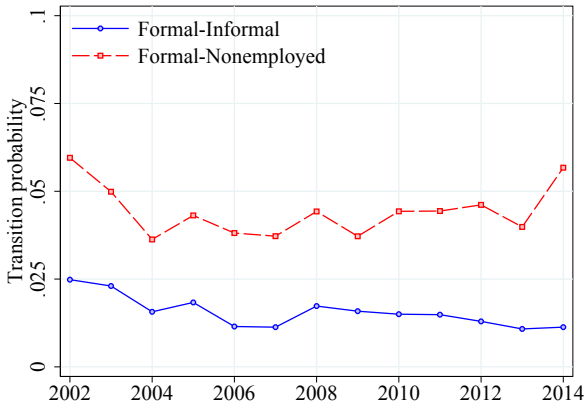
The decrease in informality in Brazil between 2002 and 2015 is closely related to the evolution of labor market flow rates over this period. Figure 15 shows the one-year-forward transition rates between formal and informal employment for formal sector workers in panel (A) and for informal sector workers in panel (B).[12] A striking observation is that transition rates out of the formal sector (panel [A]) are around four times smaller than transition rates out of the informal sector (panel [B]). Given that between 2002 and 2015, the formal sector was only between one-and-a-half and three times as large as the informal sector, a balance flow equation tells us that this observation implies a net inflow into formality over this period. A second striking observation is that the formal-to-informal transition rate has approximately halved, from around 2.5 percent to around 1.2 percent, over this period. At the same time, the informal-to-formal transition rate has slightly increased. Exit rates into nonemployment have been *U*-shaped in both sectors over this period.

There exists significant heterogeneity in sectoral flows across the earnings distribution. Figure 16

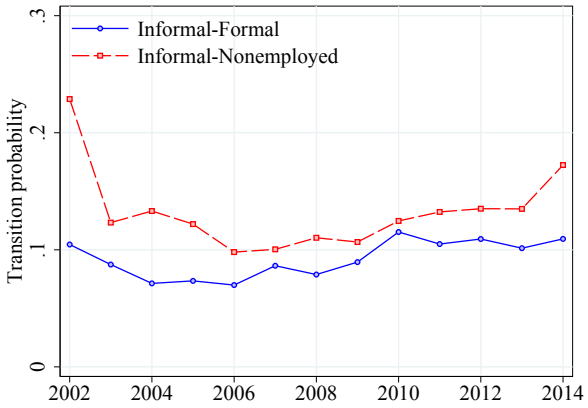
[12]Figure 41 in Appendix A.3 shows the same time series and also that of transition probabilities from either sector into nonemployment, which we define as no employment in either the formal or the informal sector.

FIGURE 15. EVOLUTION OF SECTORAL FLOW RATES, BY ORIGIN SECTOR

(A) FLOW RATES FROM FORMAL SECTOR



(B) FLOW RATES FROM INFORMAL SECTOR

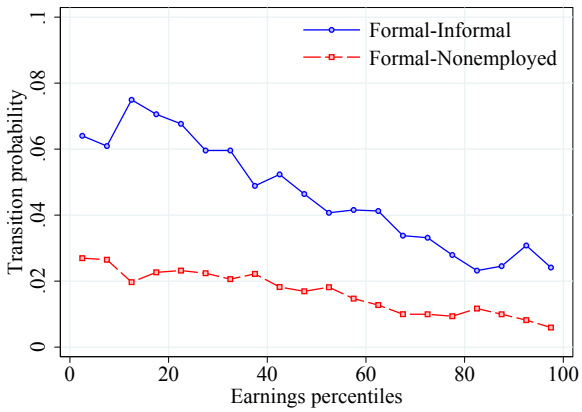


Note: Workers aged 25–55. *Source:* PME 2002–2015.

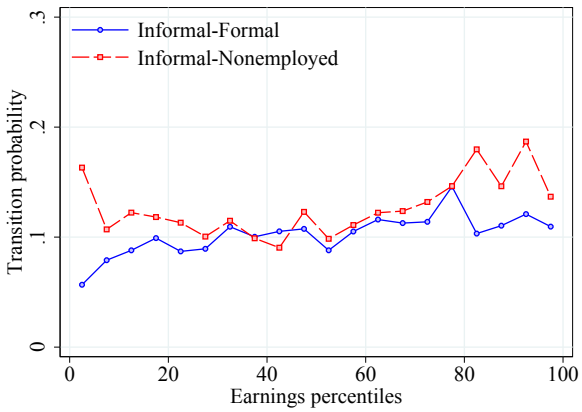
plots the mean transition rates as a function of population earnings rank for formal sector workers in panel (A) and for informal sector workers in panel (B).[13] A few points are noteworthy. First, for both formal and informal workers, the probability of staying in the same sector in consecutive years (the omitted category in each panel of Figure 16) far outweighs that of switching sectors or leaving employment altogether. Second, formal workers are relatively more attached to their sector than informal workers are. Third, there is a marked decrease in exit rates from the formal sector toward informality and nonemployment but an increase in exit rates from the informal sector toward formality and nonemployment toward higher earnings percentiles.

FIGURE 16. CROSS-SECTIONAL HETEROGENEITY IN SECTORAL FLOW RATES, BY ORIGIN SECTOR

(A) FLOW RATES FROM FORMAL SECTOR



(B) FLOW RATES FROM INFORMAL SECTOR



Note: Workers aged 25–55. *Source:* PME 2002–2015.

[13] Figure 42 in Appendix A.3 shows the same cross-sectional relationships and also transition probabilities from either sector into nonemployment, which we define as no employment in either the formal or the informal sector.

It is reasonable to wonder whether the decrease in the informal employment share in Brazil might have been driven by changes in the prevalence of workers holding multiple jobs at the same point in time, of which one or several may be informal. To investigate this, Table 2 summarizes the share of workers who hold multiple jobs in a month, broken down by whether the main job is in the formal sector (Panel A) or informal sector (Panel B). Holding multiple job is not particularly common in Brazil, with roughly 2 percent of employed workers holding multiple jobs. The fraction is modestly lower among informal sector workers. Among formal sector workers with a second job, roughly half of them contribute to social security in their second job (a proxy for the formality status of the second job). Moreover, the (un)importance of multiple job holding has remained roughly stable over time. Hence, the main margin of formalization is the extensive margin—workers switching entirely into the formal sector—as opposed to a declining prevalence of workers with multiple jobs in both the informal and formal sector.

TABLE 2. INCIDENCE AND EVOLUTION OF MULTIPLE JOB HOLDING RATES

	Panel A. Formal sector				*Panel B. Informal sector*			
	2002–04	2005–08	2009–11	2012–15	2002–04	2005–08	2009–11	2012–15
Share with secondary job (%)	2.8	2.9	2.7	2.3	2.1	2.3	2.1	2.2
Average weekly hours in main job	42.8	42.5	42.3	42.0	41.8	41.6	41.0	40.3
Average weekly hours in secondary jobs	17.5	17.2	15.0	16.7	22.2	21.8	20.2	21.6
Share with SS contributions in secondary job	51.2	52.2	54.4	59.1	25.0	23.5	25.7	30.9

Note: Workers aged 25–55. Share of formal/informal employment with a secondary job. "Average weekly hours in main job" is for the full sample population conditional on holding a job. "Average weekly hours in secondary jobs" includes hours worked in all nonprimary (i.e., secondary, tertiary, etc.) jobs and is computed among the subpopulation of workers with more than one concurrent job. *Source:* PME 2002–2015.

6.2 Earnings inequality and dynamics

In parallel to our previous analysis of the formal sector based on administrative data, we start by analyzing inequality in the informal sector based on household survey data. Figure 17 compares the distribution of residual log earnings across the two sectors in 2003 and 2015.[14] As expected, pay is higher in the formal sector, in a first-order stochastic sense. That said, there is significant overlap across the two distributions. Many informal sector workers earn better than their observationally equivalent peers working in the formal sector. Qualitatively, this pattern has not changed over time.

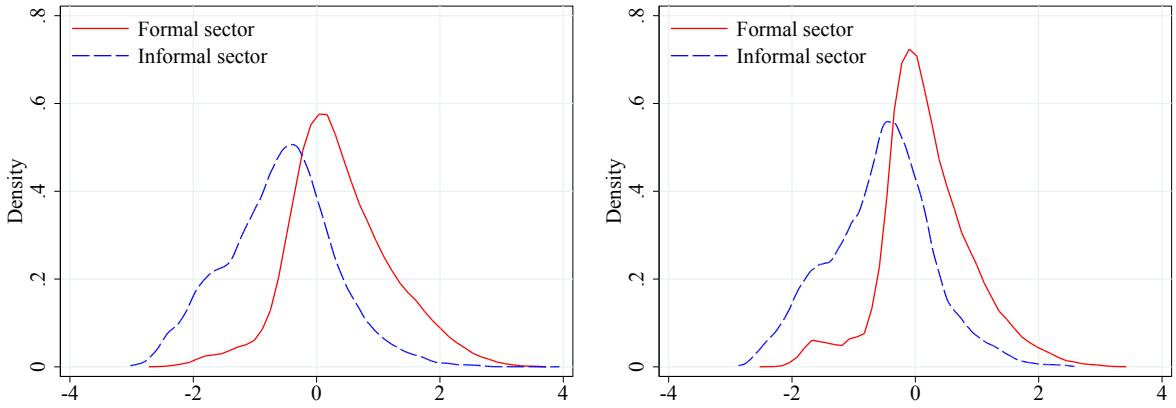
Figure 18 plots trends in inequality in the formal and informal sectors over time.[15] Inequality has

[14]For comparability reasons, we plot the density for 2003 instead of 2002 because the first interview of the PME-Nova survey took place in March 2002. In this way, we compare the earliest and latest possible years of data with coverage of all calendar months.

[15]Because we here apply the PME sample selection criteria, the pattern for the formal sector differs slightly from that in Figure 12, which applies the RAIS sample selection criteria to the PME data, even though both figures are based on data from the PME.

FIGURE 17. DENSITY OF RESIDUAL LOG EARNINGS IN EACH SECTOR, BY YEAR

(A) 2003 (B) 2015

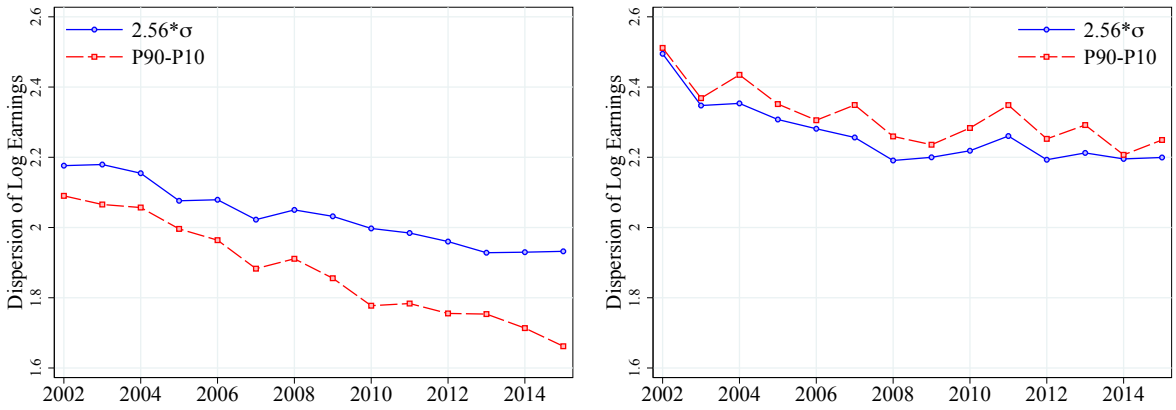


Note: Workers aged 25–55. Figure shows Kernel densities of residual log earnings for 2003 in panel (A) and for 2015 in panel (B). Residual log earnings are calculated controlling for age and survey wave fixed effects, separately by gender and year. Formal sector includes all employees with a work permit. Informal sector includes all employees without a work permit and the self-employed. *Source:* PME 2002–2015.

significantly declined in both the formal and informal sector over this period, although the fall is more pronounced in the formal sector. This is particularly true for the log 90-10 percentile ratio. One possibility is that the rapid increase in the minimum wage has contributed to a disproportionate reduction in inequality in the formal sector, since it applies only there (Engbom and Moser, 2021).

FIGURE 18. EARNINGS INEQUALITY, BY SECTOR

(A) FORMAL (B) INFORMAL

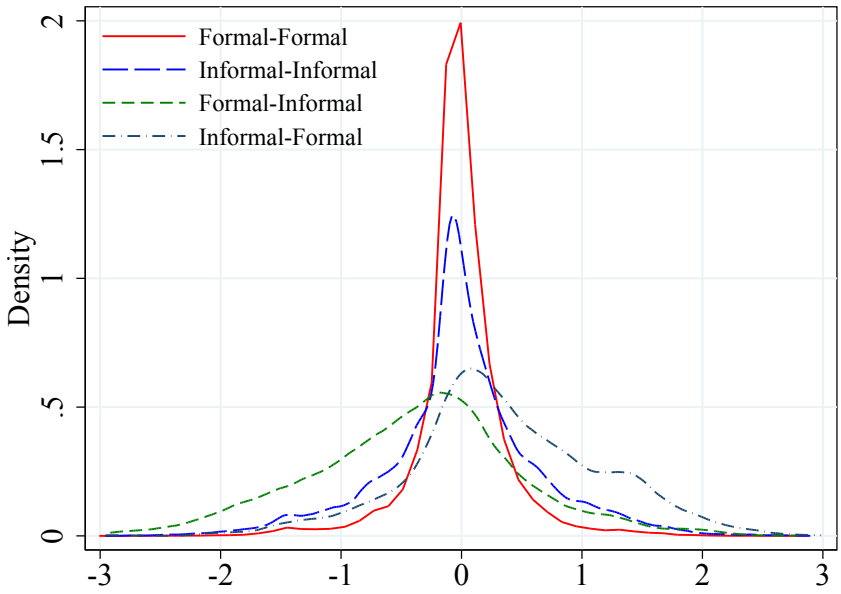


Note: Workers aged 25–55. *Source:* PME 2002–2015.

We next assess earnings dynamics in the informal sector. Figure 19 plots the distribution of one-year residual earnings innovations by worker group. Because workers may change sector across years, we construct four mutually exclusive, collectively exhaustive groups: those who work in the formal sector both in year t and in year $t+1$—henceforth "formal-formal" workers—those who work in the informal

sector in both years—"informal-informal" workers—and those who work in the formal (informal) sector in year t but in the informal (formal) sector in year $t+1$—"formal-informal" and "informal-formal," respectively. Informal-informal workers have more volatile earnings than formal-formal workers, with a higher prevalence of large negative and positive earnings innovations. Of course, this pattern should not be interpreted in a causal sense, as workers likely are not randomly assigned to sector. Formal-informal workers tend to experience earnings losses, while the opposite is true among informal-formal workers. The fact that a given worker experiences an earnings change when switching sectors suggests that the lower average earnings in the informal sector are not due purely to worker selection (Alvarez, 2020).

FIGURE 19. DENSITIES OF ONE-YEAR RESIDUAL LOG EARNINGS CHANGE, BY TRANSITION TYPE



Note: Workers aged 25–55. All panels. Kernel densities of one-year change in residual log earnings by worker group. Residuals are calculated controlling for age and survey wave fixed effects, separately by gender and year. Workers aged 25–55. Different lines denote different combinations of a worker's current sector of employment and that in the next survey wave (e.g., "Formal-Informal" denotes current employment in the formal sector and employment in the informal sector in the next survey wave). *Source:* PME 2002–2015.

Table 3 summarizes the first four moments of one-year residual earnings innovations across the four groups of workers. For comparison, we also include the corresponding moments for the US, based on Guvenen et al. (2019). The average residual earnings change is not zero within groups, because we do not let observable controls vary flexibly by sector. That said, average residual earnings changes are small among formal-formal and informal-informal workers. In contrast, as already suggested by Figure 19, workers who switch sector experience large residual earnings changes. Moreover, the average gain of workers switching into the formal sector is close to the average loss of workers leaving the formal

sector. At face value, this symmetry speaks against theories that comparative advantage drives worker mobility across sectors. Under such a view, one would expect that either all workers would make wage gains upon sector switching or that the patterns of gains and losses would be asymmetric.[16]

Furthermore, as also suggested by Figure 19, the standard deviation of earnings innovations is higher in the informal sector than in the formal sector. Indeed, while the overall standard deviation of earnings innovations is similar to the one in the US, the volatility within the informal sector is closer to that among low paid workers in the US. The standard deviation is even higher among workers who switch sector across years. For completeness, we also report higher order moments in Table 3, but we caution against attaching too much weight to them, given the modest sample size of the PME.

TABLE 3. ONE-YEAR LOG EARNINGS CHANGE MOMENTS: 2002-14

	Mean	Std. dev.	Skewness	Kurtosis
Panel A. Brazil				
All of Brazil	-0.007	0.52	-0.06	7.35
Formal-Formal	-0.014	0.38	-0.17	9.63
Informal-Informal	-0.009	0.65	-0.06	4.92
Formal-Informal	-0.388	0.88	-0.09	3.46
Informal-Formal	0.362	0.81	0.06	3.57
Panel B. US (Guvenen et al., 2019)				
Median earnings (P50)		0.49	-1.35	16.81
High earnings (P90)		0.43	-1.62	26.2
Low earnings (P10)		0.73	-0.72	6.78

Note: Workers aged 25–55. Mean, standard deviation, 3^{rd} and 4^{th} standardized moments of one-year residual log earnings change. Residuals are calculated controlling flexibly for age and survey wave fixed effects, separately by gender and year. *Source:* Panel A is based on PME 2002–2015. Panel B is based on US statistics from Guvenen et al. (2019) for men in age group 3 (age 35–39), based on the Online Data Appendix "Moments For Men" tab "L1_log_age_re."

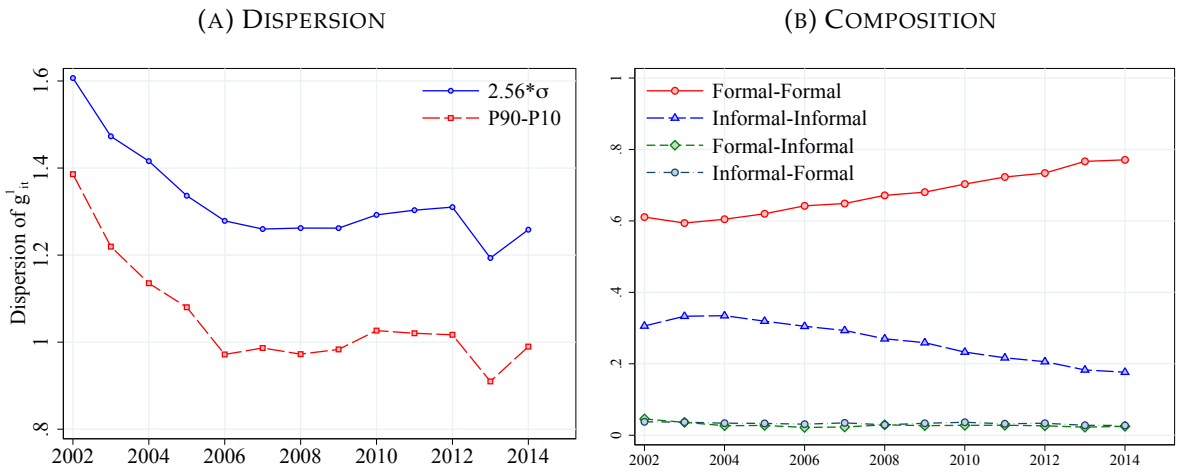
6.3 Understanding the aggregate decline in earnings volatility in Brazil

In this final section of the paper, we decompose the sources of an aggregate decline in earnings volatility in Brazil over this period, as illustrated by Figure 20. Pooling all worker groups in the left panel, we see that earnings volatility fell in the early 2000s and subsequently leveled out, mirroring the patterns in the formal sector. Given differences across sectors in the volatility of earnings, combined with labor market formalization in Brazil over this period, this aggregate trend is in turn the result of changes in composition and within-sector changes in volatility. In particular, the employment composition has shifted

[16]That is, suppose that there is an average earnings penalty ω from working in the informal sector—for instance, because the worker does not have to pay taxes on informal income such that, all else equal, a worker may require lower gross pay in the informal relative to the formal sector. If some workers are better suited for the informal sector and workers sort based on this, we would expect workers who move into the informal sector to experience an earnings change $> -\omega$, while those who switch into the formal sector experience an earnings increase $> \omega$. In other words, the earnings changes of switchers are asymmetric.

significantly toward formal-formal workers and away from informal-informal workers. In contrast, the share of workers who work in both sectors across the two years has remained relatively small.

FIGURE 20. ONE-YEAR RESIDUAL LOG EARNINGS CHANGE



Note: Workers aged 25–55. Residuals are calculated controlling for age and survey wave fixed effects, separately by gender and year. *Source:* PME 2002–2015.

To understand the role of compositional shifts behind the overall change in the volatility of earnings over this period, we start by conducting a between/within decomposition of the variance of one-year changes in residual log earnings across the formal-formal, informal-informal, formal-informal and informal-formal worker groups. That is, at a point in time, the overall variance of residual earnings changes, Δ_{it}, can be decomposed into a between-group and a within-group component,

$$\overbrace{\frac{1}{N_t}\sum_i \left(\Delta_{it} - \overline{\Delta}_t\right)^2}^{\text{Total variance}} = \overbrace{\sum_{s\in S} \frac{N_{st}}{N_t}\left(\overline{\Delta}_{st} - \overline{\Delta}_t\right)^2}^{\text{Between component}} + \overbrace{\sum_{s\in S} \underbrace{\frac{N_{st}}{N_t}}_{\text{Composition channel}} \underbrace{\frac{1}{N_{st}}\sum_{i\in s}\left(\Delta_{it} - \overline{\Delta}_{st}\right)^2}_{\text{Return channel}}}^{\text{Within component}}, \tag{3}$$

where $\overline{\Delta}_t = \frac{1}{N_t}\sum_i \Delta_{it}$ is the grand average residual in year t and $\overline{\Delta}_{st} = \frac{1}{N_{st}}\sum_{i\in s}\Delta_{it}$ is the average residual within-group s in year t. Note that the former is not zero by construction, because we residualize earnings and not earnings changes. In a balanced panel, the fact that the levels sum to zero in each year would imply that earnings changes also sum to zero, but because our panel is unbalanced, this needs not hold.[17] Note that the latter is not zero by construction, because the age and education effects do not

[17]The former claim is straightforward to verify. The average change in the residuals between year t and $t+1$ is

$$\frac{1}{N_t}\sum_i \Delta_{it} = \frac{1}{N_t}\sum_i \left(w_{it+1} - w_{it}\right) = \frac{N_{t+1}}{N_t}\frac{1}{N_{t+1}}\sum_i w_{it+1} - \frac{1}{N_t}\sum_i w_{it},$$

which is zero, since both $\frac{1}{N_{t+1}}\sum_i w_{it+1} = 0$ and $\frac{1}{N_t}\sum_i w_{it} = 0$ by the nature of their both being the sum of OLS residuals.

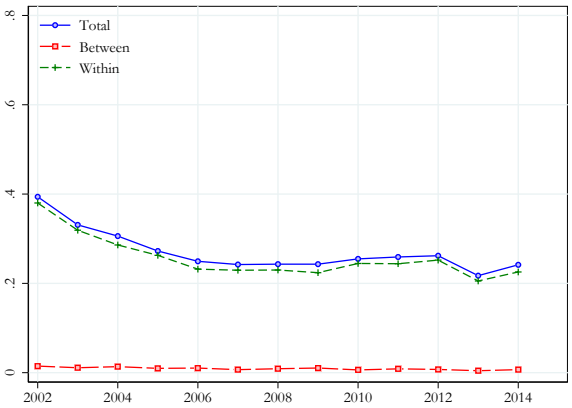
vary by group (and in addition the panel is not balanced).

Because different groups are characterized by different volatilities of earnings, two factors in turn contribute to changes in the within component in (3) over time.[18] First changes in the employment weights, $\frac{N_{st}}{N_t}$, of groups in (3) by themselves lead to changes in overall volatility through a composition channel. Second, within-group changes in volatility, $\frac{1}{N_{st}}\sum_{i\in s}(\Delta_{it}-\overline{\Delta}_{st})^2$, lead to changes in overall volatility, holding composition fixed, which we refer to as the return channel.

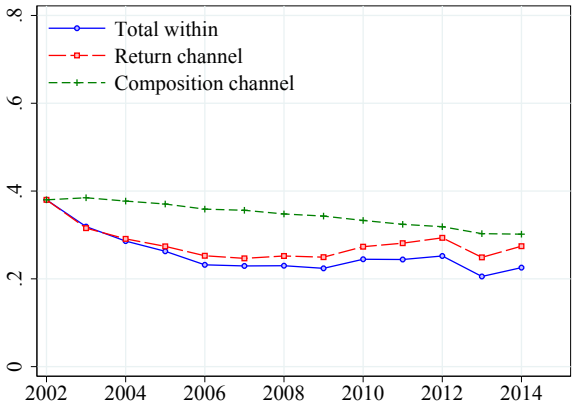
The left panel of Figure 21 decomposes the overall change in the variance of earnings changes into its between and within components based on (3). Changes within groups in the volatility of earnings account for the great majority of the fall in earnings volatility over this period. The right panel isolates the role of these two forces using a shift-share analysis (as is standard in shift-share analysis, the two components do not add up to the total change). That is, to compute the composition channel, we hold the within-group variances fixed at their initial level and change only the employment weights as in the data. To compute the return channel, we hold the employment weights fixed at their initial level and change only the within-group variances as in the data. Within-group changes lead to a larger decline in volatility than compositional shifts, although the effect of the latter is also significant. The composition effect arises primarily because employment has gravitated toward formal-formal workers over this period, a shift that is characterized by lower volatility of earnings.

FIGURE 21. DECOMPOSITION OF CHANGE IN VOLATILITY

(A) BETWEEN VS WITHIN



(B) DECOMPOSING THE WITHIN COMPONENT



Note: Workers aged 25–55. Panel A. Between/within decomposition of the variance of earnings innovations based on (3). Panel B. Shift-share analysis of the within component of (3). Return channel: Holding the sector composition fixed at its initial level and letting the within group variances evolve as in the data. Composition channel: holding the within group variances fixed at their initial level and letting the sector composition evolve as in the data. *Source:* PME 2002–2015.

[18] While the same is true also for the between component in (3), we focus on the within component, since that accounts for the great majority of the changes in volatility over this period.

The limited explanatory power of demographics. In a similar spirit to the between/within decomposition (3) of the total variance of earnings innovations across the four worker groups, we further decompose the variance of earnings innovations among formal-formal and informal-informal workers into its between versus within components across four education groups. We restrict attention to these two worker groups because they constitute the great majority of Brazilian employment. Subsequently, motivated by the fact that the within-education group component accounts for the great majority of changes in the volatility of earnings among formal-formal and informal-informal workers, we further consider a shift-share analysis of the within-education group component in the same spirit as above. We focus on educational composition because Brazil experienced a rapid increase in educational attainment over this period.[19]

Figure 22 plots the results of these exercises. As noted above, the great majority of the decline in the volatility of earnings among formal-formal and informal-informal workers, is accounted for by the within component. The great majority of the fall in the within component is, in turn, driven by changes within education groups in the variance of earnings, as opposed to changes in the educational composition of the workforce combined with differences across education groups in their volatility of earnings. The reason is that although Brazil has seen rapid changes in educational composition over this period, the differences across education groups in the within-education group volatility of earnings are not that large. While the findings of this type of accounting exercise in the absence of an equilibrium model should be cautiously interpreted, at face value, they do suggest a limited role for rising educational attainment in driving the fall in earnings volatility among formal-formal and informal-informal workers.

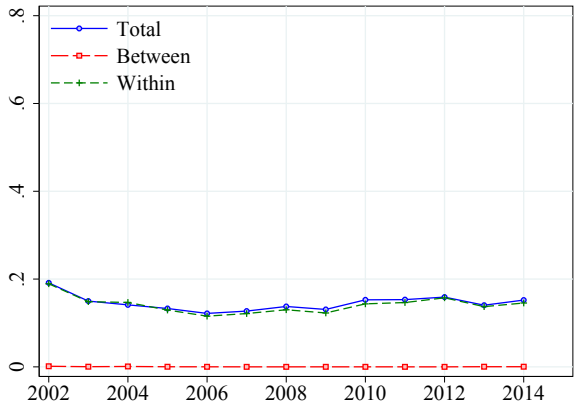
7 Conclusion

In this paper, we documented new facts on earnings inequality, dynamics, and mobility in Brazil. Among workers in Brazil's formal sector, there has been a remarkable decrease in earnings inequality, driven by bottom-led growth in real earnings, since the late 1990s. At the same time, the dispersion of earnings innovations decreased markedly. Higher-order moments of the distribution of earnings innovations differ in levels but show cyclical movements similar to those previously documented in developed countries such as the US. Earnings mobility is comparatively high in Brazil, especially at the bottom of the distribution. We also studied earnings inequality and dynamics in Brazil's formal and informal sectors. Compared with formal sector workers, there is significantly higher dispersion of earnings innovations

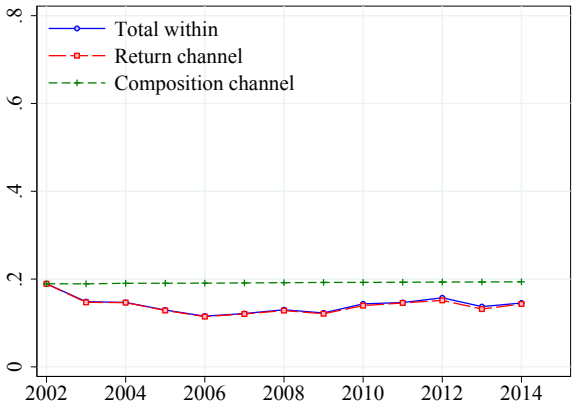
[19] In unreported results, we find that compositional shifts in other demographic dimensions such as age and gender account for even less of the overall change over this period.

FIGURE 22. THE ROLE OF CHANGES IN EDUCATIONAL ATTAINMENT

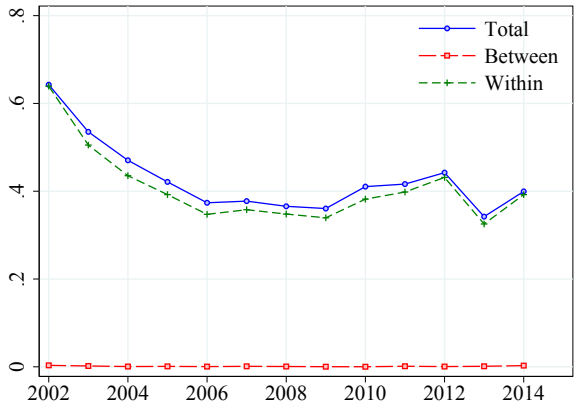
(A) BETWEEN VS WITHIN, FORMAL-FORMAL



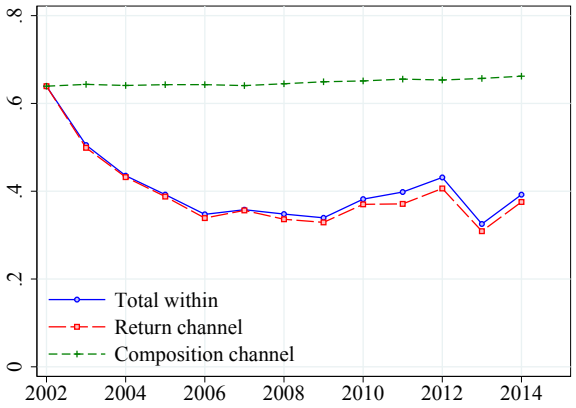
(B) WITHIN COMPONENT, FORMAL-FORMAL



(C) BETWEEN VS WITHIN, INFORMAL-INFORMAL



(D) WITHIN COMPONENT, INFORMAL-INFORMAL



Note: Workers aged 25–55. Left panels. Between/within decomposition of the variance of earnings innovations within the formal-formal (top) or informal-informal (bottom) worker groups based on (3) across four education groups. Panel B: shift-share analysis of the within-education group component of (3) across four education groups within the formal-formal (top) or informal-informal (bottom) worker groups. Return channel: holding the education composition fixed at its initial level and letting the within-group variances evolve as in the data. Composition channel: holding the within-group variances fixed at their initial level and letting the education composition evolve as in the data. *Source:* PME 2002–2015.

among informal sector workers and significantly skewed earnings innovations among sector switchers. We found a large decrease in the economy-wide dispersion of earnings innovations, which is driven mostly by the within-sector evolution of earnings volatility.

An interesting avenue for future research is to shed further light onto the microeconomic sources of the decline in earnings inequality and volatility that we document and also to assess its macroeconomic consequences.

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A Appendix

A.1 Additional summary statistics

TABLE 4. CROSS-SECTIONAL SUMMARY STATISTICS, OVERALL

Year	Obs.	Mean	Std. dev.	P1	P5	P10	P25	P50	P75	P90	P95	P99	P99.9	P99.99
1985	15.7	19,852	26,915	585	1,755	3,121	5,881	11,105	22,696	44,737	67,256	134,110	255,402	425,948
1986	16.9	20,627	26,716	635	1,751	3,038	5,932	11,865	24,215	47,043	69,680	134,984	224,955	387,154
1987	17.6	18,824	27,220	429	1,364	2,496	5,009	10,438	21,323	42,172	64,080	134,699	290,922	403,407
1988	18.6	18,859	27,307	291	1,148	2,430	4,910	10,045	21,266	42,977	66,632	137,842	256,362	396,512
1989	19.3	18,591	27,174	231	935	2,319	4,835	9,839	20,902	41,922	65,923	139,556	254,659	387,672
1990	19.7	15,268	21,970	232	962	1,873	3,766	8,078	17,521	34,687	54,200	112,631	199,526	297,985
1991	19.5	14,533	20,786	319	1,021	1,915	3,861	7,833	16,536	32,834	51,001	104,857	192,177	315,036
1992	19.4	14,399	20,297	202	826	1,804	3,936	7,844	16,229	33,058	50,913	101,826	189,134	277,698
1993	20.1	15,728	23,111	162	766	1,899	4,178	8,239	17,393	36,211	56,422	117,313	217,039	324,278
1994	20.7	16,524	23,245	244	1,046	2,074	4,260	8,671	18,903	38,908	58,775	117,161	211,849	305,908
1995	21.8	19,214	27,671	502	1,345	2,336	4,723	9,921	21,786	45,038	69,210	141,114	253,044	348,350
1996	21.9	19,335	27,785	574	1,457	2,468	4,991	10,250	21,771	44,745	68,389	141,832	262,035	373,896
1997	22.3	19,434	28,048	594	1,518	2,552	5,099	10,342	21,726	44,565	68,732	143,569	264,084	384,921
1998	22.9	19,869	29,077	623	1,581	2,687	5,301	10,594	22,129	44,593	69,648	148,988	282,161	412,739
1999	23.1	19,153	28,001	613	1,544	2,628	5,230	10,257	21,224	42,486	67,007	144,740	271,705	392,265
2000	23.7	19,013	28,187	608	1,516	2,613	5,214	10,116	20,932	42,019	66,764	146,056	276,394	393,854
2001	25.4	19,133	29,659	619	1,543	2,648	5,268	9,954	20,582	42,124	66,775	151,038	311,010	464,091
2002	26.4	18,756	30,505	623	1,551	2,660	5,292	9,708	20,055	41,195	65,011	147,759	313,361	474,376
2003	27.4	17,699	27,930	596	1,527	2,596	5,170	9,236	18,791	38,405	60,946	138,945	306,786	475,542
2004	28.8	18,017	28,201	623	1,600	2,730	5,386	9,543	19,086	39,022	61,793	140,291	305,658	486,266
2005	30.5	17,974	28,196	628	1,614	2,752	5,533	9,554	18,908	38,617	61,227	140,834	304,485	489,218
2006	32.3	18,645	29,425	664	1,736	2,955	5,992	9,892	19,412	39,774	62,802	145,559	335,661	522,767
2007	34.2	18,996	29,772	681	1,781	3,055	6,261	10,154	19,745	40,513	63,629	147,545	339,696	530,402
2008	36.5	19,464	30,495	722	1,884	3,173	6,445	10,413	20,210	41,296	64,882	151,420	339,068	544,611
2009	37.9	19,866	30,908	721	1,864	3,209	6,813	10,740	20,559	42,126	66,313	154,799	333,382	551,067
2010	40.4	20,392	31,395	773	2,017	3,451	7,150	11,161	21,166	42,969	67,674	156,655	339,306	568,684
2011	42.4	20,773	31,431	804	2,081	3,547	7,277	11,545	21,745	43,702	68,351	156,676	333,256	582,293
2012	43.9	21,589	31,614	858	2,247	3,841	7,886	12,290	22,813	45,472	70,051	157,155	326,983	577,155
2013	45.1	22,085	31,783	887	2,326	3,942	8,120	12,692	23,572	46,434	71,300	158,852	328,978	587,556
2014	45.9	22,602	32,090	924	2,454	4,104	8,313	13,143	24,181	47,504	72,443	161,116	331,021	589,361
2015	44.9	22,566	31,988	929	2,509	4,242	8,457	13,199	23,947	47,263	72,238	160,124	336,925	588,808
2016	43.0	22,342	30,764	954	2,577	4,363	8,665	13,312	23,864	46,388	70,941	154,707	317,613	563,472
2017	42.3	22,882	31,395	975	2,660	4,498	8,940	13,702	24,396	47,287	72,435	158,572	317,728	571,961

Note: Workers aged 25-55. *Source:* RAIS 1985-2017.

TABLE 5. CROSS-SECTIONAL SUMMARY STATISTICS, MEN

Year	Obs.	Mean	Std. dev.	P1	P5	P10	P25	P50	P75	P90	P95	P99	P99.9	P99.99
1985	10.9	21,806	29,738	604	1,810	3,261	6,253	12,064	24,781	49,741	75,852	147,933	276,815	452,345
1986	11.5	22,594	29,240	694	1,908	3,338	6,467	12,983	26,291	51,689	78,045	147,480	240,500	411,612
1987	11.9	20,694	29,192	478	1,483	2,753	5,566	11,583	23,246	46,531	72,300	147,748	279,048	407,918
1988	12.5	20,678	29,802	310	1,199	2,529	5,287	11,099	23,169	47,432	73,964	151,087	273,212	414,375
1989	12.9	20,447	29,666	242	954	2,390	5,206	10,947	22,825	46,691	73,473	152,709	269,575	397,090
1990	13.0	16,529	23,716	246	1,002	1,951	4,039	8,869	18,787	37,744	59,386	121,774	210,552	315,132
1991	12.9	15,800	22,601	335	1,052	1,983	4,109	8,597	17,775	35,778	56,068	114,615	202,884	340,364
1992	12.7	15,789	22,315	208	821	1,794	4,111	8,613	17,770	36,652	56,589	112,009	200,857	298,910
1993	13.1	17,225	25,278	166	747	1,851	4,356	9,037	18,915	40,227	62,608	128,325	231,322	349,415
1994	13.4	17,821	25,239	248	1,050	2,098	4,470	9,391	20,162	41,854	64,054	128,022	225,410	324,779
1995	14.0	20,857	29,942	524	1,399	2,442	5,045	10,859	23,422	48,993	75,825	153,967	265,982	369,637
1996	13.9	20,897	30,184	599	1,512	2,569	5,301	11,112	23,125	48,491	75,210	154,839	276,879	392,875
1997	14.1	20,874	30,399	612	1,533	2,617	5,362	11,132	22,875	47,940	75,304	156,928	279,669	402,947
1998	14.4	21,114	31,347	638	1,590	2,702	5,548	11,307	22,916	47,183	75,734	162,362	298,428	432,973
1999	14.3	20,281	30,187	628	1,539	2,616	5,420	10,891	21,868	44,684	72,806	157,247	288,153	413,110
2000	14.7	19,991	30,046	628	1,523	2,615	5,381	10,710	21,554	43,731	71,470	157,184	291,335	409,962
2001	15.7	20,302	32,017	629	1,558	2,671	5,468	10,556	21,361	44,346	72,585	163,447	333,319	482,633
2002	16.2	19,775	33,302	654	1,575	2,676	5,469	10,316	20,718	42,822	69,725	159,904	335,594	493,453
2003	16.7	18,711	30,140	628	1,545	2,606	5,349	9,876	19,464	40,006	65,655	151,336	331,293	499,499
2004	17.5	19,079	30,457	663	1,624	2,768	5,575	10,110	19,842	40,676	66,423	153,033	331,317	511,021
2005	18.4	19,048	30,436	668	1,671	2,825	5,721	10,205	19,709	40,218	65,629	153,618	328,746	518,375
2006	19.4	19,689	31,636	712	1,803	3,042	6,162	10,627	20,176	41,152	66,822	157,486	358,328	558,436
2007	20.5	20,062	31,930	740	1,883	3,167	6,441	10,916	20,527	41,898	67,361	159,765	357,695	568,516
2008	21.8	20,638	32,709	804	2,031	3,363	6,695	11,283	21,149	42,798	68,702	165,123	359,067	584,843
2009	22.4	21,001	33,154	785	2,000	3,371	6,938	11,570	21,433	43,537	70,143	168,102	355,285	596,351
2010	23.7	21,662	33,744	867	2,218	3,657	7,362	12,105	22,174	44,496	71,921	169,397	362,153	618,336
2011	24.7	22,178	33,898	902	2,317	3,825	7,579	12,608	22,949	45,473	72,672	169,992	357,621	623,517
2012	25.3	23,064	34,277	973	2,503	4,154	8,219	13,442	24,119	47,239	74,429	171,979	355,940	633,150
2013	25.8	23,691	34,468	999	2,582	4,257	8,435	14,033	24,991	48,562	75,997	173,752	359,881	642,189
2014	26.0	24,235	34,812	1,042	2,652	4,420	8,709	14,489	25,652	49,641	77,273	176,476	362,136	646,920
2015	25.3	24,077	34,642	1,014	2,641	4,452	8,773	14,463	25,291	49,160	76,822	175,220	364,824	643,974
2016	24.1	23,693	33,301	1,021	2,679	4,478	8,929	14,448	25,000	48,133	75,243	168,912	344,804	623,699
2017	23.6	24,233	33,968	1,037	2,743	4,595	9,190	14,788	25,503	49,042	76,947	172,357	346,970	631,279

Note: Workers aged 25-55. *Source:* RAIS 1985-2017.

TABLE 6. CROSS-SECTIONAL SUMMARY STATISTICS, WOMEN

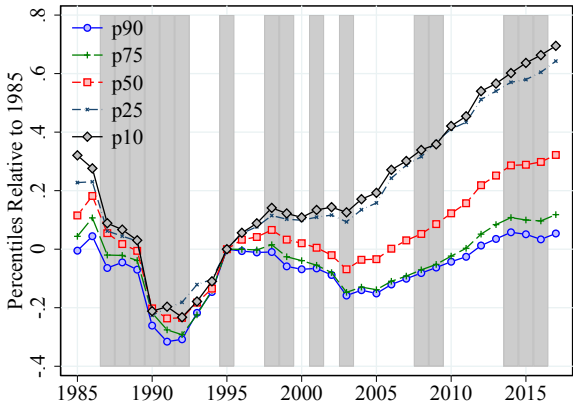
Year	Obs.	Mean	Std. dev.	P1	P5	P10	P25	P50	P75	P90	P95	P99	P99.9	P99.99
1985	4.8	15,463	18,364	533	1,661	2,857	5,378	9,299	18,347	35,186	49,613	89,725	162,360	292,297
1986	5.4	16,417	19,630	546	1,503	2,547	5,203	9,744	19,903	38,414	53,682	95,500	170,577	266,223
1987	5.7	14,943	22,087	356	1,142	2,103	4,320	8,419	17,244	34,083	48,978	95,853	349,114	390,751
1988	6.1	15,117	20,772	257	1,049	2,228	4,415	8,304	17,418	34,025	51,686	107,098	189,608	326,275
1989	6.4	14,846	20,777	211	896	2,203	4,411	8,027	17,087	33,021	49,989	106,495	194,909	343,763
1990	6.7	12,811	17,837	208	896	1,740	3,422	6,714	15,037	29,584	43,748	90,607	166,149	246,986
1991	6.7	12,095	16,477	295	961	1,792	3,534	6,540	14,030	27,533	41,404	82,045	155,255	233,028
1992	6.6	11,734	15,371	193	841	1,825	3,708	6,617	13,605	26,583	39,789	75,928	143,422	217,458
1993	7.0	12,953	18,102	157	794	1,976	3,984	7,028	14,575	28,827	44,341	92,373	170,239	253,249
1994	7.4	14,173	18,880	240	1,042	2,036	3,981	7,491	16,652	33,813	49,774	93,499	168,105	249,112
1995	7.9	16,297	22,808	473	1,269	2,166	4,330	8,455	18,752	38,458	57,993	112,305	214,995	300,946
1996	8.0	16,631	22,796	545	1,378	2,313	4,630	8,977	19,368	38,579	57,574	111,614	221,920	322,283
1997	8.2	16,970	23,283	566	1,457	2,458	4,757	9,182	19,679	39,252	58,677	115,559	222,966	331,703
1998	8.5	17,766	24,633	596	1,557	2,660	5,012	9,538	20,624	40,835	60,858	123,556	238,938	355,660
1999	8.7	17,303	23,873	594	1,545	2,648	5,003	9,341	19,935	39,492	58,859	120,402	232,289	338,864
2000	9.0	17,418	24,775	584	1,503	2,611	4,967	9,221	19,764	39,607	59,878	124,658	244,296	349,034
2001	9.7	17,251	25,295	579	1,506	2,606	5,041	9,014	19,182	39,091	58,914	125,432	266,031	397,658
2002	10.2	17,137	25,356	581	1,520	2,644	5,069	8,893	18,854	38,998	58,563	124,371	270,983	412,300
2003	10.7	16,118	23,989	560	1,491	2,576	5,029	8,458	17,511	36,165	54,682	116,725	261,294	415,282
2004	11.3	16,373	24,203	582	1,552	2,667	5,197	8,645	17,716	36,739	55,557	118,862	257,566	410,678
2005	12.1	16,334	24,289	580	1,536	2,648	5,317	8,604	17,408	36,366	55,475	119,903	261,916	399,578
2006	12.9	17,070	25,649	611	1,641	2,858	5,822	8,931	18,032	37,930	57,489	124,361	289,308	430,627
2007	13.7	17,407	26,145	624	1,658	2,873	6,140	9,150	18,300	38,647	58,693	127,225	294,307	428,367
2008	14.8	17,732	26,805	644	1,698	2,913	6,257	9,323	18,521	39,294	59,754	130,521	302,464	446,000
2009	15.5	18,222	27,248	655	1,729	2,981	6,719	9,675	19,014	40,297	61,288	134,710	300,453	443,299
2010	16.6	18,580	27,601	690	1,805	3,097	6,955	9,981	19,272	40,845	62,223	136,126	303,894	449,789
2011	17.7	18,812	27,503	715	1,856	3,186	7,076	10,270	19,620	41,436	62,755	135,569	298,549	461,458
2012	18.6	19,580	27,449	768	2,010	3,456	7,675	10,907	20,624	43,193	64,598	136,492	290,728	439,453
2013	19.3	19,942	27,655	788	2,089	3,580	7,824	11,273	21,049	43,780	65,591	137,725	290,507	451,093
2014	19.8	20,460	27,979	825	2,190	3,761	7,996	11,718	21,772	44,812	66,901	139,581	290,801	456,351
2015	19.6	20,616	28,076	843	2,318	4,004	8,141	11,855	21,794	44,813	66,863	139,654	298,356	465,040
2016	18.9	20,621	27,094	886	2,455	4,221	8,442	12,094	22,078	44,399	65,828	135,633	281,736	447,726
2017	18.7	21,179	27,723	912	2,541	4,386	8,772	12,532	22,613	45,282	67,255	139,690	280,049	459,173

Note: Workers aged 25-55. *Source:* RAIS 1985-2017.

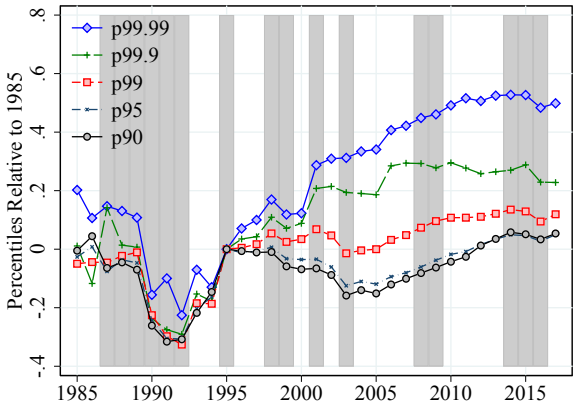
A.2 Additional figures for Brazil's formal sector

FIGURE 23. EVOLUTION OF EARNINGS PERCENTILES, MEN AND WOMEN POOLED

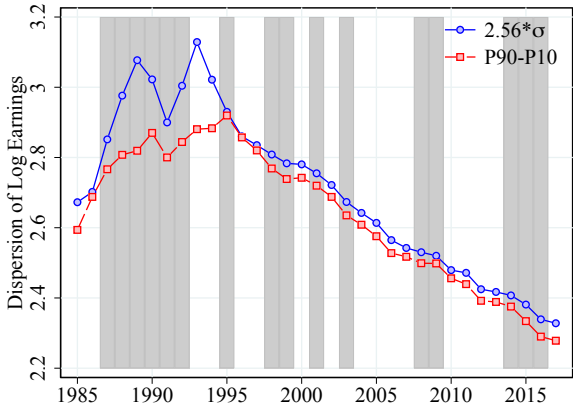
(A) PERCENTILES



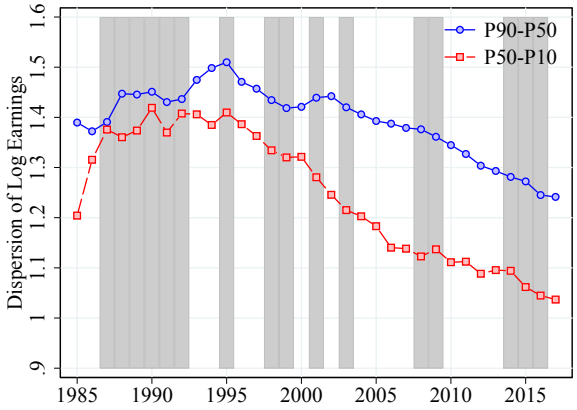
(B) TOP PERCENTILES



(C) OVERALL INEQUALITY



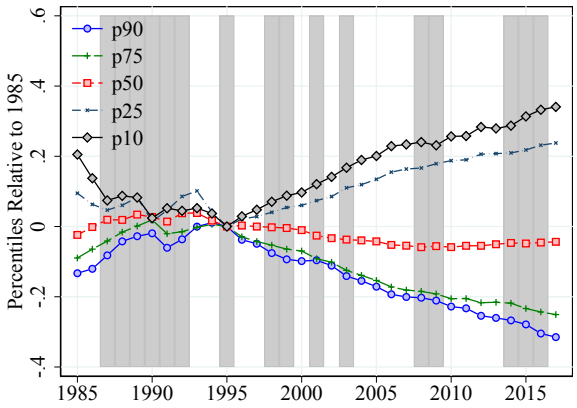
(D) RIGHT- AND LEFT-TAIL INEQUALITY



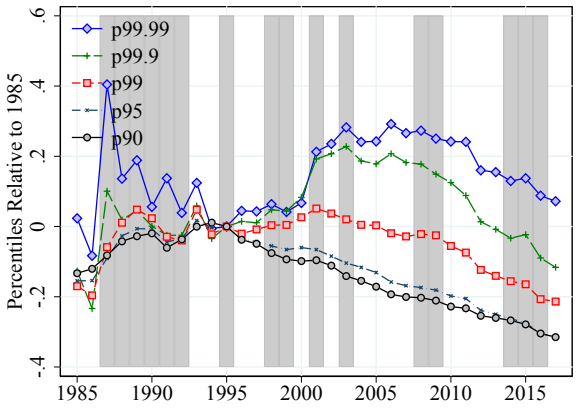
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 24. EVOLUTION OF EARNINGS PERCENTILES, MEN AND WOMEN POOLED AND CONTROLLING FOR AGE

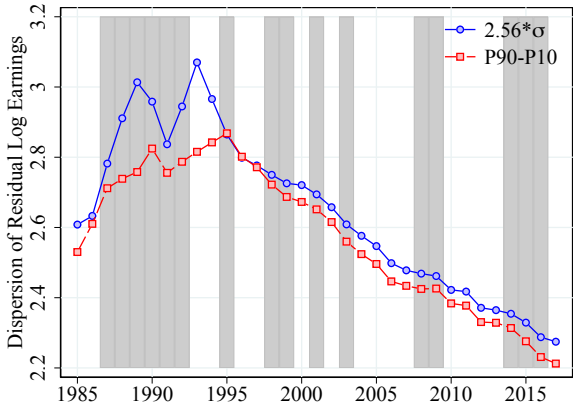
(A) PERCENTILES



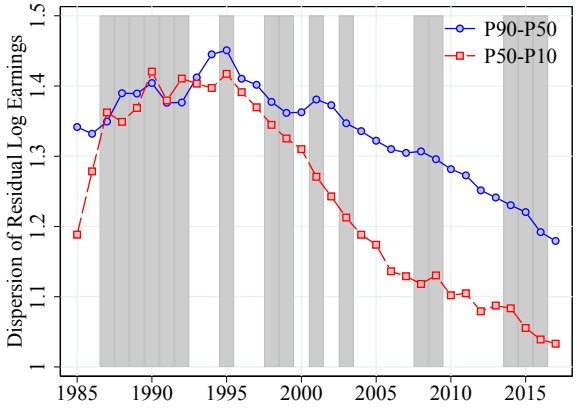
(B) TOP PERCENTILES



(C) OVERALL INEQUALITY



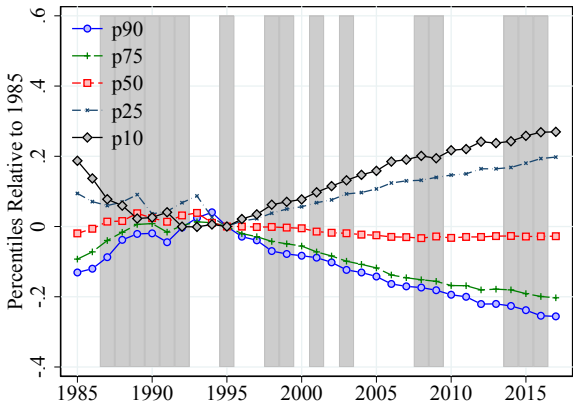
(D) RIGHT- AND LEFT-TAIL INEQUALITY



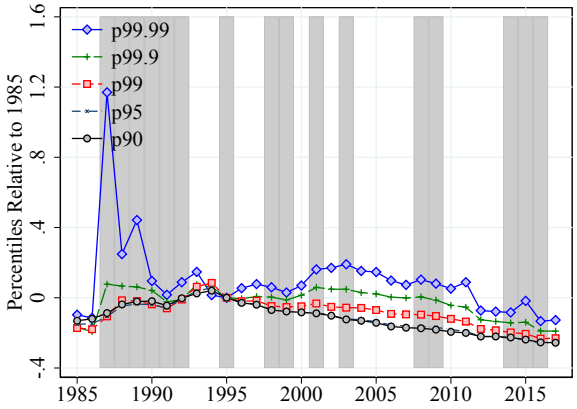
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 25. EVOLUTION OF RESIDUAL EARNINGS PERCENTILES, MEN AND WOMEN POOLED AND CONTROLLING FOR AGE AND EDUCATION

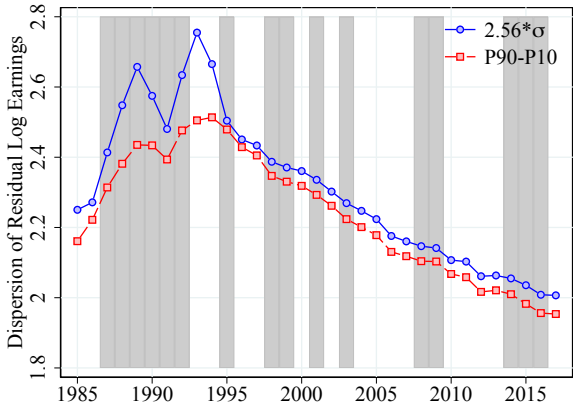
(A) PERCENTILES



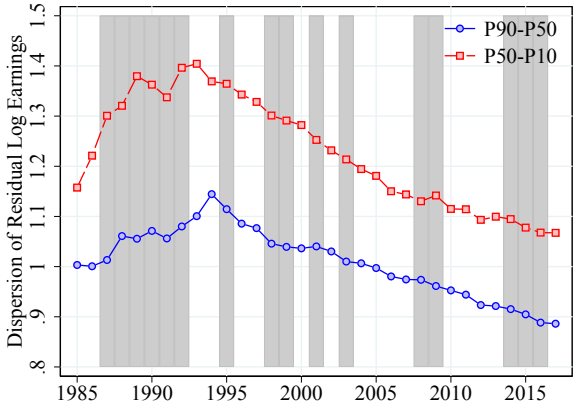
(B) TOP PERCENTILES



(C) OVERALL INEQUALITY



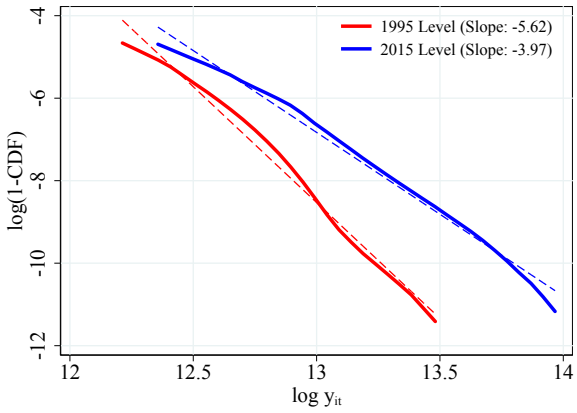
(D) RIGHT- AND LEFT-TAIL INEQUALITY



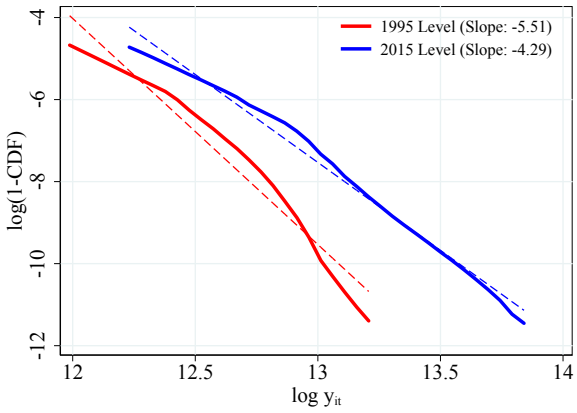
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 26. PARETO TAIL WITHIN TOP 1 PERCENT, BY GENDER

(A) MEN



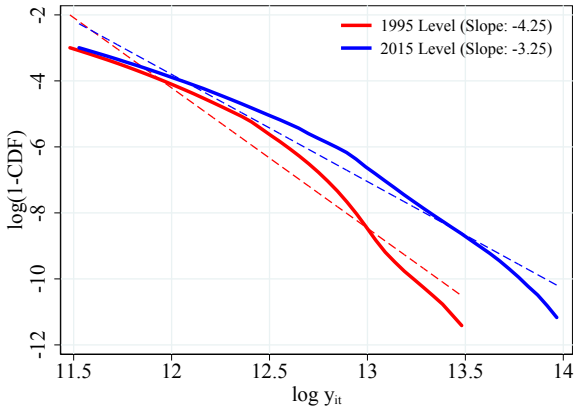
(B) WOMEN



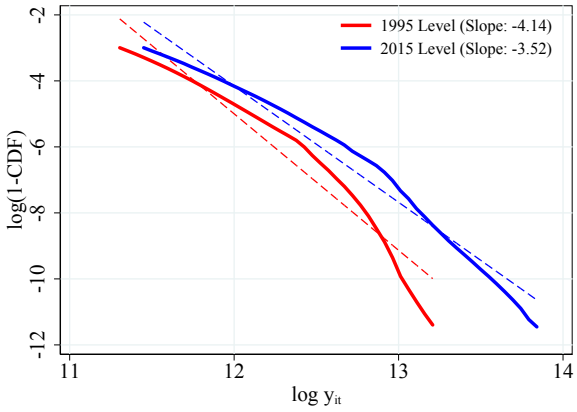
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 27. PARETO TAIL WITHIN TOP 5 PERCENT, BY GENDER

(A) MEN



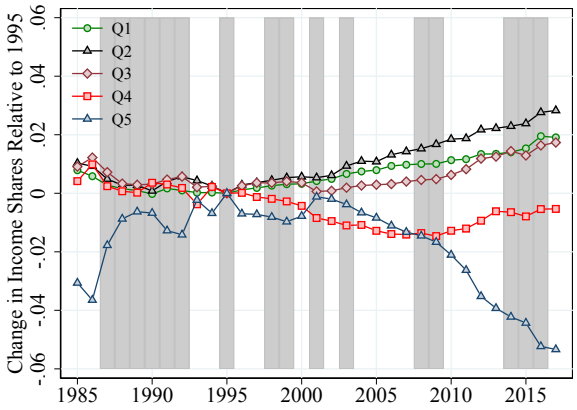
(B) WOMEN



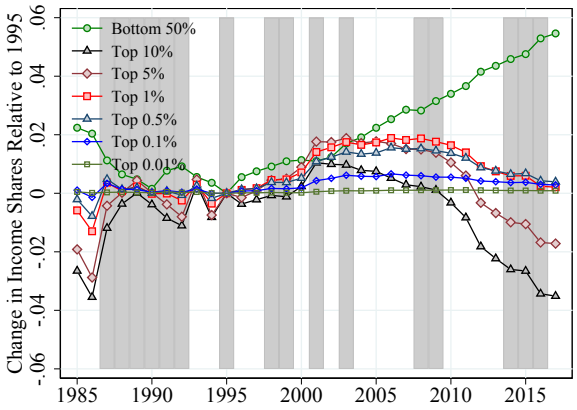
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 28. EVOLUTION OF EARNINGS SHARES, RELATIVE TO 1995

(A) INCOME SHARES OF QUINTILES

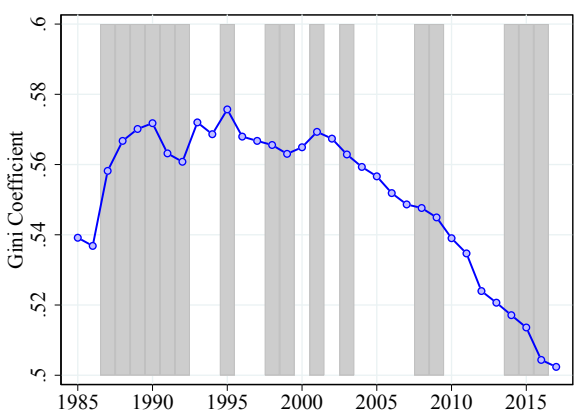


(B) SELECTED INCOME SHARES



Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

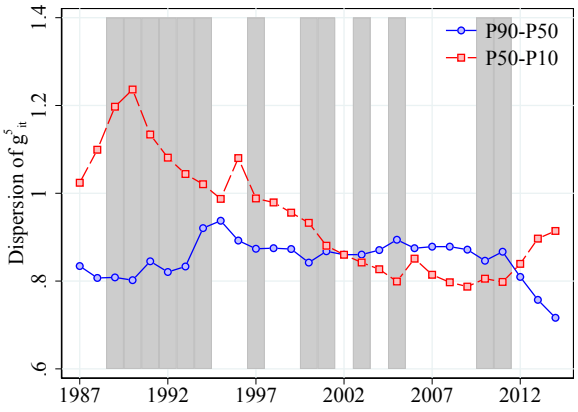
FIGURE 29. GINI COEFFICIENT OF EARNINGS



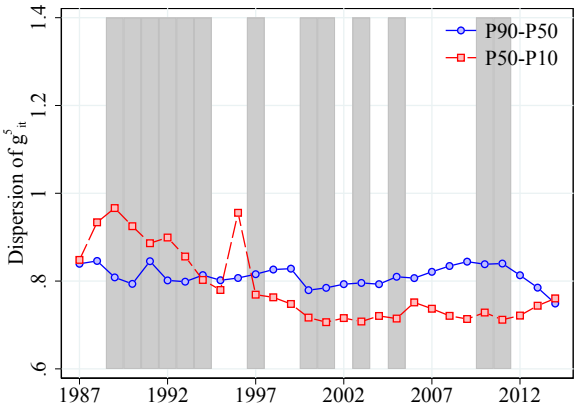
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 30. DISPERSION IN FIVE-YEAR EARNINGS INNOVATIONS, BY GENDER

(A) MEN



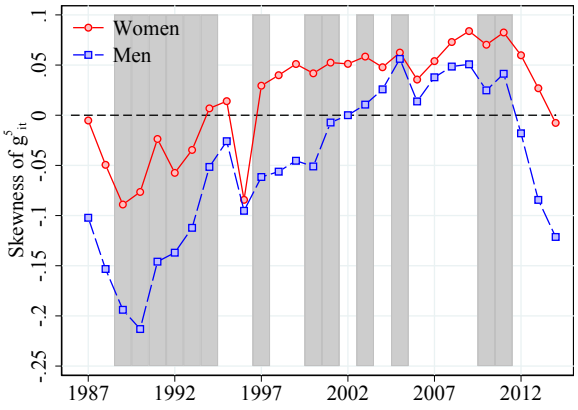
(B) WOMEN



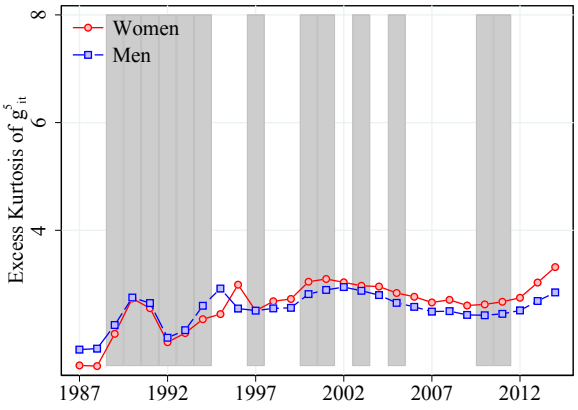
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 31. SKEWNESS AND KURTOSIS OF FIVE-YEAR EARNINGS INNOVATIONS, BY GENDER

(A) SKEWNESS



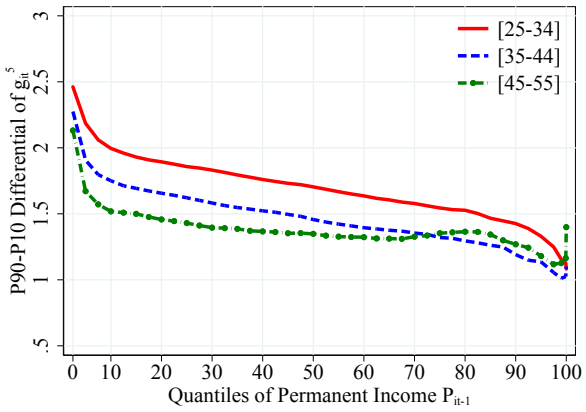
(B) KURTOSIS



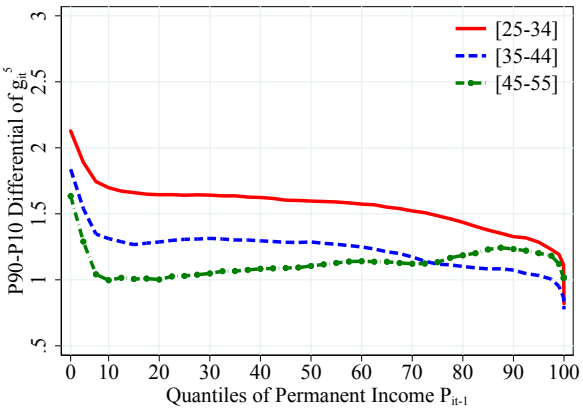
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 32. MOMENTS OF THE DISTRIBUTION OF FIVE-YEAR EARNINGS INNOVATIONS, BY GENDER

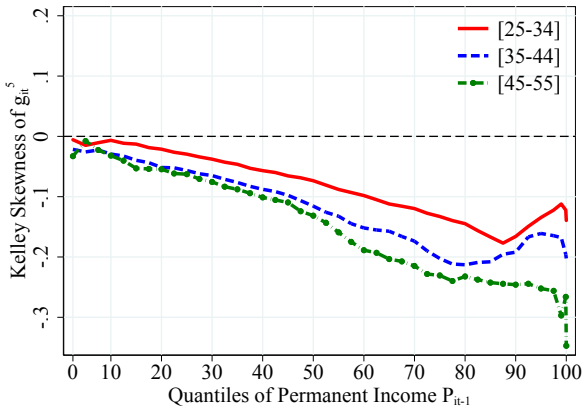
(A) P90-P10, MEN



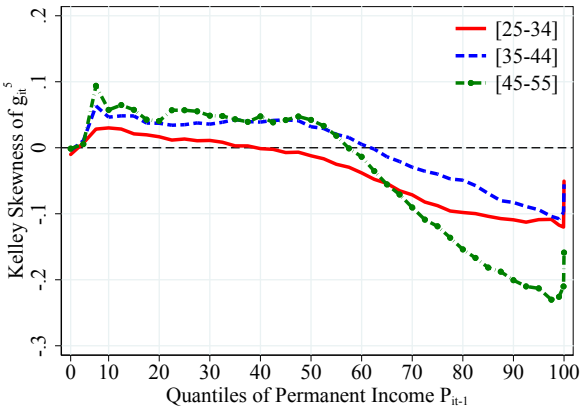
(B) P90-P10, WOMEN



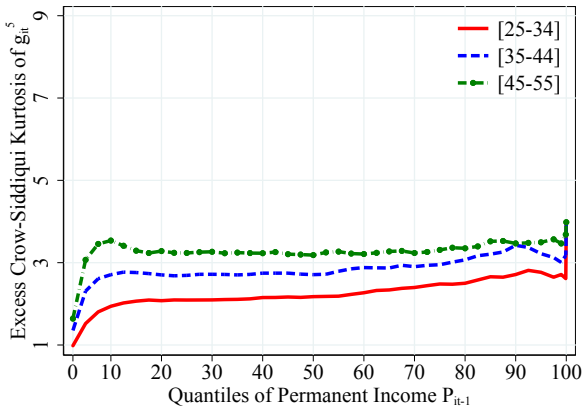
(C) KELLEY SKEWNESS, MEN



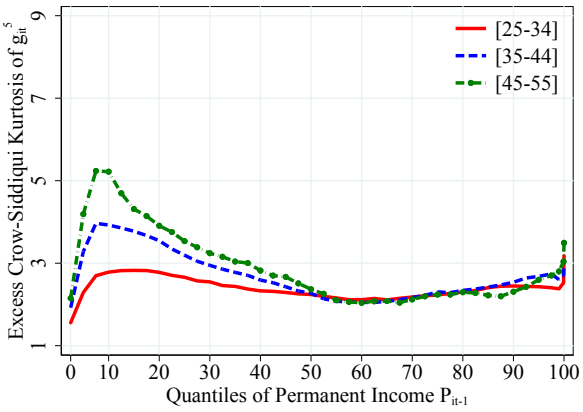
(D) KELLEY SKEWNESS, WOMEN



(E) EXCESS CROW-SIDDIQUI KURTOSIS, MEN



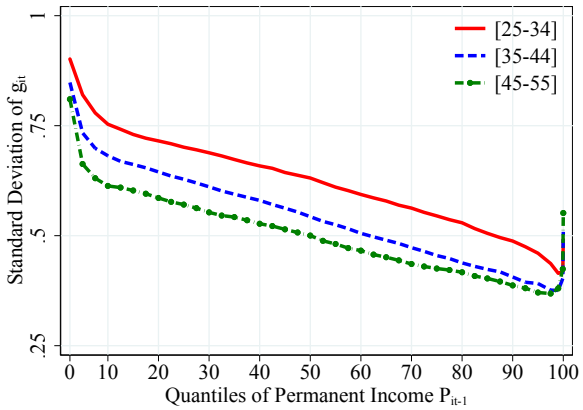
(F) EXCESS CROW-SIDDIQUI KURTOSIS, WOMEN



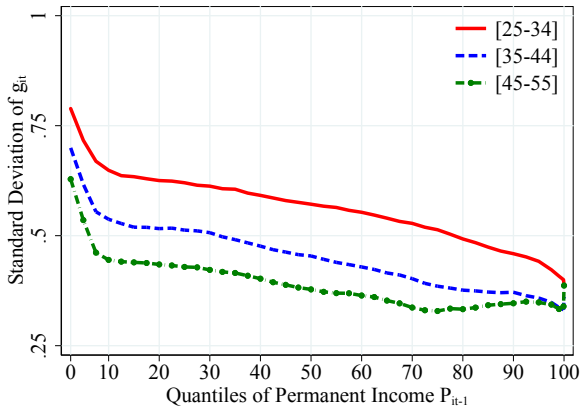
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 33. STANDARDIZED MOMENTS OF EARNINGS CHANGES

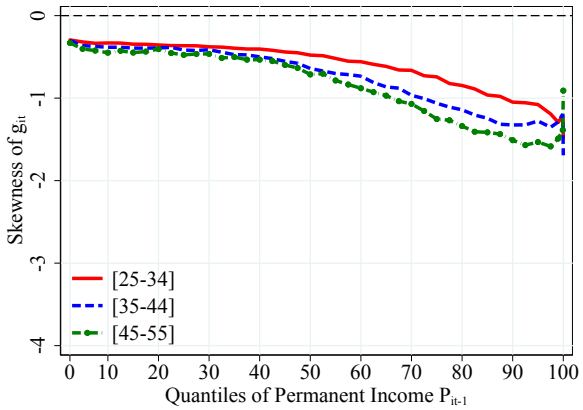
(A) P90-P10, MEN



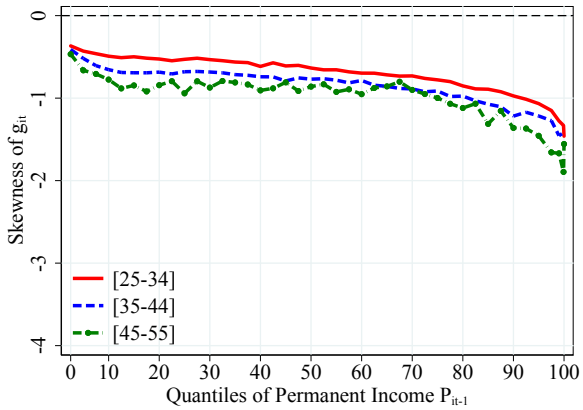
(B) P90-P10, WOMEN



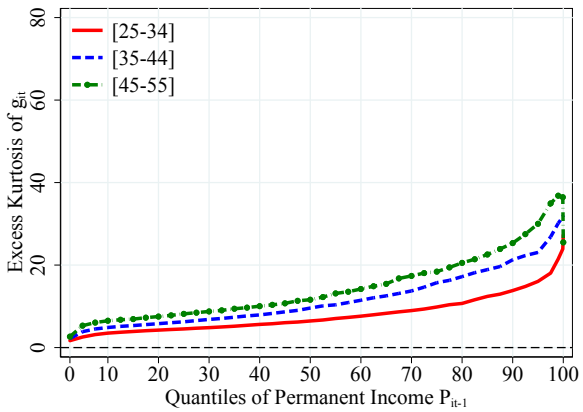
(C) KELLEY SKEWNESS, MEN



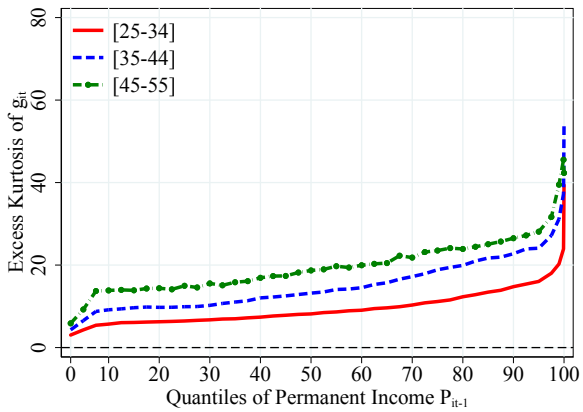
(D) KELLEY SKEWNESS, WOMEN



(E) EXCESS CROW-SIDDIQUI KURTOSIS, MEN



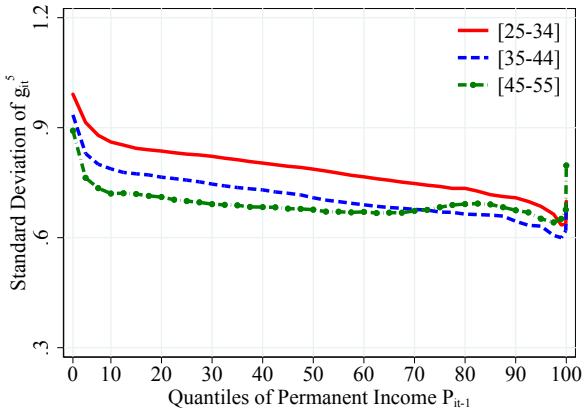
(F) EXCESS CROW-SIDDIQUI KURTOSIS, WOMEN



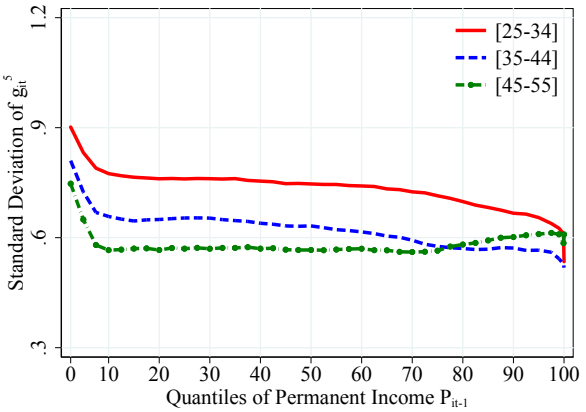
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 34. STANDARDIZED MOMENTS OF FIVE-YEAR EARNINGS CHANGES

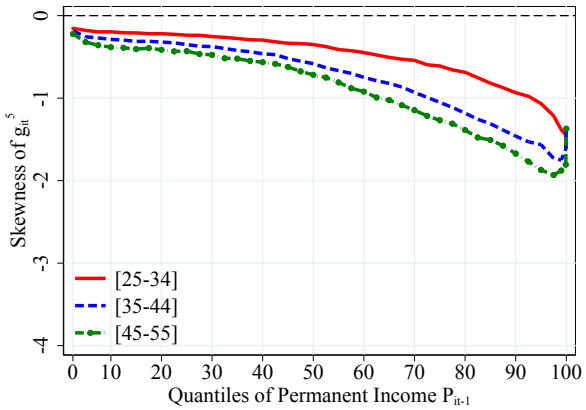
(A) P90-P10, MEN



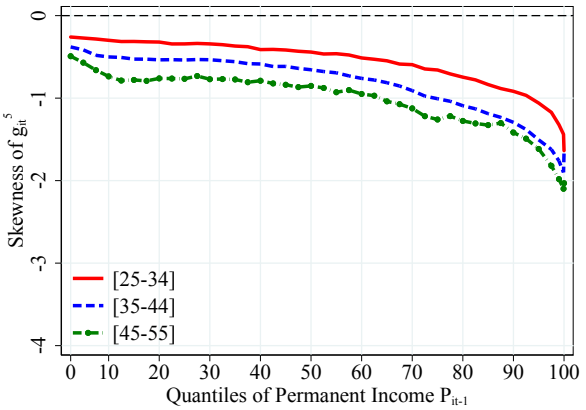
(B) P90-P10, WOMEN



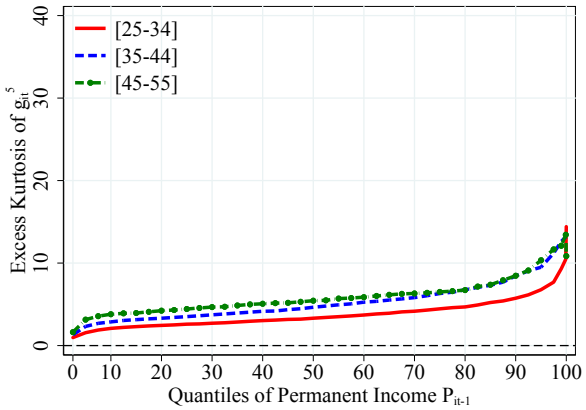
(C) KELLEY SKEWNESS, MEN



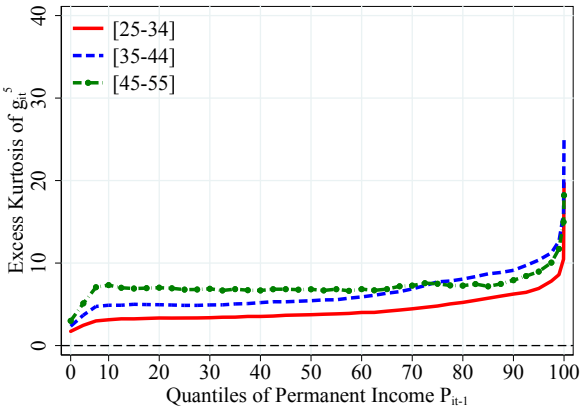
(D) KELLEY SKEWNESS, WOMEN



(E) EXCESS CROW-SIDDIQUI KURTOSIS, MEN



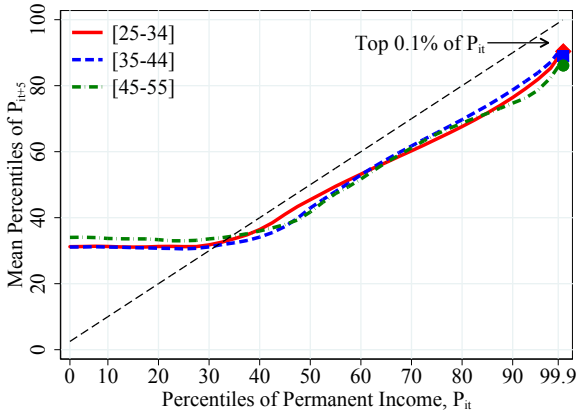
(F) EXCESS CROW-SIDDIQUI KURTOSIS, WOMEN



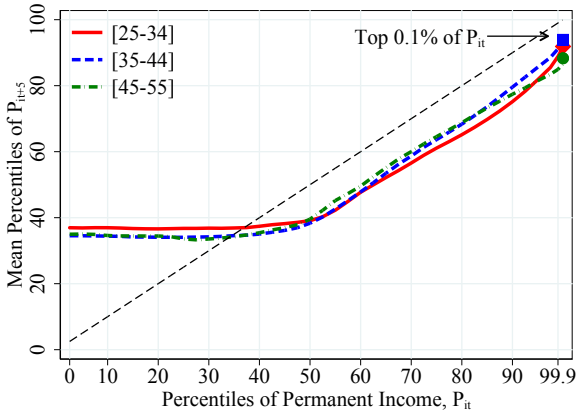
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 35. EVOLUTION OF EARNINGS MOBILITY OVER THE LIFE CYCLE, BY GENDER

(A) MEN



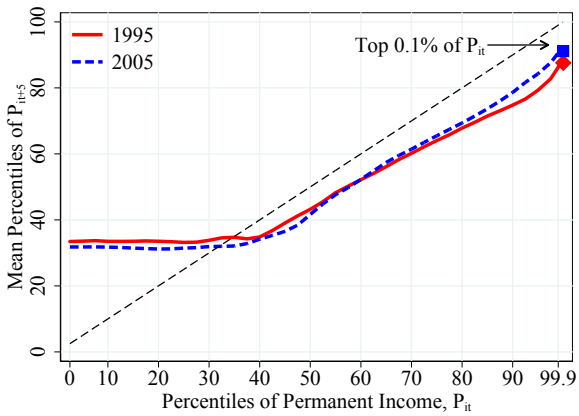
(B) WOMEN



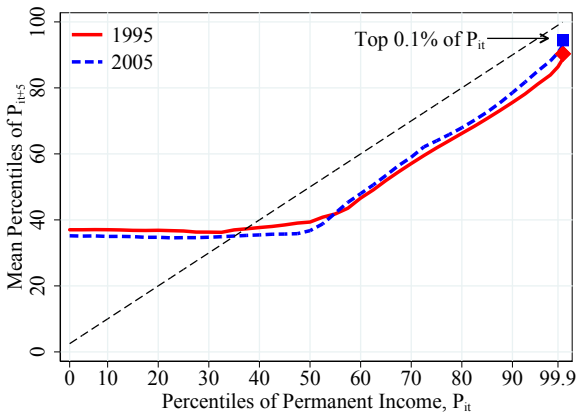
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 36. EVOLUTION OF EARNINGS MOBILITY OVER TIME, BY GENDER

(A) MEN



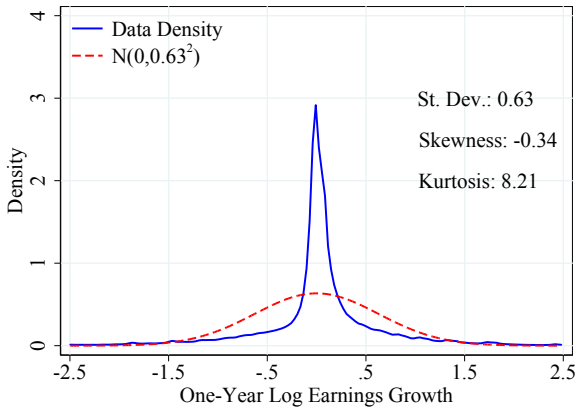
(B) WOMEN



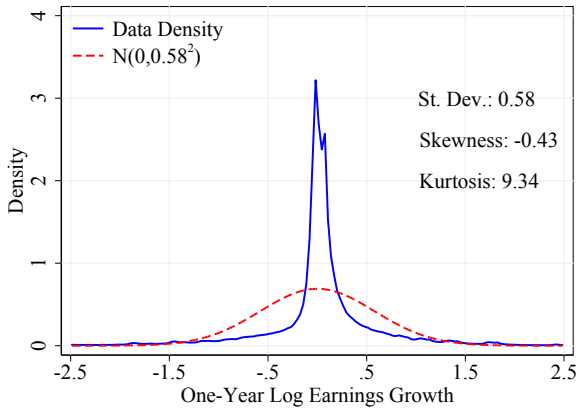
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 37. DENSITY OF ONE-YEAR EARNINGS INNOVATIONS, BY GENDER

(A) MEN



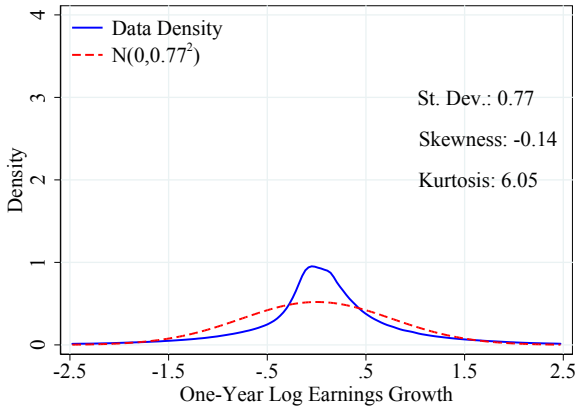
(B) WOMEN



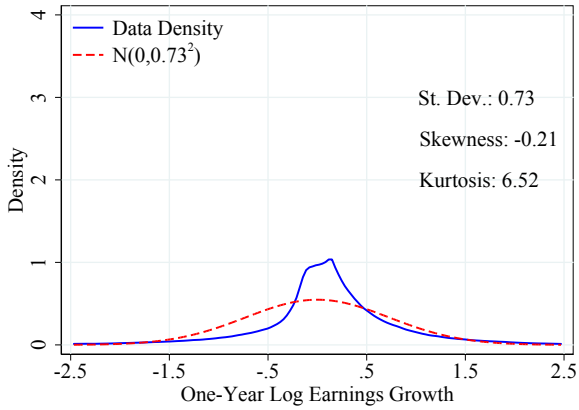
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 38. DENSITY OF FIVE-YEAR EARNINGS INNOVATIONS, BY GENDER

(A) MEN



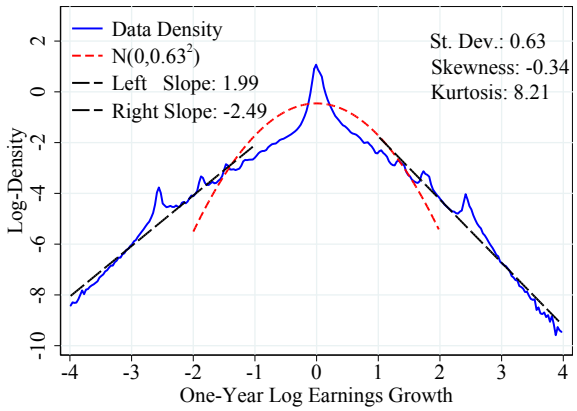
(B) WOMEN



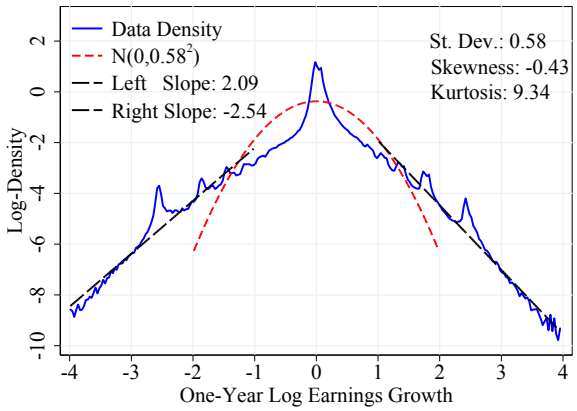
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 39. LOG-DENSITY OF ONE-YEAR EARNINGS INNOVATIONS, BY GENDER

(A) MEN



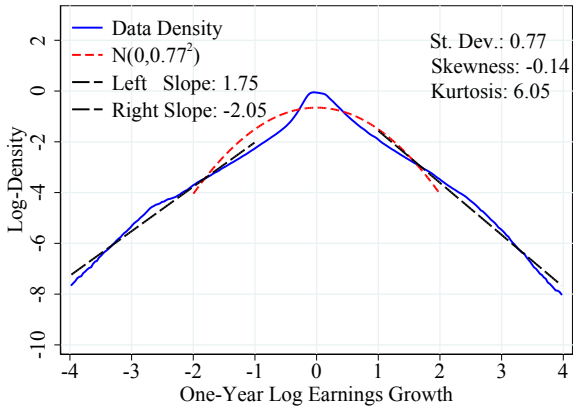
(B) WOMEN



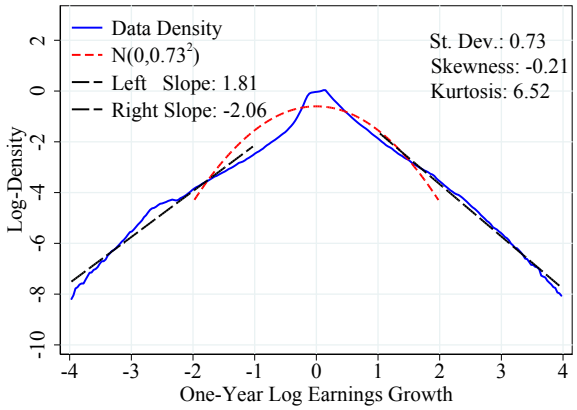
Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

FIGURE 40. LOG-DENSITY OF FIVE-YEAR EARNINGS INNOVATIONS, BY GENDER

(A) MEN



(B) WOMEN

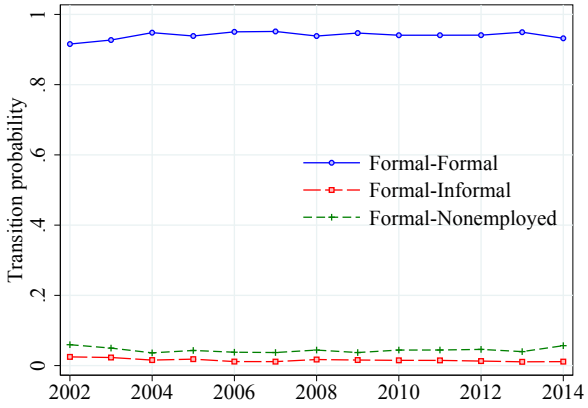


Note: Workers aged 25–55. *Source:* RAIS 1985–2017.

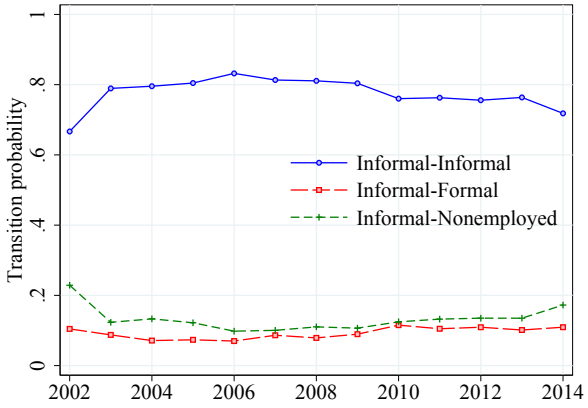
A.3 Additional figures for Brazil's informal sector

FIGURE 41. EVOLUTION OF SECTORAL FLOW RATES, BY ORIGIN SECTOR

(A) FLOW RATES FROM FORMAL SECTOR



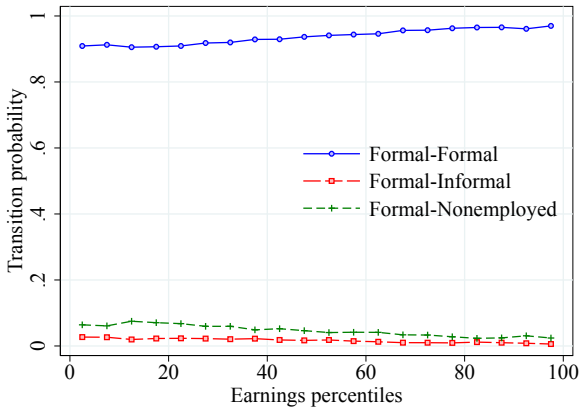
(B) FLOW RATES FROM INFORMAL SECTOR



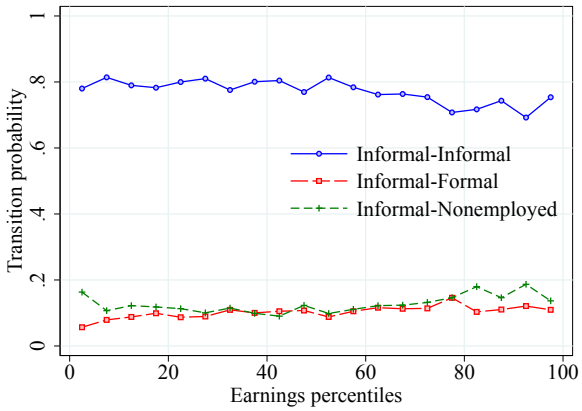
Note: Workers aged 25–55. *Source:* PME 2002–2015.

FIGURE 42. CROSS-SECTIONAL HETEROGENEITY IN SECTORAL FLOW RATES, BY ORIGIN SECTOR

(A) FLOW RATES FROM FORMAL SECTOR



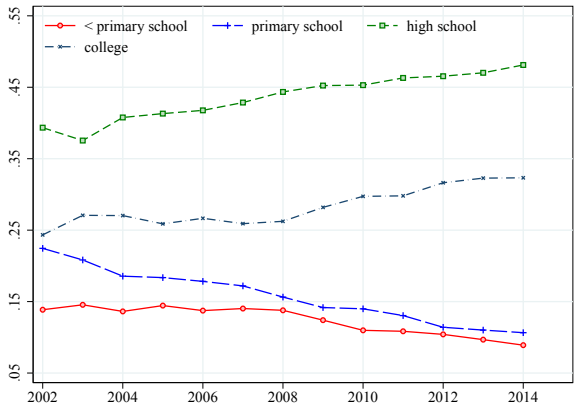
(B) FLOW RATES FROM INFORMAL SECTOR



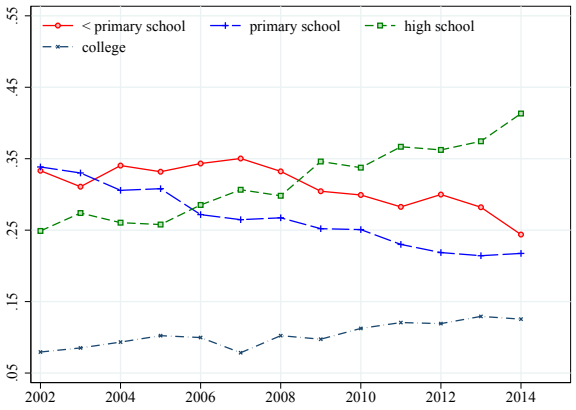
Note: Workers aged 25–55. *Source:* PME 2002–2015.

FIGURE 43. EDUCATION COMPOSITION OF SECTORAL TRANSITIONS, BY ORIGIN AND DESTINATION SECTOR

(A) FORMAL-FORMAL



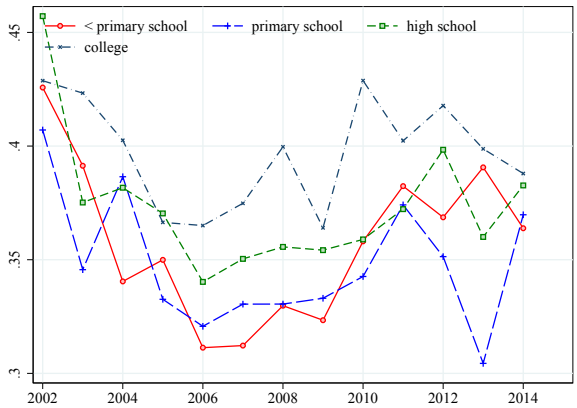
(B) INFORMAL-INFORMAL



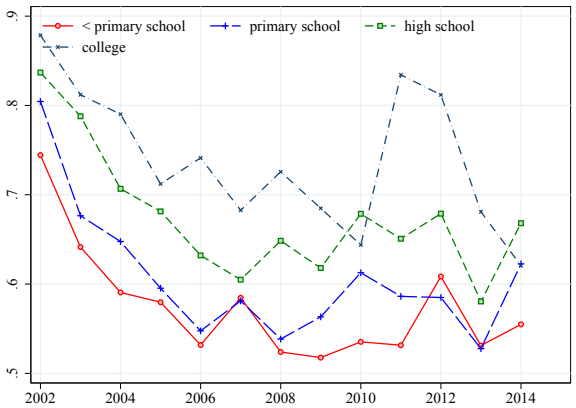
Note: Workers aged 25–55. *Source:* PME 2002–2015.

FIGURE 44. DISPERSION OF EARNINGS INNOVATIONS ACROSS EDUCATION GROUPS, BY ORIGIN AND DESTINATION SECTOR

(A) FORMAL-FORMAL



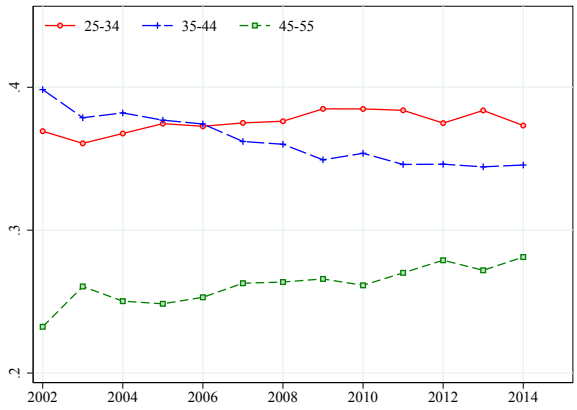
(B) INFORMAL-INFORMAL



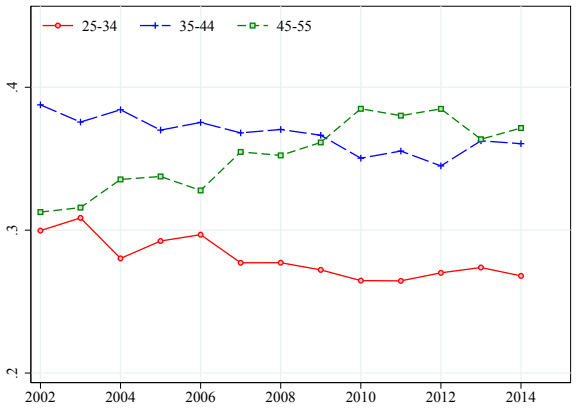
Note: Workers aged 25–55. *Source:* PME 2002–2015.

FIGURE 45. AGE COMPOSITION OF SECTORAL TRANSITIONS, BY ORIGIN AND DESTINATION SECTOR

(A) FORMAL-FORMAL



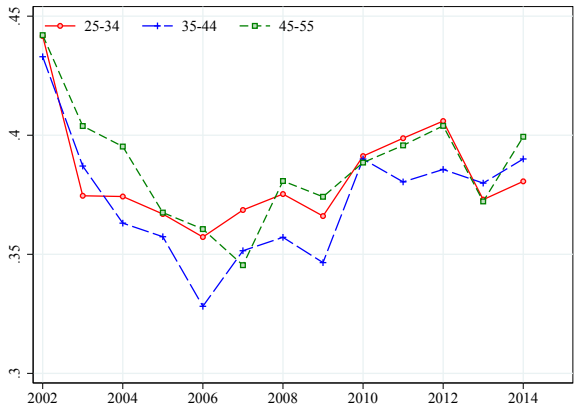
(B) INFORMAL-INFORMAL



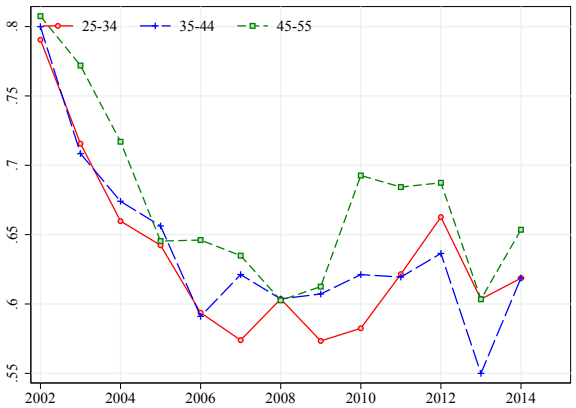
Note: Workers aged 25–55. *Source:* PME 2002–2015.

FIGURE 46. DISPERSION OF EARNINGS INNOVATIONS ACROSS AGE GROUPS, BY ORIGIN AND DESTINATION SECTOR

(A) FORMAL-FORMAL



(B) INFORMAL-INFORMAL



Note: Workers aged 25–55. *Source:* PME 2002–2015.