

# Inequality, income dynamics, and worker transitions: The case of Mexico

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We characterize the salient features of the distribution of (log) earnings of formal workers in Mexico using social security records for the period 2005–2019. The analysis is based on a nonparametric approach and is focused primarily on the properties of the distribution of earnings changes. We find strong evidence of deviations from normality of this distribution in terms of negative skewness and high kurtosis, with these deviations varying with income and along the worker's life cycle. A comparison between results obtained with administrative data and household survey data suggests that this latter source of information is inadequate to

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The views and conclusions presented in this paper are the authors' exclusively and do not necessarily reflect those of Banco de México and its Board of Governors. The IMSS data used in this paper are confidential and were made available through the Econlab at Banco de México. Inquiries regarding the terms and conditions for accessing these data should be directed to: [econlab@banxico.org.mx](mailto:econlab@banxico.org.mx). We are grateful to the participants of the Global Income Dynamics conferences (at Stanford and University of Minnesota), the 55th Annual Canadian Economics Association Meetings, and the Informal Seminar at Banco de México's research department for insightful comments. We are particularly thankful for the many valuable and constructive suggestions that we received from two anonymous referees. We also want to acknowledge Alejandro Trujillo for outstanding research assistance. All remaining errors are our own.

fully capture the evolution of inequality and the properties of earnings changes as nonresponse is nonrandom and concentrated among formal and highly educated workers—likely the highest earners. Due to the relative size of the informal sector in the Mexican economy, which results in a large number of workers maintaining a weak attachment to formal employment, we also study the impact of transitions out of and back into formal employment on wages earned in the formal sector. We document that workers who exit formal employment experience a significant wage penalty upon reentry taking, on average, 3 or more years to achieve comparable preexit wage levels.

**KEYWORDS.** Earnings dynamics, higher-order earnings risk, inequality, kurtosis, skewness, worker transitions.

**JEL CLASSIFICATION.** E24, J24, J31, J46.

## 1. INTRODUCTION

There is a large and growing literature studying the salient features of the distribution and dynamics of earnings and life-time income that has focused primarily on advanced economies such as the United States, the United Kingdom, Germany, and Spain, to name a few (see, e.g., [Bonhomme and Hospido \(2017\)](#) and [Güvenen, Karahan, Ozkan, and Song \(2021\)](#)). Comparatively, little attention has been devoted to emerging and developing countries. The goal of this paper is to contribute to this literature along two dimensions. First, we characterize the defining properties of the distribution of earnings and of transitory earnings changes and the extent to which they display deviations from normality using administrative records of workers employed in the formal sector. We explore how these properties vary across genders and age groups, and along the income distribution.<sup>1</sup> Second, we analyze the effect of transitions out of and back into formal employment on the earnings of workers. On both fronts, to the best of our knowledge, we are the first to explore these issues in the Mexican context.

Regarding the distribution of earnings, we find that overall inequality (P90–P10 dispersion) remained fairly stable during the 2005–2015 decade but started to fall after 2016. We also find that inequality increased during the period of the 2008–2009 financial crisis, more so for men than for women, and for younger workers than for older ones. Initial inequality (P90–P10 dispersion at age 25) has also been fairly stable between 2005 and 2019, with the exception of a marginal increase registered during the financial crisis. Within the limited time span covered by our data, we observe relatively stable earnings mobility patterns with lower income workers moving upward in the permanent income distribution and higher income workers being more likely to move downward, except in the top 0.1% of the distribution where there is essentially no mobility.

With respect to the distribution of 1-year earnings changes, we encounter evidence of strong deviations from normality whose extent varies across income levels, age

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<sup>1</sup>The statistics reported in the paper, as well as many additional ones that we computed on the administrative data and are not explicitly included in the paper, will be publicly available through the Global Repository of Income Dynamics (GRID) that will house harmonized and comparable statistics for all countries participating in the Global Income Dynamics Project and included in this issue of *Quantitative Economics*.

groups and genders. Similar to the findings of [Guvenen et al. \(2021\)](#), we document very high kurtosis across all demographic groups, more so for women, even though it has been steadily decreasing for both men and women since 2009. While the distribution of transitory earnings innovations is asymmetric, we find that skewness can be positive or negative depending on age, gender, and income. This contrasts with what [Guvenen et al. \(2021\)](#) document for the United States where this distribution is negatively skewed for all workers.

To document these facts regarding the distribution of earnings and earnings changes for Mexican workers, our analysis relies on social security records from the Instituto Mexicano del Seguro Social (IMSS) covering the period from 2005 to 2019 and the universe of (private sector) formal workers. Unlike previous work based on Mexican survey data (see, e.g., [Binelli and Attanasio \(2010\)](#)), our social security records have large sample sizes and allow for following workers continuously throughout their employment history in the formal sector.

Social security data have the advantage of providing accurate, reliable, and consistent information on millions of Mexican workers, but they also suffer from important limitations.<sup>2</sup> First, as it is commonly the case with administrative data, earnings are top and bottom coded. Second, it is not possible to separate wage effects from labor-supply effects on earnings since no information on the number of hours worked or the full versus part-time status of a worker is available. Third, Mexican social security records do not provide important information on worker characteristics such as educational attainment or occupation of employment, precluding the possibility of exploring how the distribution of earnings or earnings changes varies along these dimensions. The main limitation of our data, however, is that they only cover workers employed in the formal private sector. Hence, while the power of millions of administrative records can be exploited to establish key features of the distribution of earnings and earnings changes for workers employed in the formal sector, this source of information has nothing to say about these distributions for informal workers, who constitute a large fraction of the Mexican labor market.

Motivated by this lack of information on the informal sector, we explore additional data sources. In particular, we contrast some of our baseline results obtained with the administrative data with results obtained selecting a comparable sample from household surveys. Even if several of the key insights from our analysis, especially those regarding inequality, are maintained across different data sources and for both formal and informal workers, we also find important differences. In our context, these differences are likely associated with the fact that the share of workers not responding to income-related questions in the household survey has been growing over time and that this missing information is nonrandom: nonresponse is mostly concentrated among formal and highly educated workers who tend to belong to the upper part of the income distribution (see also [Campos Vázquez \(2013\)](#) and [Campos Vázquez and Lustig \(2019\)](#)).

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<sup>2</sup>It has been documented that employers used to underreport wages to IMSS, such practice, however, has substantially declined since the 1997 reform of the pension system in Mexico. Hence, underreporting does not appear to be a problem for the period covered in our study; see [Kumler, Verhoogen, and Frías \(2020\)](#).

This comparison suggests that household surveys may be inadequate to fully capture the evolution of inequality and the properties of earnings changes.

Lastly, given that one of the consequences of a large informal sector is that many workers maintain a tenuous attachment to formal employment, we study how time away from formal employment shapes earnings dynamics. We provide empirical evidence that workers who temporarily exit formal employment experience a wage penalty upon reentry, with earnings taking up to 3 years to gradually grow toward preexit levels. This suggests that the ability to maintain a continuous attachment to the formal sector is likely to be an important source of heterogeneity in the distribution of earnings changes across Mexican workers.

*Related literature* Methodologically, the first half of this paper is related to the work of [Arellano, Blundell, and Bonhomme \(2017\)](#), [Guvenen, Kaplan, Song, and Weidner \(2017\)](#), and [Guvenen et al. \(2021\)](#), among others. These authors propose nonparametric methods to characterize key features of the distribution of earnings shocks and of life-time income. The strength of these methods is that nonlinearities and nonnormalities, that may be important attributes of the earnings process, can be more easily uncovered by avoiding strong parametric assumptions.

An early important paper in this strand of the literature is [Guvenen, Ozkan, and Song \(2014\)](#) that documents that the distribution of earnings changes is negatively skewed and becomes more so during recessions. Thus, during recessions large upward earnings movements become less likely, while large drops in earnings become more likely. [Guvenen et al. \(2021\)](#) go further by analyzing life-cycle variation in skewness and other properties of the distribution of earnings changes, such as kurtosis, and how they vary with earnings levels and age. Relative to these papers, our contribution is to analyze the same issues in the context of the Mexican labor market, a market that significantly differs from the American labor market studied by those authors and the labor markets in more advanced economies. Unlike the United States and other developed countries, the labor market experience of Mexican workers is heavily shaped by the lack of a strong social safety net, such as unemployment insurance, and the prevalence of informality—both in terms of informal jobs at formal firms and informal jobs at informal firms.

Our work is also related to [Binelli and Attanasio \(2010\)](#) who analyze the level and dispersion of earnings using data from Mexican household surveys for the period 1987–2002. These authors document a significant increase in wage and income inequality (P90–P10 dispersion) during the first half of the 1990s. For hourly wages, they find that the increase was characterized by inequality growing faster at the top (P90–P50) than at the bottom (P50–P10) of the distribution. For the second half of the 1990s, they observe a drop or stable trend, with the slowdown in income and wage inequality being explained primarily by the top of the distribution—top-tail dispersion (P90–P50) of hourly wages and household income dropped significantly, while bottom-tail dispersion (P50–P10) decreased slightly for wages and maintained an upward trend for income. Relative to these authors, we examine a later period in the Mexican economy (2005 to 2019) and base our analysis on social security records, instead of household surveys, that are particularly suited to study earning dynamics—our primary focus is on the distribution of

earnings changes rather than on the distribution of earnings levels. Other contributions to the study of income inequality in the Mexican context are [Esquivel, Lustig, and Scott \(2010\)](#), [Lustig, Lopez-Calva, and Ortiz-Juarez \(2013\)](#), and [Campos Vázquez and Lustig \(2019\)](#). The first two find that inequality decreased in Mexico from the mid 1990s to 2006, mainly due to equalizing changes in the distribution of labor income imputable to the skill premium—measured as the gap between the wages of workers with tertiary education (or secondary) and workers with no schooling or incomplete primary school—falling systematically. The third one argues that issues such as nonresponse and underrepresentation of high-wage earners and weights assignment in survey data, are relevant and can lead to mixed results in terms of evaluating the evolution of inequality. In contrast with these authors, we quantify inequality using exclusively administrative data that, while lacking potentially valuable information on education, do not suffer from the same, possibly severe, problems of survey data.

Finally, some of our findings illustrate how trying to answer the same question using different data sources may lead to different results, a pattern that has been well documented in the literature (see, e.g., [Celik, Juhn, McCue, and Thompson \(2012\)](#), [Armour, Burkhauser, and Larrimore \(2013\)](#), or [Abowd and Stinson \(2013\)](#)). This highlights that conclusions regarding the evolution and dynamics of earnings can be sensitive to the choice of information sources and that not every source is equally adequate to answer a specific research question.

## 2. DATA AND MACROECONOMIC CONTEXT

### 2.1 *Overview of the data*

The core statistics presented in the next section of the paper are based on social security records from the Instituto Mexicano del Seguro Social (IMSS), one of the main Mexican social security institutions. All formal private sector workers who receive a salary are required by law to register with IMSS. The set of workers affiliated with IMSS represents approximately 80% of formal sector workers with access to social security, according to estimates from the Secretaría de Trabajo y Previsión Social (the Mexican Ministry of Labor), but does not include government workers or workers employed in the informal sector. Since informality is prevalent in Mexico, a large portion of the labor force is not included in the social security data. Own-account workers—individuals that work on their own and without employees—can register with IMSS to obtain access to some parts of the social security system, and hence may appear in the social security records. By default, they are recorded with a wage equal to the minimum wage. For any given month, the share of enrolled workers that are own-account workers is roughly 0.1% of the total observations.

The social security data have a monthly frequency for the period January 2005 to December 2019, and cover approximately between 13 million workers at the start of the sample and 20 million workers toward the end. For the purposes of the first half of the analysis, the key variable contained in the social security data is the information on wages, reported as a worker's daily taxable income (“salario base de cotización”). This means that the data on daily wages can include various forms of compensation received

by the worker other than wages (usually paid vacation and end of the year bonus), but may exclude others (in general any additional benefit or compensation that is not subject to labor income taxation), hence not necessarily reflecting the total labor income a worker receives. The data is top and bottom coded. At the bottom, the threshold is set by the minimum wage, while at the top the cap is set at 25 minimum wages before February 2017, and 25 UMAs (unit of measure and update) afterward. On average, only 1.3% of the observations are bottom coded and 1.7% are top coded. There is, however, no information on the number of hours, days, etc. worked and on whether employment was part-time or full-time. An important issue pertaining to the measurement of a worker's labor income is that, in a given month, the data may contain multiple observations for the same social security number (SSN), corresponding to different jobs held by the same worker (possibly with different employers). There can also be multiple observations for pairs of SSN and employer id ("registro patronal"), for which the value of the wage variable does not coincide. Multiple SSNs, nevertheless, represent no more than 2% of the observations and affect on average just 1.4% of the original records. In the absence of information on hours worked in each job and to avoid overstating earnings, we consider only the highest wage for those few workers who report more than one salary.

Since the information on wages is available as a daily wage with monthly frequency, we first express daily wages as monthly wages multiplying the "salario base de cotización" by 30 and then add the monthly wages up to obtain the annual labor income for each worker in a given year. For the period 2005–2019, this results in over 315 million worker-year pairs with observations per year ranging between 17 and 26 million for workers aged 14–75 years old. This constitutes our universe of potential observations. By imposing two "admissibility" conditions on the population, we construct the master sample for the analysis carried out in Sections 3.1–3.3. In particular, we impose that: (i) individuals must be between 25 and 55 years of age (i.e., the prime-age labor force), and (ii) individuals must display "meaningful attachment to the labor force," in the sense that their earnings must be above a minimum earnings threshold  $Y_{\min,t}$ . Since in Mexico the minimum wage is defined as a daily wage, rather than as an hourly wage as it is common in other countries, we set  $Y_{\min,t}$  equal to 45 days of minimum wage, that corresponds to half a quarter of full-time minimum wage employment.<sup>3</sup> Within the subset of the sample that satisfies the first admissibility condition, the fraction of observations that are above the minimum earnings threshold varies between 97.5 and 98.5% throughout the sample period.

Table 1 presents some basic descriptive statistics and demographic characteristics in selected years for the cross-sectional sample used to carry out the analysis presented in Sections 3.1–3.3. Additional details regarding the IMSS data and some relevant summary statistics for the master sample are provided in Appendix A of the Online Supplementary Material (Puggioni, Calderón, Cebreros Zurita, Fernández Bujanda, Inguanzo González, and Jaume (2022)).

<sup>3</sup>Note that for most other countries in the Global Income Dynamics Project, the threshold  $Y_{\min,t}$  is defined as 13 weeks of part-time (20 hours a week) minimum wage employment. We chose the threshold for Mexico to be as close as possible to this common definition.

TABLE 1. Descriptive statistics for selected cross-sectional samples.

Year	Obs. (Millions)	Mean Income		Women % Share	Age Shares %		
		Men	Women		[25–35]	[36–45]	[46–55]
2005	12.43	6114	5006	34.75	52.41	31.24	16.35
2019	19.58	6543	5564	38.70	46.03	31.64	22.33

Year	P5	P10	P25	P50	P75	P90	P95
2005	401.89	682.54	1584.90	3191.88	6483.40	12,492.76	19,602.04
2019	523.28	850.17	1939.84	3442.34	7093.79	13,490.63	20,679.88

*Note:* Based on authors’ calculations with IMSS data. The table shows summary statistics and demographic characteristics in selected years for the cross-sectional sample used to carry out the analysis presented in Sections 3.1–3.3. The mean and percentiles of the income distribution are calculated using raw real earnings deflated with the Mexican CPI for 2018 and then converted to US dollars to facilitate the comparison across countries. Since the data are top coded, the percentiles above P95 are not reported. The Mexican administrative data do not contain information about the educational level of the worker.

### 2.2 Macroeconomic context in Mexico

Before moving to the core analysis, we provide a brief overview of the macroeconomic context in Mexico during the period covered by our administrative data, 2005–2019. This overview is intended to offer a minimal relevant background that may aid in the interpretation of the inequality and income dynamics results presented in the upcoming sections.

The first panel of Figure 1 presents the evolution of real GDP growth. Unsurprisingly, there is a brief but noticeable contraction in GDP during the period of the 2008–2009 financial crisis. After the recovery from that recession, we observe a slowdown in growth

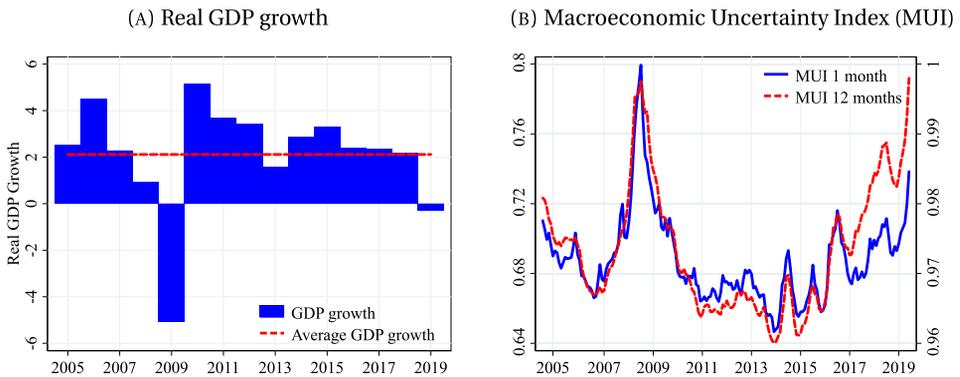


FIGURE 1. Aggregate activity and economic uncertainty. *Note:* Based on authors’ calculations with data from INEGI (the Mexican statistical agency). In panel (A), the horizontal dashed line refers to the average GDP growth during the sample period. In panel (B), the MUI is calculated based on information from 125 monthly economic series using the methodology outlined in Jurado, Ludvigson, and Ng (2015). The MUI 1-month (left axis) refers to the uncertainty index constructed based on 1-month ahead forecast errors and the MUI 12-months (right axis) refers to the index constructed based on 12-month ahead forecast errors.

during 2013 and a moderate contraction in 2019. Outside of those years, the 2005–2019 period can be overall characterized as one of weak, but steady growth. The second panel of Figure 1 presents a Macroeconomic Uncertainty Index (MUI) for Mexico constructed using the methodology outlined in Jurado, Ludvigson, and Ng (2015).<sup>4</sup> The economic slowdown during the financial crisis is paired with increased levels of uncertainty, which also steadily increased from mid-2016 onward. That latter trend can be associated with both external and internal factors. On the external side, the renegotiation of NAFTA, along with a generalized more protectionist stance from the United States, represented a large and significant increase in trade policy uncertainty for Mexico, namely its largest trading partner. This source of uncertainty did not fully subside until early 2020 with the enactment of the USMCA. On the internal side, a period of increasing uncertainty commenced with the presidential election and the sudden cancellation of the new Mexico City airport project in the second half of 2018.

Regarding aggregate labor market conditions, Figure 2 presents the unemployment and informality rates. The informality rate is the percentage of the employed population (15 years and older) that is employed in an informal job. In Mexico, a job is classified as informal if it is performed without legal or institutional protection, regardless of the nature of the economic unit/firm in which said job is carried out, while a worker is classified as informal if he/she is a wage earner who does not have access to social security and/or a own-account worker who does not follow a formal accounting system. The unemployment rate increased during the financial crisis, reaching 5.5% in 2009. This number is low compared to the United States, where it increased to 10% in the same period.

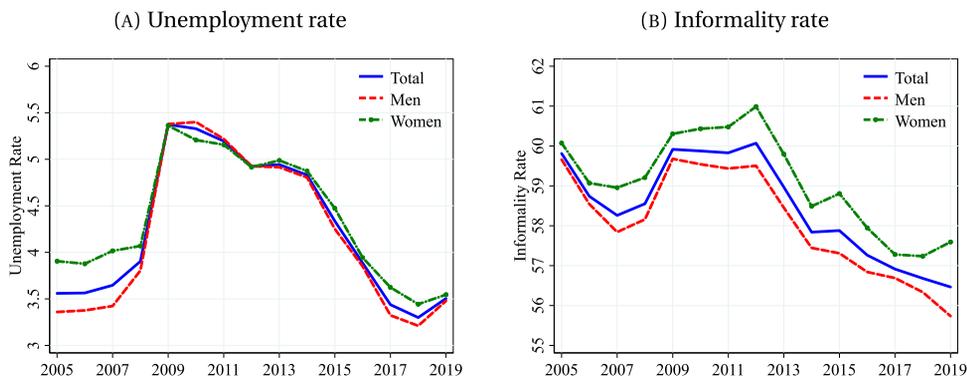


FIGURE 2. Unemployment and informality. *Note:* The unemployment rate in year  $t$  corresponds to the average quarterly unemployment rate in that year. The rate of informality for year  $t$  corresponds to the average monthly rate of informality throughout that year. The official statistics published by INEGI are the quarterly and monthly rate, respectively.

<sup>4</sup>In the presence of adjustment costs in both labor and capital inputs, uncertainty can have a significant impact on firm's investment, job creation/destruction decisions, and hence, on labor market outcomes. For example, Bloom (2009), Jurado, Ludvigson, and Ng (2015), and Baker, Bloom, and Davis (2016) have shown that increases in uncertainty can be associated with reductions in employment and investment, while Mathy (2020) finds evidence suggesting that an increase in uncertainty can negatively affect wages.

Between 2012 and 2014, unemployment remained stable before resuming its decreasing trajectory toward prefinancial crisis levels. By the end of the period under consideration, it started to moderately increase. Differentiating by gender, we see that the unemployment rate is fairly similar for men and women, with the exception of the 2005–2008 and 2016–2018 periods when unemployment for women was noticeably higher than for men. The relatively low unemployment rate in Mexico, even in the middle of a crisis of significant magnitude, is consistent with workers being unable to stay unemployed due to the lack of a social safety net, particularly unemployment insurance. The rate of informality is quite high, ranging between 56 and 60% during the entire period with the exception of the years 2008–2012 when it displayed a steady downward trend. Informality is higher for women than for men. Over the period considered, there is a strong correlation between the rate of informality for men and women, except in 2017–2019 when the rate of informality for men kept trending downward, while that for women showed a moderate increase.

The left panel of Figure 3 shows the evolution of labor productivity, based on the employed population and the total hours worked. During the financial crisis, there was a sharp drop in labor productivity, and precrisis levels were not reached again until 2014. Starting in 2013, there was a strong increase that peaked in 2017. From 2017, labor productivity started trending downward. The sharp increase in labor productivity between 2013 and 2017 coincides with a broad labor market reform that was approved at the end of 2012 and addressed a variety of issues such as outsourcing, conditions for trial hires and hires with flexible schedules, paternity leave, union transparency, regulation of underage work, among others. The right panel in Figure 3 illustrates the evolution of the (real) minimum wage that remained largely unchanged for most of the period of analysis. Starting in 2014, the minimum wage has been increasing steadily and substantially. The evolution of the minimum wage will be particularly useful for understanding the

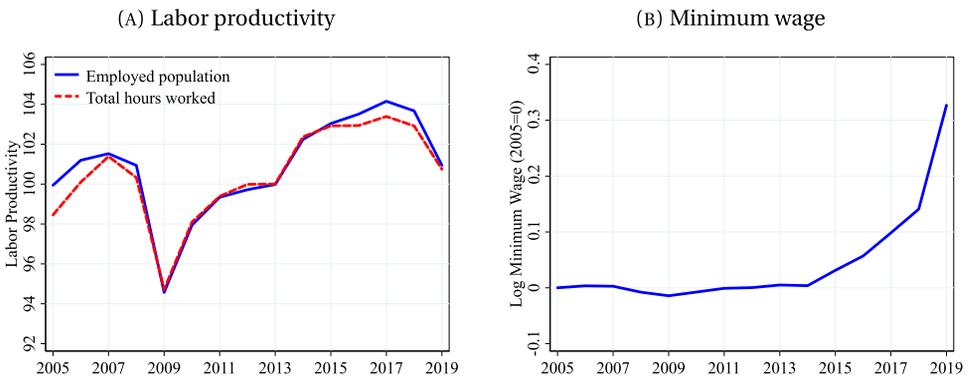


FIGURE 3. Labor market conditions. *Note:* Based on authors' calculations with data from INEGI. Labor productivity in year  $t$  corresponds to the average, seasonally adjusted, quarterly labor productivity index for all the quarters of year  $t$ . The labor productivity index is calculated as the ratio between value of production and hours worked or employed workers at constant prices. The minimum wage, in logs, is annualized, deflated with the 2018 Mexican CPI and normalized to 0 in 2005.

time-series patterns of earnings for the lowest percentiles of the income distribution, since the social security data are bottom coded at the minimum wage. Remarkably, the sharpest increases in the minimum wage have occurred from 2017 onward, a period that also coincides with the decrease observed in aggregate labor productivity.

### 3. CORE STATISTICS ON INEQUALITY, MOBILITY AND INCOME DYNAMICS: EVIDENCE FROM SOCIAL SECURITY DATA

In this section, we present a descriptive characterization of inequality, earnings dynamics, and mobility based on Mexican administrative records. The nonparametric approach used in our analysis is closely related to the work of [Bonhomme and Hospido \(2017\)](#) for Spain and [Guvenen et al. \(2017\)](#) and [Guvenen et al. \(2021\)](#) for the United States. To the best of our knowledge, we are the first to provide such a characterization of the earnings distribution of private-sector formal workers in Mexico that is based on administrative records and, together with [Engbom, Gonzaga, Moser, and Olivieri \(2022\)](#) and [Blanco, Díaz de Astarloa, Drenik, Moser, and Trupkin \(2022\)](#), the first to do so in the context of an emerging economy whose labor market significantly differs from those of more advanced economies.<sup>5</sup> Note that all the results presented in Sections 3.1–3.3 distinguish between men and women, and results for the whole sample are presented in Appendix B of the Online Supplementary Material.

#### 3.1 *Income inequality*

We begin our descriptive analysis by characterizing the most salient properties of the distribution of (log) real earnings. Figure 4 presents the evolution of the percentiles (relative to 2005) of the earnings distribution for both men and women.<sup>6</sup> Notably, the 2008–2009 financial crisis had a negative impact on earnings across the whole earnings distribution, but especially so for men and for workers at the bottom of the distribution. The earnings of workers at the very top proved to be more resilient to the negative shock associated with the crisis. Between 2013 and 2014, there was a decrease in the earnings of the lowest percentiles, particularly sharp for men. This is likely associated with the fact that 2013 was a year of below-average GDP growth and stalled growth in labor productivity (see Figures 1 and 3). Outside of these two periods, real earnings have shown an upward trend that is more noticeable for women than for men. Male workers showed more ups and downs at the bottom of the earnings distribution and flatter profiles at the top. In contrast, female workers displayed a steadier upward trend across the entire earnings distribution.

<sup>5</sup>[Binelli and Attanasio \(2010\)](#) present some results that are related to the analysis presented in this section and in Appendix B of the Online Supplementary Material, particularly concerning income inequality. These authors base their analysis on Mexican household surveys, rather than administrative data, and their results are focused on the period 1987 to 2002, a period that is not covered by our administrative records.

<sup>6</sup>When looking at Figure 4, it is important to note that, as the administrative data are top coded, only the percentiles up to P95 are derived using actual data. The percentiles after P95 are imputed by fitting a Pareto tail distribution around the top code. We include these upper percentiles for completeness and for the sake of comparison with other countries even though the information provided after P95 is inevitably noisy and should be interpreted with caution.

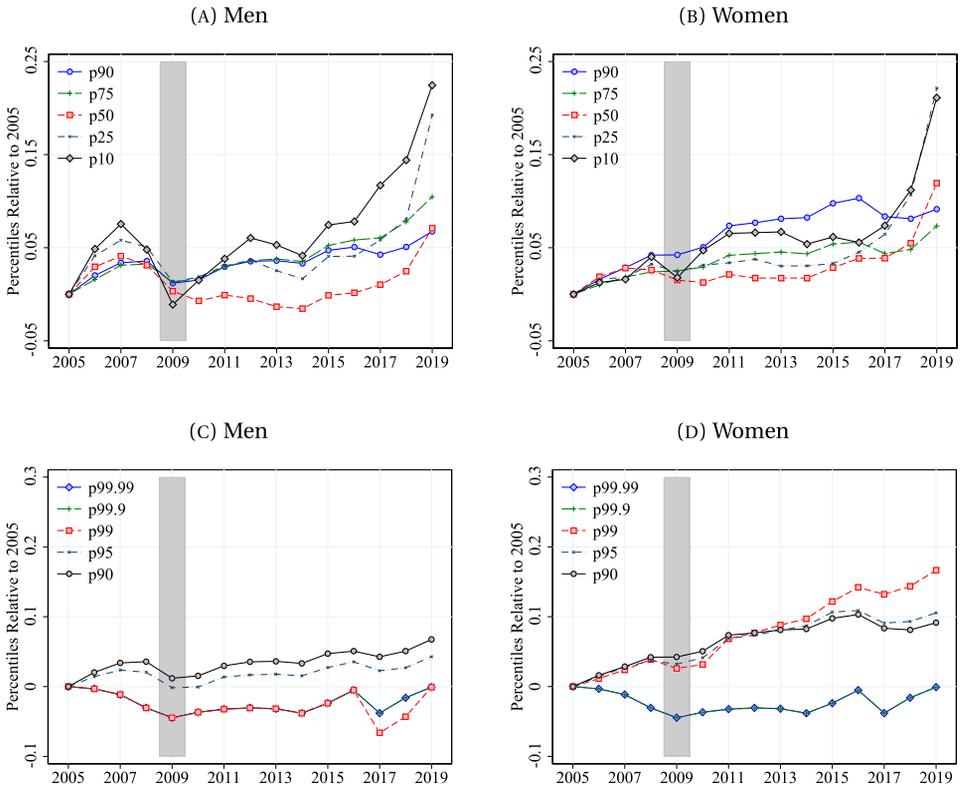


FIGURE 4. Evolution of the percentiles of the log real earnings distribution. *Note:* Based on authors’ calculations with data from IMSS. Using the CS+TMax sample, this figure plots against time the following percentiles of the distribution of log real earnings: (A) Men: P10, P25, P50, P75, P90; (B) Women: P10, P25, P50, P75, P90; (C) Men: P90, P95, P99, P99.9, P99.99; (D) Women: P90, P95, P99, P99.9, P99.99. Since the data are top coded, the percentiles above P95 are imputed by fitting a Pareto distribution around the top code. All percentiles are normalized to 0 in 2005, the first available year. Shaded areas are recessions.

Starting in 2014 for men and in 2016 for women, the lowest percentiles of the earnings distribution (P10 and P25) display a significant upward trend relative to previous years with log earnings increasing by roughly 20 log points between 2016 and 2019. This pattern appears to be highly correlated with the evolution of the minimum wage (see the right panel of Figure 3). The fact that the evolution over time of the lowest percentiles of the log earnings distribution correlates with the evolution of the minimum wage is not particularly surprising since the administrative data are bottom coded at the minimum wage. It is, however, noteworthy to observe that this correlation can be observed through P25, suggesting that increases in the minimum wage may have spillover effects on wages higher up in the earnings distribution. This result, known in the literature as the “lighthouse effect,” echoes the findings of Engbom and Moser (2021) for Brazil and Kaplan and Pérez-Arce Novaro (2006) and Campos Vázquez and Rodas Milián (2020) for Mexico. The increase in earnings in low percentiles that are not directly affected by the minimum wage may also relate to increases in labor productivity after 2013. Even

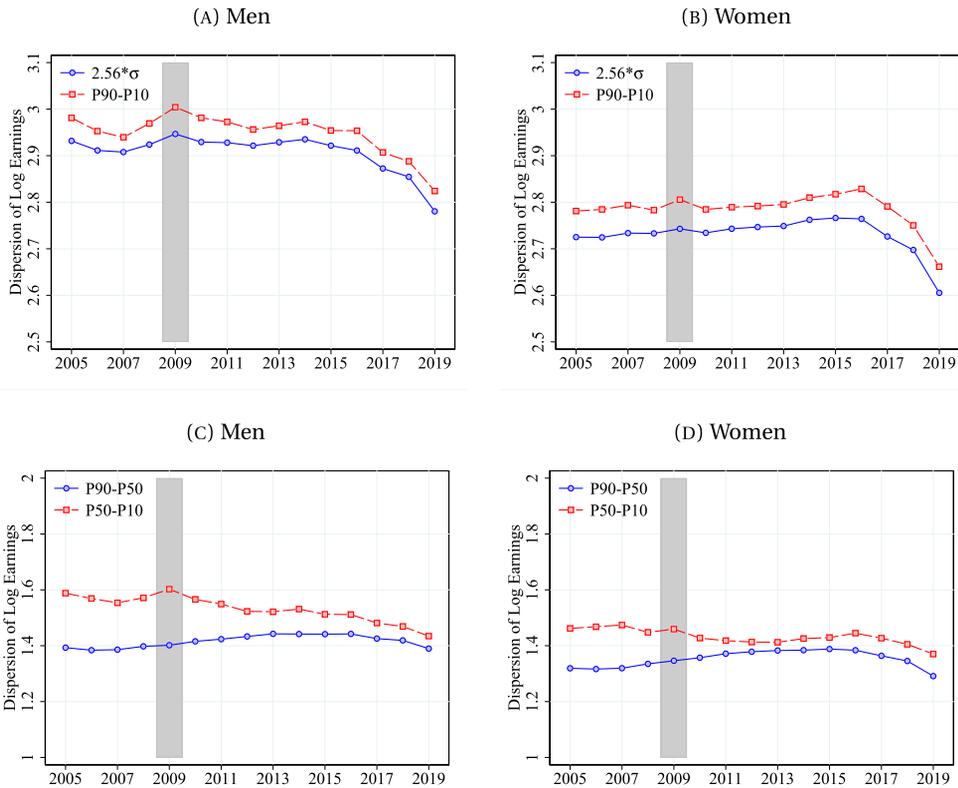


FIGURE 5. Earnings inequality: Dispersion of log real earnings. *Note:* Based on authors’ calculations with data from IMSS. Using the CS+TMax sample, this figure plots against time the following measures of overall, top- and bottom-tail dispersion of the distribution of log earnings: (A) Men: P90–P10 and  $2.56 \cdot \sigma$  (sigma is the standard deviation); (B) Women: P90–P10 and  $2.56 \cdot \sigma$  of log income; (C) Men: P90–P50 and P50–P10; (D) Women: P90–50 and P50–P10. Shaded areas are recessions.  $2.56 \cdot \sigma$  corresponds to the P90–P10 differential for a Gaussian distribution.

though labor productivity declines slightly toward the very end of our sample period, its levels in 2018 and 2019 are still above 2013’s levels.<sup>7</sup>

<sup>7</sup>Historically, there have been several additional economic factors related to changes in wages in Latin America and, in particular, in Mexico. Trade and globalization have been identified as relevant to the Mexican economy, given that NAFTA integration in the 1990s reduced unemployment, and boosted employment and wages, while Chinese competition tended to have the opposite effect in the 2000s (Chiquiar, Covarrubias, and Salcedo Cisneros (2017), Blyde, Busso, and Romero (2020)). Increases in education of the workforce were also relevant to rise low-skilled wages during the 2000s and to reduce skill premia (Jaume (2021)), consistent with the race between education and technology discussed in the literature (Katz and Murphy (1992), Goldin and Katz (2010)). The role of education, however, has been less pronounced in Mexico due to a lower educational upgrading with respect to other Latin American countries (Lustig, Lopez-Calva, and Ortiz-Juarez (2013), Acosta, Cruces, Galian, and Gasparini (2019)). To disentangle the relative importance of each of these factors in contributing to the increases in the lowest percentiles of the earnings distribution that we document in this paper constitutes an important research agenda but is beyond the scope of this paper.

The evolution of several measures of dispersion in the distribution of real earnings is documented in Figure 5. Panels (A) and (B) show that the overall dispersion in this distribution is very similar for men and women and seems to closely match the dispersion that would be observed in a normal distribution. The dispersion is, on average, slightly higher for men, who are also those who experienced a more noticeable increase in earnings dispersion during the crisis of 2008–2009. Outside of this recessionary period, the dispersion remained fairly stable between 2005 and 2015, but started to display a steady decreasing trend from 2015 onward.<sup>8</sup> The behavior of the P90–P10 measure presented in panels (A) and (B) can be further understood by looking at the the evolution of the upper and lower tails of the distribution—P90–P50 and P50–P10, respectively—presented in panels (C) and (D). The relative stability of P90–P10 from 2005 through 2015 is the result of a slight downward trend in the lower tail of the distribution that is barely offset by a slight upward trend in the upper tail. The downward trend of P90–P10 from 2015 onward can be associated with a downward trend in both the lower (P50–P10) and upper (P90–P50) tails of the distribution. Referring back to Figure 4, the reduction in the inequality of log earnings is mainly driven by the growth of the lower percentiles paired with the relative stability in the highest percentiles.

Finally, Figures 6 and 7 describe how initial inequality, for workers aged 25, has evolved over time and how life-cycle inequality differs across different cohorts of workers. In Figure 6, we see that the lower tail (P50–P10) experiences a modest downward trend, while the upper tail (P90–P50) experiences a very slight upward trend. These

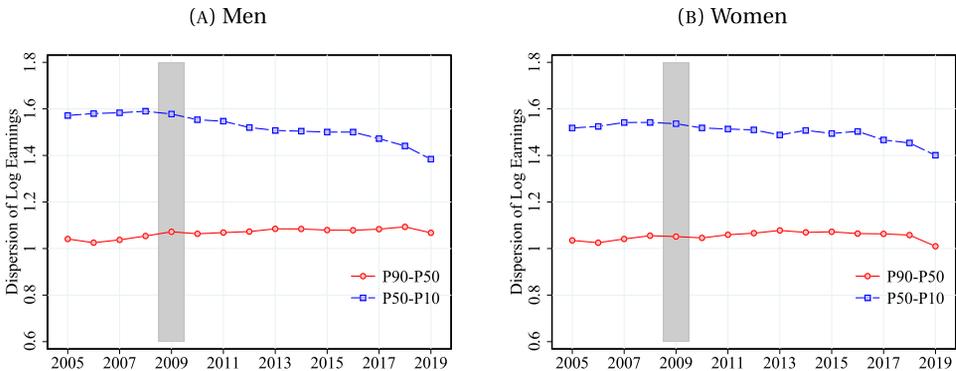


FIGURE 6. Initial inequality: Dispersion of log real earnings for workers at age 25. *Note:* Based on authors’ calculations with data from IMSS. Using the CS+TMax sample, this figure plots against time the following measures of top- and bottom-tail dispersion of the log earnings distribution: (A) Men: P90–P50 and P50–P10 for workers at age 25; (B) Women: P90–P50 and P50–P10 for workers at age 25. Shaded areas are recessions.

<sup>8</sup>Figures B.4 and B.5 in Appendix B of the Online Supplementary Material are also consistent with decreasing earnings inequality from 2016 onward. In particular, Figure B.4 shows that the share of income that accrues to the bottom 50% of the earnings distribution grew during that period, while the income share of the top 10% of the distribution decreased. Similarly, Figure B.5 shows that the Gini coefficient of the earnings distribution decreased substantially between 2016 and 2019, relative to the trend it had displayed in previous years.

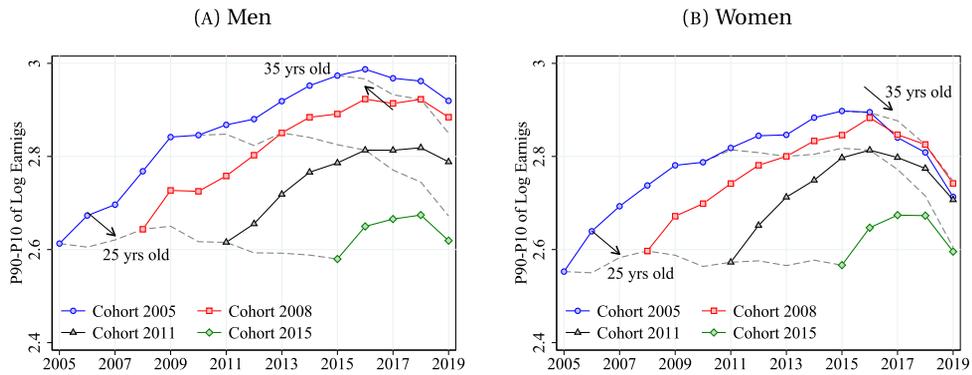


FIGURE 7. Life-cycle earnings inequality across cohorts. *Note:* Based on authors' calculations with data from IMSS. Using the CS+TMax sample, this figure plots against time measures of overall dispersion of the log earnings distribution: (A) Men: P90–10 over the life cycle for the 2005, 2008, 2011, and 2015 cohorts; (B) Women: P90–10 over the life cycle for the 2005, 2008, 2011, and 2015 cohorts. The grey dashed lines link across cohorts the years corresponding to ages 25, 30, and 35.

trends are similar for men and women, but are marginal as new cohorts of young workers faced relatively stable earning dispersion throughout our sample period. The patterns of life-cycle inequality across different cohorts are also very similar for men and women as illustrated in Figure 7. Specifically, for any given cohort, dispersion of log earnings increases until the last years of the sample (until 2016 or 2018 depending on the cohort) and displays a downward trend thereafter. Once again, this is likely associated with the increase in earnings for minimum wage workers starting around 2016 and the relative stability of the real earnings for workers at the top of the earnings distribution. Across cohorts, the dispersion of earnings for workers aged 25 shows a very slight downward trend, except for those being 25 around the time of the 2008–2009 crisis when dispersion increased. In contrast, there is a more noticeable downward trend in the dispersion of earnings across cohorts for workers 30 and 35 years of age. Given the relatively short window covered by our social security records, it is however unclear to what extent the eventual decrease in dispersion documented in Figure 7 can be attributed to features of a worker's life cycle as opposed to the overall decrease in dispersion observed in the latter part of our sample period.

### 3.2 Income dynamics

The results of this section constitute the core of our analysis of the administrative data. We characterize the most relevant properties of individual earnings dynamics, with an emphasis on the statistics that provide a diagnostic of the extent to which the distribution of earnings changes deviates from normality. As in Guvenen et al. (2021), the approach is nonparametric to avoid the strong assumptions embedded in benchmark econometric models of earnings dynamics, as those could mask important features of the distribution of earnings changes. Deviations from normality are important to study

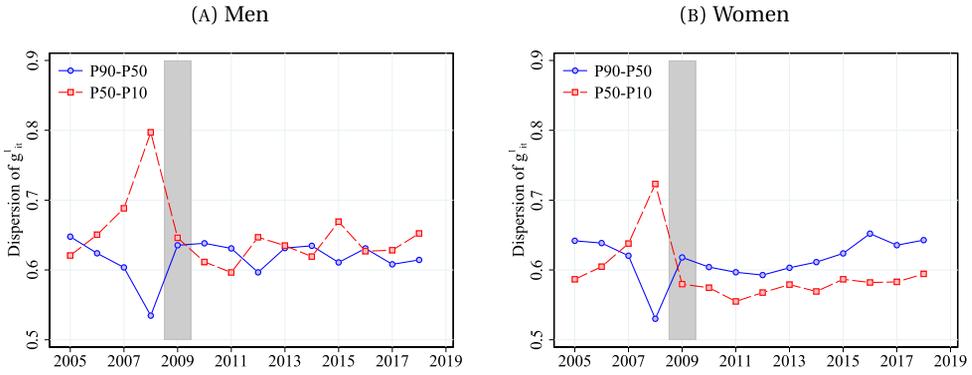


FIGURE 8. Dispersion of 1-year log earnings changes. *Note:* Based on authors’ calculations with data from IMSS. Using the LS+TMax sample, this figure plots against time the following measures of top- and bottom-tail dispersion of the distribution of 1-year earnings changes: (A) Men: P90–P50 and P50–P10 differentials; (B) Women: P90–P50 and P50–P10 differentials. Shaded areas are recessions.

because they have direct implications for the kind of income shocks a worker may experience, such as their magnitude, direction (higher likelihood of positive vs. negative shocks), and frequency of extreme events.

Defining (residualized) log earnings changes as  $g_{it}^k = \Delta^k \varepsilon_{it} = \varepsilon_{i,t+k} - \varepsilon_{it}$ , with  $\varepsilon_{it}$  being the residuals of a regression of log earnings on a full set of age dummies, separately by gender and year, Guvenen et al. (2021) show that as  $k$  becomes larger, the distribution of earnings changes  $\Delta^k \varepsilon_{it}$  reflects more closely the distribution of the permanent component of earnings changes rather than that of transitory innovations. Here, we focus on 1-year earnings changes (i.e.,  $k = 1$ ), that reflect mainly transitory innovations to earnings, and present results for  $k = 5$ , the more permanent innovations, in Appendix B of the Online Supplementary Material.

Figure 8 illustrates the dispersion in the upper (P90–P50) and lower (P50–P10) tails of the distribution of 1-year log earnings changes. For both men and women, we see that between 2008 and 2009, that is between the onset and bottoming out of the depressed economic conditions caused by the financial crisis, there was an increase in dispersion in the lower tail and a decrease in the upper tail of the distribution. The magnitude of these opposing movements suggests that overall dispersion (P90–P10) increased for men but remained relatively stable for women during the time of said crisis. It is worth noting that these spikes in dispersion coincide with the sharp increase in unemployment and informality that occurred between 2008 and 2009 (see Figure 2). Outside of this recessionary period, we observe only modest movements in P90–P50 and P50–P10. These two measures of dispersion move up and down in opposing directions for men, albeit the movements are small so that P90–P10 remains relatively stable. In contrast, from 2011 onward women experience a slight upward trend in both P90–P50 and P50–P10 resulting in a greater overall dispersion in their distribution of 1-year earnings changes. This period of increasing dispersion for women coincides with a post-labor market reform period in which female labor force participation grew in Mexico, likely

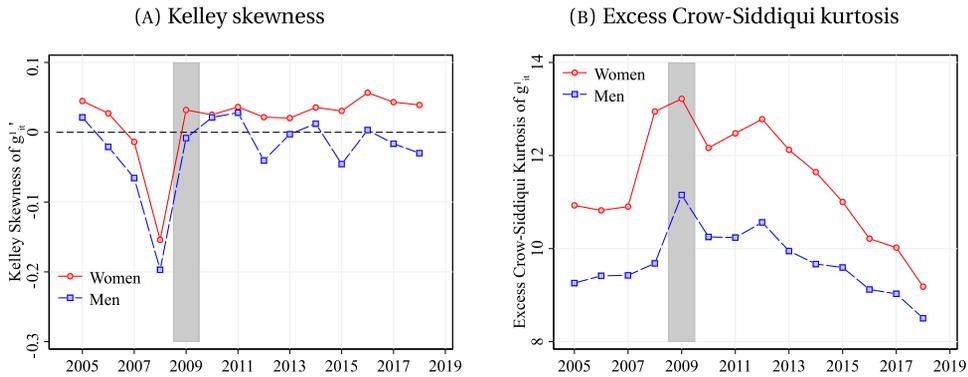


FIGURE 9. Skewness and kurtosis of 1-year log earnings changes. *Note:* Based on authors' calculations with data from IMSS. Using the LS+TMax sample, this figure plots against time the following higher-order moments of the distribution of 1-year earnings changes: (A) Men and Women: Kelley skewness calculated as  $\frac{(P_{90}-P_{50})-(P_{50}-P_{10})}{P_{90}-P_{10}}$ ; (B) Men and Women: Excess Crow-Siddiqui kurtosis calculated as  $\frac{P_{97.5}-P_{2.5}}{P_{75}-P_{25}} - 2.91$ , where the first term is the Crow-Siddiqui measure of kurtosis and 2.91 corresponds to the value of this measure for the Normal distribution. Shaded areas are recessions.

due at least in part, to the more flexible conditions encouraged by the reform.<sup>9</sup> Thus, it is possible that the greater flexibility in hiring practices induced the entry of women into the labor market, but particularly so for those who may demand more flexible work arrangements.

For the purpose of detecting significant deviations from normality, Figure 9 plots higher-order moments of the distribution of 1-year earnings changes. In particular, we consider Kelley skewness and excess Crow-Siddiqui kurtosis and whenever we mention skewness and/or kurtosis in this section we are referring to these two measures. Notice that, other than the particularly sharp decrease and rebound of skewness during the period of the financial crisis observed across genders, skewness remains fairly stable and relatively close to zero for both men and women from 2009 onward. Regarding kurtosis, we find that the distribution is leptokurtic, implying that, while most workers experience transitory earning changes of a small magnitude, a nonnegligible mass of them experiences extreme shocks. Qualitatively, the evolution of kurtosis is fairly similar for both men and women, although its level is significantly higher for women. Kurtosis had been trending slightly upward before the financial crisis, but increased significantly during this recession, particularly so for women. From 2011 onward, nonetheless, we see both a strong downward trend and a significant reduction in the gap level between men and women. Despite this significant downward trend in the kurtosis of 1-year earnings changes, by the end of our period of study its level remains quite high. Note that, even if the levels of excess kurtosis of 1-year earnings changes in the Mexican adminis-

<sup>9</sup>De la Cruz Toledo (2018) finds that the higher preschool enrollment associated with the rollout of a universal preschool policy led to an increase in female labor force participation in Mexico. Growing female labor force participation is also reflected in our administrative data with the share of women in the IMSS master sample increasing from 36.4 to 38.7% between 2011 and 2019.

trative data are high, they are not out of line with what Guvenen et al. (2021) report for the United States, particularly those that prevail in the latter part of our sample period. While our results suggest an average kurtosis for 1-year earnings changes that is higher than the one for the United States, Guvenen et al. (2021) also find high levels of excess kurtosis of up to 11 for workers aged 45 to 54 in the 60th percentile of the distribution of recent earnings, a level that is comparable to ours for men during the whole sample period and for women from 2015 onward. Conversely, if we look at the excess kurtosis of 5-year income changes (see Figure B.8 in Appendix B of the Online Supplementary Material), the levels are significantly smaller than those depicted in Figure 9, suggesting that the distribution of transitory earnings shocks is significantly peakier than that of permanent shocks, that is, extreme shocks to earning changes are more likely to be transitory than permanent.

It is also of interest to understand how the properties of the distribution of 1-year earnings changes may vary along the permanent income distribution and along the life cycle of workers.<sup>10</sup> To this end, Figure 10 presents dispersion, skewness, and kurtosis conditional on age (for age groups 25 to 34, 35 to 44, and 45 to 55) and conditional on the percentile of a worker's permanent income. The permanent income is calculated aggregating over a period of 15 years, the maximum number of years available in our sample, from 2005 to 2019. Several relevant patterns are qualitatively similar across genders, but there are also important differences. Specifically, dispersion is monotonically decreasing with both age and permanent income, meaning that transitory shocks to earnings are the most volatile for younger and lower-income workers. Skewness seems to be increasing with age. This is evident in the case of women, and for men at the bottom and top of the permanent income distribution; between P30 and P70 skewness is fairly similar across age groups. Along the distribution of permanent income, skewness decreases monotonically up to the 55th percentile approximately, and then remains relatively stable, with a slight upward trend from P85 in the case of men. Men also display skewness that is positive for the lower part of the permanent income distribution and negative for the upper percentiles and this applies to all age groups. In contrast, for women aged 35 and older, skewness is positive along the entire distribution of permanent income. For young women, as it was the case with young men, skewness is positive at the bottom of the permanent income distribution but becomes negative from around the 40th percentile onward. The positive skewness of 1-year earnings changes observed for all women 35 or older and for men of all ages in the lower part of the permanent income distribution implies that the earnings of these workers have more room to move up and less room to fall. This contrasts with the patterns observed during the financial crisis when skewness became noticeably negative, meaning that this recessionary episode, albeit brief, temporarily and significantly increased the chances for all Mexican workers of experiencing larger and more frequent negative shocks. Finally, kurtosis is monotonically increasing with age for men. The same is true for women as well, but only up to

<sup>10</sup>Permanent income for each worker is defined as  $P_{it-1} = \frac{\sum_{s=t-3}^{t-1} y_{is}}{3}$ . This measure takes average raw earnings  $y_i$  (including zeros or earnings below the threshold determined by the "meaningful attachment to the labor force") over the previous 3 years. It is constructed only for those workers who have at least 2 years of earnings above the threshold.

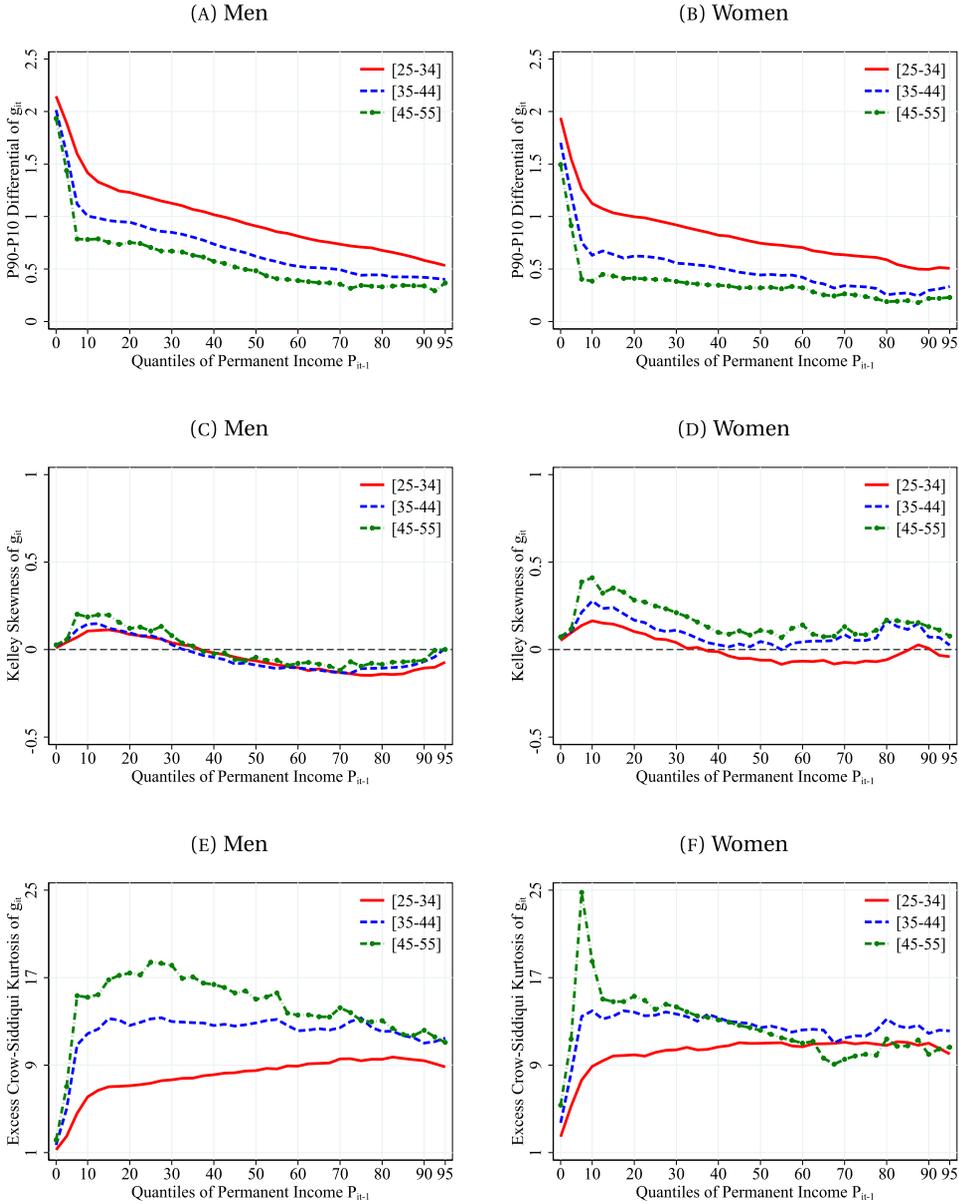


FIGURE 10. Dispersion, skewness, and kurtosis of 1-year log earnings changes conditioning on permanent income for workers of different ages. *Note:* Based on authors' calculations with data from IMSS. Using the H+TMax sample, this figure plots against percentiles of the permanent income distribution, and for three different age groups, the following moments of the distribution of 1-year earnings changes: (A) and (B) Men and Women: P90–P10 differential; (C) and (D) Men and Women: Kelley skewness; (E) and (F) Men and Women: Excess Crow–Siddiqui kurtosis. The permanent income is calculated aggregating over a period of 15 years, the maximum number of years available in our sample, from 2005 to 2019. Since the data are top coded, the percentiles of the permanent income distribution are plotted only until P95.

about the 40th percentile of the permanent income distribution. For the youngest workers, kurtosis increases sharply up to the 15th percentile, it continues to increase, but very gradually, up to roughly the 85th percentile, after which it slightly trends downward. In contrast, for the oldest workers kurtosis increases up to the 25th and 8th percentile for men and women, respectively, and then trends downward. Men experience this downward trend gradually, while for women the decrease is sharp between P8 and P10 and then kurtosis starts a gradual downward trend along the rest of the permanent income distribution. Overall, older and lower-income workers face the most concentrated (peakiest) distribution of transitory income shocks.

### 3.3 Income mobility

We now turn to the analysis of mobility over time in the distribution of earnings. Figure 11 shows long-term mobility for workers aged 25–34 and workers aged 35–44, tracking their movements along the distribution of permanent income over a 10-year time horizon. We observe upward mobility at the bottom and downward mobility at the top of the permanent income distribution, except at the very top. These patterns of mobility are qualitatively similar for men and women. For both age groups under consideration, there is upward mobility up to about P45 and P35 for men and women, respectively, with upward mobility being slightly higher for younger workers. In contrast, individuals located in the top percentiles of the permanent income distribution experience downward mobility that is also higher for younger workers. At the very top of the permanent income distribution, top 0.1%, there is essentially no income mobility.

Looking at long-term mobility over time, Figure 12 shows the evolution of 10-year mobility for two different starting years, 2007 and 2009. The patterns are again very similar across men and women, but it is worth noting that 10-year mobility within the distribution of permanent income is essentially unchanged between 2007 and 2009, despite 2007 being a precrisis year and 2009 coinciding with the large macroeconomic shock associated with the financial crisis (see Figure 1).

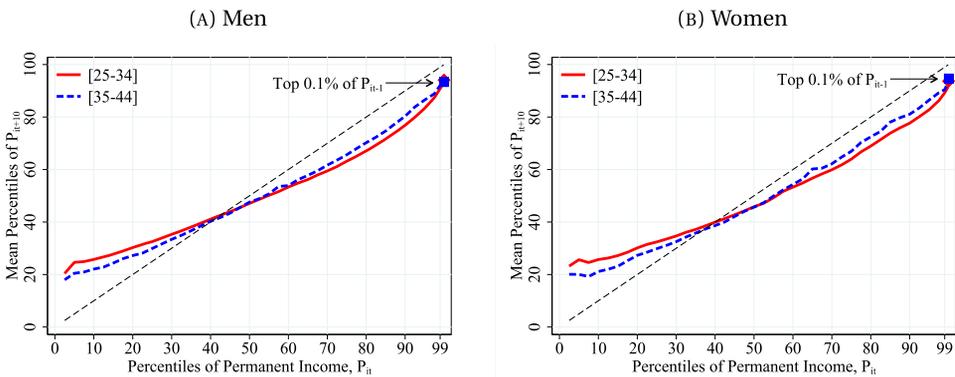


FIGURE 11. Evolution of 10-year mobility over the life cycle. *Note:* Based on authors’ calculations with data from IMSS. The figure shows average rank-rank long-term (10-year) mobility for male (A) and female (B) workers of different ages.

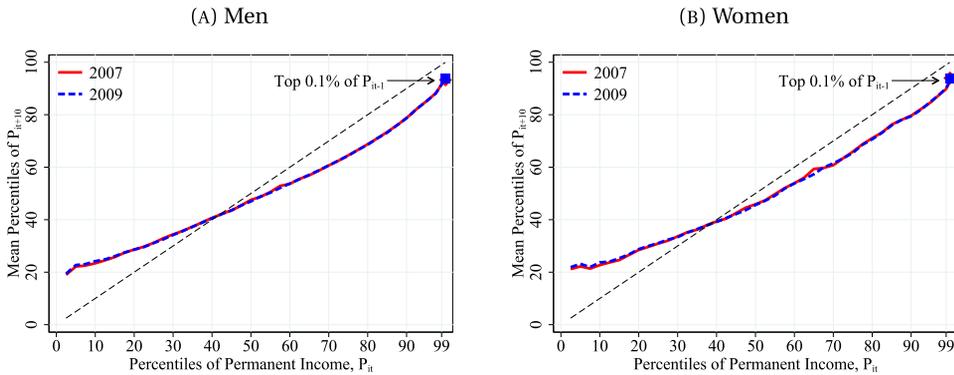


FIGURE 12. Evolution of 10-year mobility over time. *Note:* Based on authors' calculations with data from IMSS. The figure shows average rank-rank long-term (10-year) mobility for male (A) and female (B) workers in selected years of the sample, 2007 and 2009.

#### 4. ADMINISTRATIVE VERSUS SURVEY DATA AND WORKER TRANSITIONS

An important limitation of the social security data, and hence, of the results presented in Section 3 for understanding inequality and the dynamics of income in the Mexican labor market, is that these data only cover workers in the formal sector. As such, they are not informative about a large segment of the Mexican labor market: informal workers. In contrast to developed countries, a notorious characteristic of developing and emerging economies, such as Mexico, is that the informal sector is responsible for a large share of all economic activity and commands a significant proportion of the economy's productive resources. During the period considered in our analysis, 2005–2019, the quarterly rate of informality ranged between 56 and 60% at the aggregate level (see Figure 2), with this rate being somewhat larger for women than for men. Furthermore, Levy (2018) shows that informal firms in Mexico represent 90% of all firms and absorb 40% of the economy's capital stock. Thus, these firms are present throughout the economy and are not confined to activities deemed “traditional” or “less modern,” implying that the informal economy fully coexists alongside the formal economy.

Due to the pervasiveness of informality in the Mexican economy and the fact that the relative size of the informal sector may affect the overall functioning of the labor market and the opportunities available to workers in terms of job security, social mobility, and life-time earnings, any analysis that omits a discussion of informal employment can only provide a partial perspective regarding the labor market outcomes, including earnings, of a large share of Mexican workers. With this in mind, we devote the second part of our analysis to two exercises. First, we contrast some of the results from the previous section, based on IMSS data, with results obtained from a comparable sample from the Encuesta Nacional de Ocupación y Empleo (ENOE for its acronym in Spanish), the main household survey on employment in Mexico. In addition, we provide results for informal workers and the pooled sample of formal and informal workers. This exercise is informative about the extent to which household survey data could be used to provide a more comprehensive view of the Mexican labor market by offering information on both

formal and informal workers. Second, we study the wage dynamics of workers who exit and subsequently reenter the IMSS database, as a large number of workers in Mexico maintain a tenuous connection with formal employment. Even though we cannot track workers upon exit from the social security data, the very low levels of unemployment and absence of a social safety net in Mexico suggest that the majority of these workers are likely to be transitioning in and out of formal employment via job spells in the informal sector. This is especially plausible for men, whose labor participation rate is above 90% for the age group considered in the analysis.

Our main results can be summarized as follows. First, the evolution of log earnings based on IMSS data and those based on ENOE are very comparable for the lower percentiles of the earnings distribution (roughly up to P25), but not for the upper percentiles (P50 and above). We argue that the most plausible reason behind this finding is that household survey data suffer significantly from an issue of nonresponse in questions related to labor earnings that is concentrated among those workers most likely to be in the upper segment of the earnings distribution (formal and highly educated workers). Since nonresponse is nonrandom, has been increasing during the sample period, and the observable characteristics of nonresponders have changed to some extent over time, nonresponse is a significant issue that limits the usefulness of Mexican household survey data for constructing statistics on inequality and earnings dynamics that are comparable to those presented in Section 3. Second, workers who exited the formal sector can take, on average, 3 or more years upon reentry to achieve yearly wages that are comparable to those earned before exit. This suggests that most workers do not transition out of formal employment because of better opportunities elsewhere, otherwise it is improbable that they would accept to reenter formal employment at lower wages. The earnings recovery process appears to be faster for women than for men.

The rest of this section is organized as follows. Section 4.1 presents the comparison between IMSS-based statistics and ENOE-based statistics. Section 4.2 analyzes the impact of transitioning out of and back into IMSS-affiliated employment on the wages earned within the formal sector.

#### 4.1 *Earning inequality and dynamics: Comparing administrative and survey data*

To provide a more comprehensive picture of the distributions of earnings levels and changes of Mexican workers and evaluate the evolution of income inequality for formal and informal workers, we rely on an additional source of information, the Encuesta Nacional de Ocupación y Empleo (ENOE) in this section. The ENOE is the primary official source of employment and occupation data in Mexico. It is a quarterly household survey at the national level run by the Mexican Statistical Agency (INEGI) and is specifically designed to collect information on the employment situation of individuals in rural and urban areas. It also collects information on labor income and socioeconomic characteristics of the individuals surveyed. It has a rotating panel structure: every quarter, INEGI replaces one-fifth of the sample (i.e., each household is followed for five consecutive quarters before being dropped from the survey). The ENOE is representative at the

national and state level, and for one selected city in each state. It is conducted continuously throughout the year, surveying approximately 120 thousand households in each quarter.

It is well known that using survey data presents several challenges, such as measurement error, lack of representativeness in the tails of distributions, small sample size, increasing nonresponse, and declining response quality (see Council (2013) and Meyer, Mok, and Sullivan (2015)). Despite these limitations that the ENOE also suffers from, it provides the necessary information to compute different indicators that can be compared to those constructed using the administrative data presented in Section 3.1 (cross-sectional evolution of income inequality) and Section 3.2 (transitory shocks to earnings).<sup>11</sup>

While the underlying structure of the ENOE does not allow for selecting a sample that is identical to the one used in Section 3 (i.e., IMSS is a census with a true panel structure while ENOE is a survey sample with a rotating panel structure), we select a sample of workers present in ENOE that is as close as possible to the master sample constructed with the administrative data. We then proceed to calculate statistics analogous to those of Sections 3.1 and 3.2. In particular, we only consider individuals who are sampled for 5 consecutive quarters, report a positive income for at least one of the 5 quarters, and report to be employed in an IMSS-affiliated job for at least one of the 5 quarters. This sample of workers is representative of the “formal base population” (i.e., the population of formal workers that is our reference) that more closely resembles that of IMSS. We then apply to this sample a set of restrictions that make it as similar as possible to the IMSS master sample. That is, we impose the same bottom and top coding as in the administrative data, we only consider monetary labor income from the main occupation as this is the earning measure that more closely matches the one reported in the IMSS records, we restrict the sample to workers aged 25 to 55, and we impose the same *meaningful attachment to the labor force* condition that we imposed to the workers in the administrative data (annual income equivalent to at least 45 days paid at the minimum wage). Since workers in the ENOE report their typical monthly income in each quarter,

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<sup>11</sup>Another well-known household survey run by INEGI that is commonly used to measure poverty and income inequality in Mexico is the Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH). We chose to use the ENOE instead of the ENIGH for this comparison exercise for several reasons. First, while the ENIGH provides information on various sources of household income, we only need information on (monetary) labor earnings as this is the income variable that is relevant for the comparison with the IMSS-based statistics from Section 3. On this front, both surveys provide comparable information. But it is not clear that the ENIGH has a clear advantage over the ENOE as the ENIGH is primarily designed to capture overall wealth, not labor income. Second, the ENIGH is only available every 2 years, while the ENOE is run every quarter. Third, the ENIGH only provides one data point for labor income for each worker in each year, while the ENOE can provide up to five data points. Using more frequently available information has the advantage of minimizing noise and measurement error in the data. Fourth, the ENIGH went through some important methodological changes during the period studied in this paper that limit comparability across the rounds of this survey. Finally, and most importantly, given the nature of the Global Income Dynamics Project, it is impossible to capture any dynamics of income with the ENIGH. Despite all these limitations that lead us to prefer the ENOE, we conducted a similar exercise to the one presented in this section and found that the main trends in inequality that we document with IMSS and ENOE are also observed when using ENIGH data for formal workers and for the total workforce (formal and informal).

we calculate their annual income by averaging the monthly income for all the quarters they are observed and then multiplying it by 12. Finally, we recalibrate the expansion factors (weights) originally assigned to the individuals included in the ENOE sample selected by applying these restrictions using a variable that stratifies labor income in terms of number of minimum wages (strata being: at most one minimum wage; between 1 and 2 minimum wages; between 2 and 3; between 3 and 5; more than 5). This ensures that the share of individuals present in each stratum is equal in the original ENOE sample that represents the formal base population and in the final ENOE sample obtained once the restrictions just mentioned are applied.

We start by comparing the features of the distribution of log earnings calculated with information from IMSS (left) and from ENOE—formal workers only—(right). The upper panel of Figure 13 shows the evolution of the percentiles of this distribution. The lowest percentiles, up to approximately P25, have remarkably similar patterns in both IMSS and ENOE, particularly to the extent that they display a significant increase, from 10 to 30% in comparison to 2005, from 2014 onward. The upper percentiles, however, differ starkly when comparing IMSS with ENOE. The ENOE-based top percentiles display very large drops ranging between 15% for P75 and almost 40% for P95 relative to 2005. These significant changes observed in the ENOE data are rather implausible and suggest that the household survey is most likely inaccurate for capturing earnings at the top of the distribution.

To understand the source of this discrepancy in the upper part of the log earnings distribution, we analyze a problematic issue that is very common in surveys—non-response. In ENOE, nonresponse regarding income/earnings for employed workers has increased from 9% in 2005 to more than 25% in 2019. Moreover, the nonresponse is nonrandom and concentrated among highly educated formal workers. For university-educated workers, nonresponse almost doubled between 2005 and 2019, reaching 40% in 2019. For workers with primary education or less, nonresponse also increased but it never exceeded 20%. Formal and urban workers are also more likely to not provide information about their income. More details that document these facts are provided in Appendix C of the Online Supplementary Material. The fact that nonresponse is so pervasive for specific categories of workers who are usually the top earners, that it has been increasing over time, and that observable characteristics of nonresponders have also somewhat changed throughout the sample period, indicates that this issue is likely to be the reason why the ENOE is inaccurate in characterizing the upper part of the earnings distribution.

Looking at the middle and bottom panels of Figure 13, we observe a decrease in overall dispersion, and hence, a decrease in inequality, that accelerates from 2016 and is more strongly driven by the declining inequality in the lower part of the earnings distribution. These patterns hold with data from both IMSS and ENOE even if the levels are not the same. Our results are reassuring in terms of confirming that administrative and survey data are able to provide a similar picture of the evolution of earnings in the lower percentiles of the distribution. But they also point to the fact that survey data can be particularly unreliable for studying the evolution of the top percentiles, where the

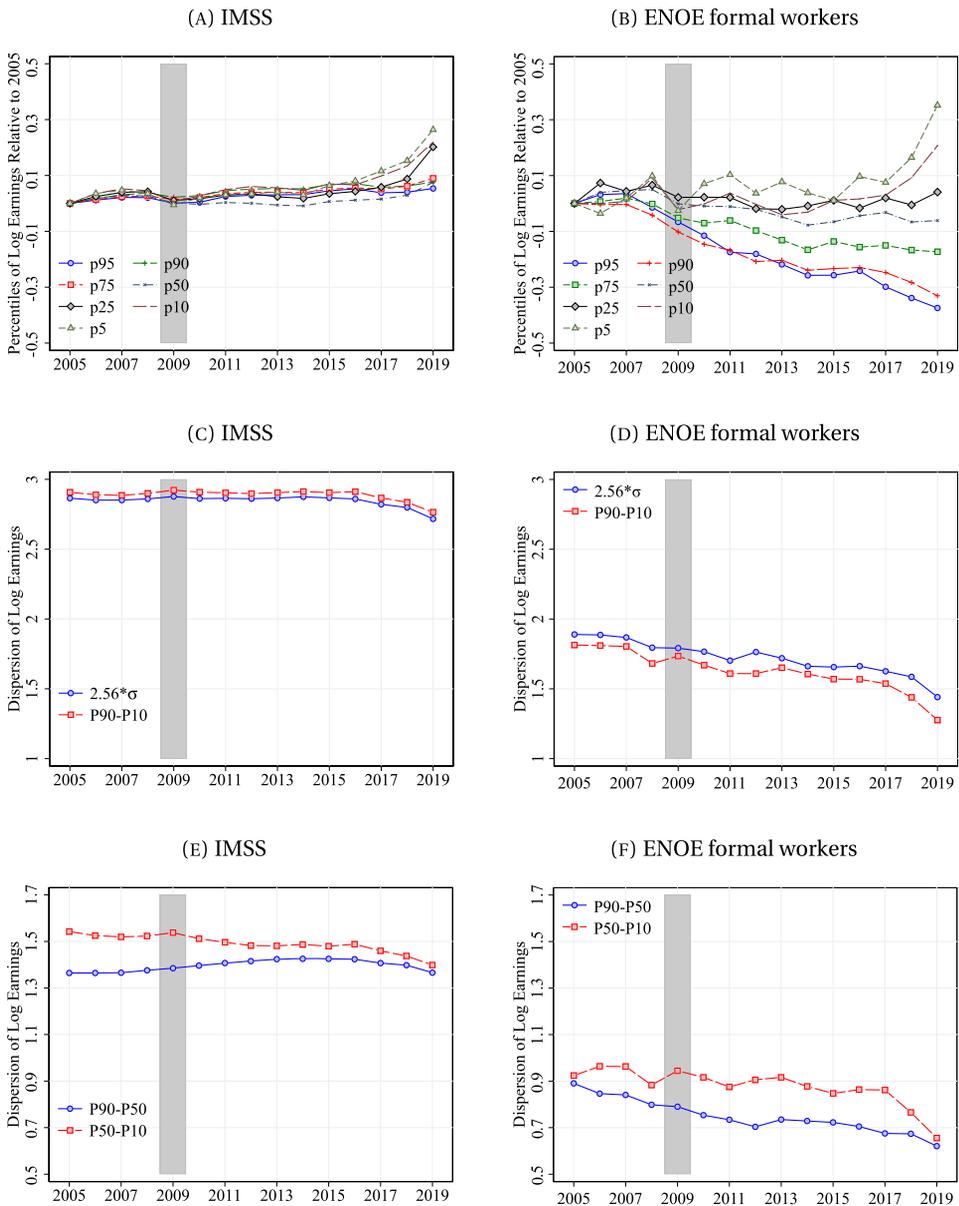


FIGURE 13. Comparison between administrative and survey data: Distribution of log real earnings. *Note:* Based on authors' calculations with data from IMSS and ENOE. Using the CS+TMax sample for the IMSS data and a sample from ENOE (only formal workers with access to social security) constructed to match the CS+TMax sample as closely as possible, this figure plots against time the following statistics of the distribution of log earnings: (A) IMSS: P5, P10, P25, P50, P75, P90, P95; (B) ENOE formal workers: P5, P10, P25, P50, P75, P90, P95; (C) IMSS: P90–P10 and  $2.56 \cdot \sigma$ ; (D) ENOE formal workers: P90–P10 and  $2.56 \cdot \sigma$ ; (E) IMSS: P90–P50 and P50–P10; (F) ENOE formal workers: P90–P50 and P50–P10. Shaded areas are recessions.

nonresponse tends to be more concentrated and severe, and for computing measures of inequality.

To provide a more comprehensive picture and to better understand how our analysis from Section 3 that includes only workers employed in the formal private sector can be representative of all workers in Mexico, we present figures similar to Figure 13 in appendix C of the Online Supplementary Material. These figures analyze the evolution of the percentiles of log earnings and measures of inequality for informal workers and for the whole pool of workers (formal and informal). We find comparable trends indicating that the statistics we calculate for formal workers with both administrative and household survey data are relevant and informative for all employed workers.

Next, we compare the distribution of transitory earnings shocks. Note that, given the short, rotating panel structure of the ENOE (only 5 quarters), we can only construct a measure of 1-year income changes with the ENOE, and this measure is inevitably very noisy because we can only use 2 data points for each worker (i.e., information on income in his/her first and last quarter).<sup>12</sup> Figures 14 and 15 show the comparison between the evolution of the percentiles of the distribution of transitory earnings shocks and measures of dispersion, symmetry, and concentration in this distribution, respectively, using data from IMSS and ENOE. We see that the overall trends in the percentiles and moments of the distribution are similar throughout the whole period of analysis

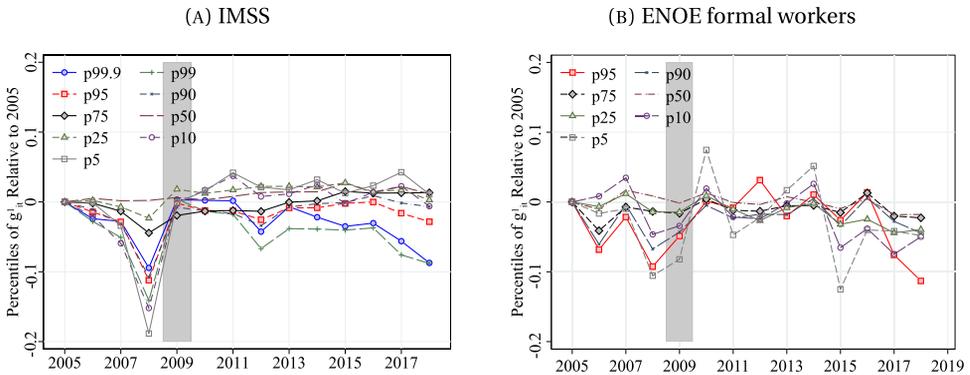


FIGURE 14. Comparison between administrative and survey data: Evolution of the percentiles of the distribution of 1-year log earnings changes. *Note:* Based on authors’ calculations with data from IMSS and ENOE. Using the CS+TMax sample for the IMSS data and a sample from ENOE (only formal workers with access to social security) constructed to match the CS+TMax sample as closely as possible, this figure plots against time the following statistics of the distribution of 1-year log earnings changes: (A) IMSS: P5, P10, P25, P50, P75, P90, P95, P99, P99.9; (B) ENOE formal workers: P5, P10, P25, P50, P75, P90, P95. All percentiles are normalized to 0 in 2005, the first available year. P99 and P99.9 are omitted in panel (B), because due to the lack of a sufficient number of observations, they are too noisy to be informative. Shaded areas are recessions.

<sup>12</sup>We use the information on income in the first quarter each worker appears in the survey to construct his/her annual income in year  $t$  and the information in his/her fifth (last) quarter to construct his/her annual income in year  $t + 1$ . As we can only use one monthly data point for  $t$  and  $t + 1$ , the annualized income, and hence, the changes in this income, are very noisy.

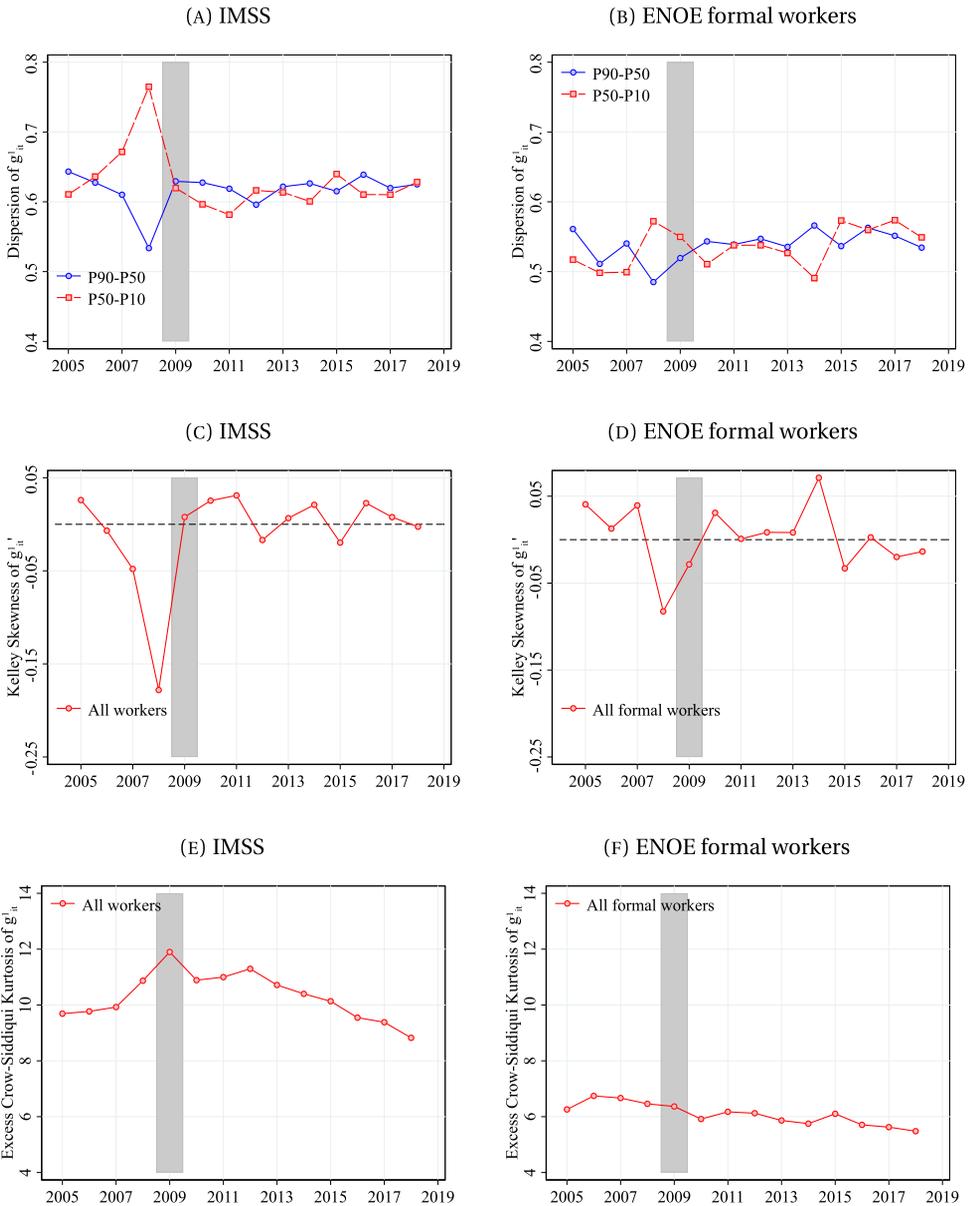


FIGURE 15. Comparison between administrative and survey data: Measures of dispersion, symmetry, and peakedness of the distribution of 1-year log earnings changes. *Note:* Based on authors' calculations with data from IMSS and ENOE. Using the CS+TMax sample for the IMSS data and a sample from ENOE (only formal workers with access to social security) constructed to match the CS+TMax sample as closely as possible, this figure plots against time the following statistics of the distribution of 1-year log earnings changes: (A) IMSS: P90–P50 and P50–P10; (B) ENOE formal workers: P90–P10 and P50–P10; (C) IMSS: Kelly skewness; (D) ENOE formal workers: Kelly skewness; (E) IMSS: Excess Crow–Siddiqui kurtosis; (F) ENOE formal workers: Excess Crow–Siddiqui kurtosis. Shaded areas are recessions.

with both IMSS and ENOE data. The most notable exception is the financial crisis when some of the deviations from the observed patterns are more evident in the administrative data than in the survey ones. These results suggest that transitory earnings shocks from ENOE and IMSS display more similar patterns than log earnings percentiles. We explore a possible explanation for this finding by verifying how levels of earnings are correlated with 1-year earnings changes in the ENOE sample. We calculate that in a given year  $t$  their correlation is quite small and statistically significant, ranging between  $-0.3$  and  $-0.4$ . But if we focus on the upper part of the distribution of log earnings (from P50 onward), where we know that the nonresponse is more severe, this correlation is significantly smaller, dropping by more than 30%.<sup>13</sup> This implies that the income level of an individual is not strongly correlated with his/her transitory earnings shocks. That is, individuals with both low and high earnings can experience both small and large earnings changes, and this is particularly true for high earners. Hence, the issues that the nonresponse causes in the upper part of the distribution of log earnings are not automatically transmitted to the distribution of earnings changes, limiting the extent to which nonresponse affects the comparability between administrative-based and survey-based measures of temporary earnings shocks.

#### 4.2 *Transitions in and out of formal employment and their impact on wage dynamics*

A distinctive feature of the formal labor market in Mexico is that there is continuous entry and exit of workers into and out of IMSS-affiliated jobs. For example, during the sample period covered by our analysis, only 8.8% of workers maintained an IMSS-affiliated (formal) job throughout. Additionally, about one-fourth of workers have two or more spells of formal employment where a spell is defined as a sequence of contiguous years in which we observe a worker's income within our data (see Appendix A of the Online Supplementary Material for descriptive statistics regarding active employment spells). Thus, in general, most Mexican workers do not seem to have a very strong attachment to formal employment. This tenuous bond can potentially have an important impact on the lifetime earnings and welfare of workers given that informal employment typically implies lower average wages and does not entail social security benefits, nor grants any of the employment protection associated with formal employment.

The movements in and out of the formal employment can be associated with transitions between IMSS-affiliated employment, non-IMSS-affiliated employment (either in the formal public sector or in the informal sector), unemployment, or exit from the labor force. It is important to emphasize that, once workers leave the IMSS database, we are unable to track them, and thus cannot ascertain the state into which they transition (nor the state from which they transition back into formal employment). Given that we are focusing on prime-age workers, it is most likely that the bulk of these transitions occur between (private) formal and informal employment, as the informal labor market is one of the most important mechanisms for Mexican workers to smooth income

<sup>13</sup>This is consistent with Figure 10 that shows that in the administrative data the dispersion of 1-year changes in residualized earnings is high in the lowest percentiles of the permanent income distribution but mostly flat everywhere else.

shocks. While information on transitions is not available in the administrative data, the household survey ENOE permits to follow workers across different states (i.e., employed in the formal sector through IMSS; employed in the formal sector through a different social security institution; employed in the informal sector, unemployed; out of the labor force). We use the ENOE to characterize transitions across these states using a sample of workers comparable (in terms of age) to the sample from the IMSS data that we use in the first part of the paper and during the same period (2005–2019), and document that indeed the majority of workers transitioning out of IMSS-affiliated jobs move to informality. In particular, we find that in a given quarter, on average, 18% of the male and 19% of female workers leave IMSS-affiliated employment. Out of these transitioning workers, 63% of men and 45% of women end up being informally employed in the next quarter. Similarly, 62% of all male and 46% of all female workers who get employed in an IMSS-affiliated job in one quarter worked in the informal sector in the previous quarter. These patterns confirm that informality is the most recurrent employment option outside the formal sector for both men and women.<sup>14</sup> As this entry and exit can affect the dynamics of income, we now turn the focus of our analysis to investigating whether spells out of formal employment imply a penalty on earnings upon reentry and, if so, how large this penalty is and how long it takes for workers to recoup their previous wages.

We restrict our sample to the group of workers with two spells of formal employment.<sup>15</sup> Almost one-fifth of all workers who have been formally employed during the sample period have only two spells of formal employment (see Appendix A of the Online Supplementary Material), which implies that they have exited and reentered after a break that lasted at least 1 year, and hence, have only one gap in formal employment. On average, these workers are present in the database 3.2 years before leaving, stay out of formal employment 2.6 years, and then come back for another 3.6 years. The distinguishing features of this subsample are: (i) the proportion of males is slightly larger than for the whole sample (61.2% vs. 60.4%); (ii) their average age at the beginning of their first spell of formal employment is slightly lower (31.7 years old vs. 32.6 years old); and (iii) their average age at the conclusion of their second spell of formal employment is 40.4 years old, substantially lower than the retirement age. To analyze the potential penalty on earnings implied by this mechanism of entry, exit and subsequent reentry into formal employment, we compare preexit wage trajectories with the post reentry trajectories. In particular, we adopt an event-study approach around the beginning and the end of the gap in formal employment. In our baseline specification, we examine a 3-year event window before and after each worker exits the database. We balance the panel by keeping only workers that can be observed for three consecutive years before

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<sup>14</sup>The survey data also confirm the well-known fact that in Mexico men have a much stronger attachment to the labor force than women. In fact, 79% of male workers who exit IMSS-affiliated jobs remain in the labor force and find employment mainly in the informal sector or in formal jobs not affiliated with IMSS. In contrast, the share of female workers who remain employed upon leaving IMSS-affiliated jobs is only 60%, with almost three quarters of these workers finding employment in the informal sector, but with a considerable share, about 30%, leaving the labor force (the remaining 10% transitions to unemployment).

<sup>15</sup>The descriptive statistics and estimates relative to this part of the analysis are based on a random sample of 4 million workers obtained from the universe of workers that were present at least 1 year in the master sample used to carry out the analysis presented in Section 3.

leaving the data set and for 3 consecutive years after reentry. The 3-year event window is chosen as the benchmark as it maximizes sample size while mimicking the average duration of these workers' active spells.<sup>16</sup>

The comparison is performed by estimating the following specification, separately by gender:

$$\ln(w_{it}) = \beta_0 + \sum_{\tau=-2}^3 \beta_\tau \mathbb{I}_\tau + \sum_{\kappa=1}^9 \beta_\kappa \mathbb{I}_\kappa + \sum_{\tau=-2}^3 \sum_{\kappa=1}^9 \beta_\tau^\kappa \mathbb{I}_\tau \mathbb{I}_\kappa + \gamma_g \mathbb{I}_g + \alpha_e + \alpha_s + \alpha_t + \varepsilon_{it}. \tag{4.1}$$

Here,  $\ln(w_{it})$  is the logarithm of the average monthly wage of worker  $i$  in year  $t$ .  $\mathbb{I}_\tau = \mathbb{1}[\text{event} = \tau]$  are dummy variables for the number of years before or after leaving the sample:  $\tau = 0$  is the year right before leaving the sample (i.e., the last year of a worker's first job spell in the formal sector),  $\tau = -1$  refers to 2 years before leaving the sample,  $\tau = 1$  is the first year upon reentering (i.e., the first year of a worker's second job spell in the formal sector), and so on.  $\mathbb{I}_\kappa = \mathbb{1}[\text{duration} = \kappa]$  is a set of dummy variables that take the value of 1 depending on the  $\kappa$  number of years during which the worker was out of formal employment. We consider durations out of formal employment that go from 1 up to 9 years because these are the durations observed in the data.  $\mathbb{I}_g = \mathbb{1}[\text{age}_{it} = g]$  are dummy variables for the age group to which worker  $i$  belongs in year  $t$ .  $\alpha_e$ ,  $\alpha_s$ , and  $\alpha_t$  are fixed effects for sector of economic activity  $e$  and federal state  $s$  where the worker is employed, and year  $t$ , respectively, and  $\varepsilon_{it}$  is the error term. Standard errors are clustered at the worker and sector-year levels.

The coefficients of interest are the  $\beta_\tau$ , that capture how wages in different event periods  $\tau$  compare to the base year,  $\tau = 0$ , the year right before leaving the sample. A graphical representation of the estimates of these coefficients is shown in Figure 16.<sup>17</sup> On average, wages decrease the year before leaving the sample, both for male and female workers. Men appear to be experiencing a more marked downward trend 2 years before leaving, while women seem to have more stable wages in the years before exit. Upon reentry, our results indicate that, in the first year of their second formal job spell, workers suffer a wage penalty of around 15% compared with the wage they earned in the year right before concluding their first spell of formal employment. This holds for men and women, although men seem to fare worse than women in terms of the speed of wage

<sup>16</sup>As we widen the analysis window, we lose observations since it is difficult to find many workers that are present in the data many years before leaving as well as after reentering. As a robustness check, we also analyze a 5-year event window to assess whether wage trajectories change as the event window widens. Inevitably, the 3-year event panel is comprised of a different set of workers than those included in the 5-year event window. Results hold when using the specification with the wider event window (see Appendix D of the Online Supplementary Material).

<sup>17</sup>The complete estimation output for this regression is provided in aAppendix D of the Online Supplementary Material. In the same Appendix, we present additional results obtained with a larger sample of workers, those with at least two spells of formal employment, where we consider only their first two spells. We also present results from adding worker fixed effects to equation (4.1). The main insights are maintained across these different specifications.

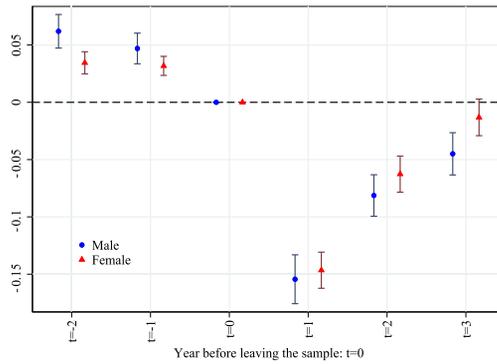


FIGURE 16. Estimates of wages trajectories (log differences) of workers who exit and reenter formal employment. *Note:* Based on authors’ estimates with data from IMSS. The figure plots differences of log wages obtained by estimating equation (4.1) using a subsample of workers with only two spells of formal employment. Markers for men and women are positioned to the left and right, respectively, of each event year  $t$ . Standard errors are clustered at the worker and sector-year levels and 95% confidence intervals are plotted together with point estimates.

recovery.<sup>18</sup> Wages start to catch up in the second year upon reentry, but men are still not able to fully regain their preexit wages in the third year after reentering, whereas women are able to recoup almost entirely.

The fact that wages are lower upon reentry suggests that the wage penalty is likely associated with most of these workers transitioning to lower-paying jobs, possibly in the informal sector, after (temporarily) leaving formal employment. As a consequence, these workers may suffer a negative income shock that the analysis in Section 3 is not able to capture. On the other hand, regaining formal employment may also entail a positive income shock. Since our results suggest that the unobserved positive (reentry) income shock is smaller than the initial negative (exit) one, some of the measures of income dynamics discussed in Section 3 may be unable to fully capture the effects of these shocks on earnings as they cannot take into account the impact of transitions in and out of formal employment.

We also characterize the behavior of wages, in levels, during the event window under analysis. We use the estimated coefficients from equation (4.1) and calculate the conditional means of log wages with respect to a worker in the base category of the regression,<sup>19</sup> for each event period  $\tau$  and each duration of the spell outside of formal employment  $\kappa$ . Specifically, we compute  $\mathbb{E}[\ln w_{it} | X = X_0, \tau = t, \kappa = k] = \hat{\beta}_0 + \hat{\beta}_\tau + \hat{\beta}_\kappa + \hat{\beta}_\kappa^\kappa$ , where  $X_0$  is the base category. Once again standard errors are clustered at the worker

<sup>18</sup>We test for differences in the coefficients  $\beta_\tau^{\text{male}}$  and  $\beta_\tau^{\text{female}}$ . In the first year upon reentry, the log difference between wages of men and women is not statistically significant, that is, we cannot reject that  $\beta_{1,\text{male}} = \beta_{1,\text{female}}$ . But if we perform a test on the difference in these coefficients along the whole recovery path, namely we jointly test that  $\beta_{1,\text{male}} = \beta_{1,\text{female}}$ , and  $\beta_{2,\text{male}} = \beta_{2,\text{female}}$ , and  $\beta_{3,\text{male}} = \beta_{3,\text{female}}$ , and we find that these differences are indeed statistically significant confirming that overall men experience a slower wage recovery toward preexit levels than women.

<sup>19</sup>The base category of this regression,  $X_0$  is defined as: age = 25; sector = agriculture; state = Aguascalientes; year = 2005;  $\tau = 0, \kappa = 1$ .

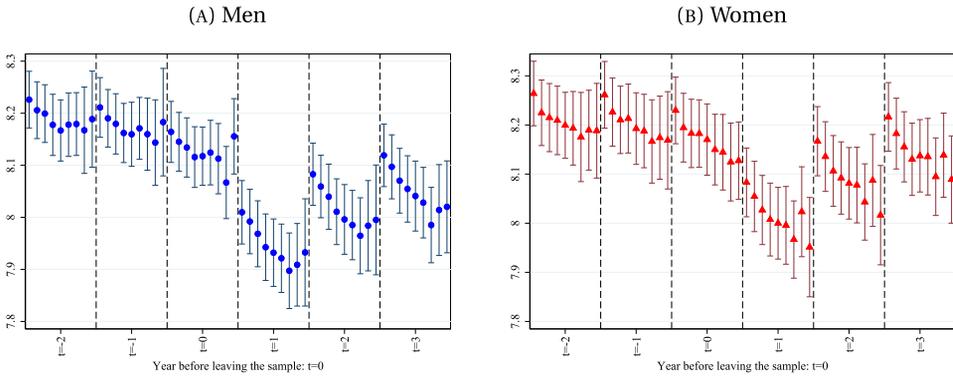


FIGURE 17. Estimates of wages trajectories (levels) of workers who exit and reenter formal employment. *Note:* Based on authors’ estimates with data from IMSS. The figure plots the conditional means of log wages computed as  $\mathbb{E}[\ln w_{it} | X = X_0, \tau = t, \kappa = k] = \hat{\beta}_0 + \hat{\beta}_\tau + \hat{\beta}_k + \hat{\beta}_\tau^\kappa$  where  $X_0$  are the observable characteristics of the worker in the base category of regression (4.1) and the tuple  $(\tau, \kappa)$  accounts for every possible pair of event  $\tau$  and duration  $\kappa$ . Standard errors are clustered at the worker and sector-year levels and 95% confidence intervals are plotted together with point estimates. Standard errors and confidence intervals are obtained with the delta method.

and sector-year levels. In addition to the patterns that we already discussed in relation to Figure 16, we see in Figure 17 that, on average, women have higher wages than men upon reentry<sup>20</sup> and wages for both men and women tend to decrease with the number of years they remained out of the formal sector between their first and second spell of formal employment. Panel (B) of Figure 17 shows more clearly that in the third year upon reentry, women whose stint out of formal employment was relatively brief are able to fully catch up with the wage they earned in the year right before exiting, while men, even those with the shortest duration between spells of formal employment, are still lagging behind.

For robustness, we verify that our results are not driven by other possibly confounding factors. For instance, we look at the preexit and post reentry wage trajectories of workers whose first spell of formal employment came to an end due to the 2009 financial crisis. We find that the wage patterns we document in our benchmark specification are a general feature of the transitions out and back into formal employment and do not seem to be driven by the specific exit/reentry that occurred during the financial crisis (see Appendix D of the Online Supplementary Material for a more in-depth discussion of the findings of this exercise).

As an additional robustness check, we also run a placebo test by comparing the wage trajectories of workers with two spells of formal employment with the trajectories of the group of workers who stayed in the database the entire period in a fashion very simi-

<sup>20</sup>We formally test that the difference in the conditional means of female and male workers is different in each event period by running the regression:  $\ln(w_{it}) = \beta_0 + \beta_{\text{female}} \mathbb{I}_{\text{female}} + \sum_{\tau=-2}^3 \beta_\tau \mathbb{I}_\tau + \sum_{\tau=-2}^3 \beta_\tau \mathbb{I}_\tau \mathbb{I}_{\text{female}} + \alpha_e + \alpha_s + \alpha_t + (\alpha'_e + \alpha'_s + \alpha'_t) \times \mathbb{I}_{\text{female}} + \varepsilon_{it}$  and testing whether  $\mathbb{E}[\ln(w_{it}) | X, \mathbb{I}_{\text{female}} = 1, \tau = t] - \mathbb{E}[\ln(w_{it}) | X, \mathbb{I}_{\text{female}} = 0, \tau = t] = 0$ . We confirm that, starting from  $\tau = 2$  on, this difference is indeed statistically different than zero.

lar to a difference-in-differences event study design. This design is based on assigning placebo exits and duration of spells out of formal employment to individuals who remained formally employed throughout the whole period. Even though we do not intend to interpret these results as causal, they serve as a useful tool for assessing whether the features that we find in the group of workers who leave and reenter formal employment are peculiar to this group.

To carry out this exercise, we construct a control group comprised of workers who are present in the IMSS data the whole 15 years for which information is available and compare their wage dynamics with those of workers who constitute our treatment group—workers who leave formal employment only once and then come back. We use the Coarsened Exact Matching (CEM) method described in [Iacus, King, and Porro \(2012\)](#) to obtain a balanced sample of the treatment and control groups. Through this methodology we find for 66.3% of workers who could potentially be in the treatment group an exact match in terms of age (age is coarsened into 5-year age groups), gender, sector of economic activity and locality (state) who were observed in their last year before exiting formal employment. Consistent with this methodology, the exact match is chosen randomly among potential candidates, so that we can construct placebo exit events for the individuals in the control group. We assume that each worker in the control group left the database in the same year as his/her match in the treatment group, and that he/she was out of formal employment for the same number of years as his/her treatment group counterpart. Having defined the placebo events for the control group, we then proceed to estimate the following specification:

$$\ln(w_{it}) = \sum_{\tau=-2}^3 \beta_{\tau} \mathbb{I}_{\tau} + \delta_{\text{treated}} \mathbb{I}_{i, \text{treated}} + \sum_{\tau=-2}^3 \beta_{\tau}^{\text{treated}} \mathbb{I}_{\tau} \mathbb{I}_{i, \text{treated}} + \gamma_g \mathbb{I}_g + \alpha_e + \alpha_s + \alpha_t + \varepsilon_{it}, \quad (4.2)$$

where  $\mathbb{I}_{i, \text{treated}}$  is a dummy variable that takes the value of 1 if worker  $i$  is part of the treatment group and 0 otherwise. We cluster the standard errors at the worker and sector-year levels.

Mean log wages are displayed in [Figure 18](#) and are obtained using the estimated coefficients from equation (4.2) to calculate  $\mathbb{E}[\ln w_{it} | X = X_0, \tau = t, \mathbb{I}_{i, \text{treated}} = 1] = \hat{\beta}_{\tau} + \hat{\delta}_{\text{treated}} + \hat{\beta}_{\tau}^{\text{treated}}$ .<sup>21</sup> On average, workers in the control group have higher wages in each event and show a slight upward trend in their wages (more so for women), as opposed to the fall observed in the year before exit for workers in the treatment group. These results suggest that the patterns that we estimate in our benchmark specification are not driven by the treatment group merely reflecting a pattern that is also present for workers who do not incur the exit event (i.e., the control group). That is, the wage dynamics for workers who exit and reenter formal employment can be associated with the fact that these workers spent some time out of the formal sector. For instance, workers who suffer an exit event have lower average preexit wages than those who remained continuously

<sup>21</sup>The estimation output of equation (4.2) is available in Appendix D of the Online Supplementary Material.

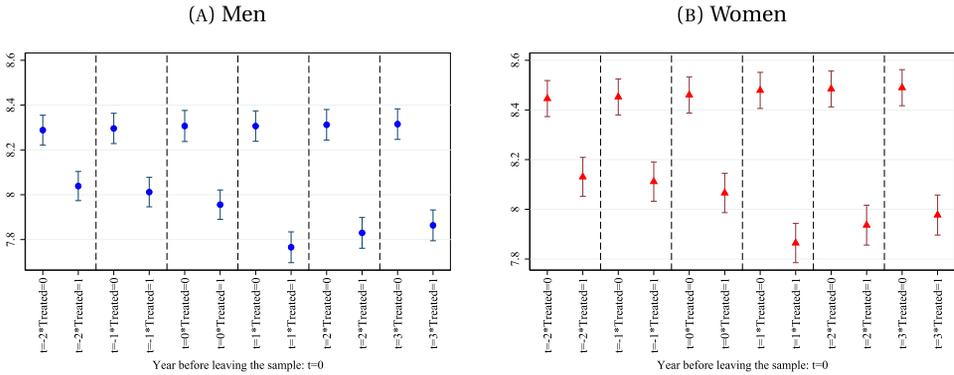


FIGURE 18. Estimates of wages trajectories: treatment versus control group. *Note:* Based on authors’ estimates with data from IMSS. The figure plots the mean of log wages for the worker in the base category of the regression, conditioning on the worker belonging to the treatment or to the control group, for each event period  $\tau$ . We compute  $\mathbb{E}[\ln w_{it} | X = X_0, \tau = t, \mathbb{I}_{i,treated} = 1] = \hat{\beta}_\tau + \hat{\delta}_{treated} + \hat{\beta}_\tau^{treated}$  using the estimated coefficients from equation (4.2) where we use a control group of workers randomly selected among those who are always present in the IMSS data and a subsample of workers with only two spells of formal employment as the treatment group. Standard errors are clustered at the worker and sector-year levels and 95% confidence intervals are plotted together with point estimates.

attached to a formal job. This suggests that workers at the bottom of the residualized earning distribution described in Section 3.2 may be more likely to exit formal employment. In turn, lower income workers face both a temporary income shock upon exiting formal employment and a more persistent effect on future earnings due to the wage penalty upon reentry. Thus, entry and exit into and out of formal employment are likely to exacerbate residualized earnings inequality.

### 5. CONCLUDING REMARKS

Using social security records for millions of Mexican formal sector workers, we have studied the distribution of earnings, mobility patterns in this distribution, and the distribution of earnings changes that characterize the dynamics of earnings. Following a nonparametric approach, we reach the following conclusions: the distribution of 1-year earnings changes displays significant deviations from normality, with these deviations varying over the life cycle, across the permanent income distribution, and to a lesser extent, across genders. We find that lower-income and younger workers face, on average, more dispersion in earnings changes, while lower-income and older workers face a distribution of 1-year earnings changes with a more pronounced peak. The distribution of earnings changes is not symmetric, but whether it is left or right skewed depends on gender, age, and income: the distribution is most right skewed for lower-income and older women, and it is most left skewed for higher income and younger men. Additionally, the distribution of log earnings displays decreasing dispersion (or inequality) starting in 2015. Finally, we find that upward mobility within the earnings distribution is highest

for lower-income and younger workers, while downward mobility is highest for higher-income and younger workers. At the very top of the distribution (top 0.1%), we find little to no mobility.

After establishing these results, we compare them with results based on a comparable sample of workers from the household survey. The main takeaway of this comparison exercise is that, even if the administrative data do not contain information on an important part of the labor force—informal workers—they are a particularly valuable source of information for studying the top portion of the income distribution and, more importantly, for analyzing income dynamics. Survey data have the advantage of including both formal and informal workers but suffer from important limitations, such as nonrandom nonresponse concentrated among high earners (formal and more educated workers), that may provide an inaccurate picture of important issues such as income inequality and the dynamics of top earnings. We further extend our analysis on the dynamics of earnings of Mexican workers by studying how transitions out of and back into formal employment affect earnings. In this regard, we find that workers who transition out of formal employment are subject to an earnings penalty upon reentry. This penalty is a cost that workers must bear for 3 years or more before achieving a level of earnings that is comparable to preexit levels.

We hope that our findings can inform future research and policy analysis regarding the Mexican labor market and that studying more in depth its structure and peculiar traits can shed light on the key factors that are germane to the distribution of earnings and earnings shocks in Mexico. Understanding and giving context to these factors is also crucial for performing meaningful cross-country comparisons of these distributions. Future research could benefit from access to tax records that could help overcome the limitations of our analysis for the very top of the earnings distribution. Further work regarding the dual nature of the Mexican labor market, a feature that is also important in other developing countries, and the ways in which earnings dynamics are shaped by workers' transitions across formal and informal employment is also a promising and relevant avenue for future research (see [Engbom et al. \(2022\)](#) for an insightful contribution in this direction).

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