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The evolution of the earnings distribution in a volatile economy: Evidence from Argentina

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The Evolution of the Earnings Distribution in a Volatile Economy: Evidence from Argentina*

Andres Blanco† Bernardo Diaz de Astarloa‡ Andres Drenik§

Christian Moser¶ Danilo Trupkin||

February 4, 2021

Abstract

This paper studies earnings inequality and dynamics in Argentina between 1996 and 2015. Following the 2001–2002 crisis, the Argentine economy transitioned from a low- to a high-inflation regime. At the same time, the number of collective bargaining agreements increased, and minimum wage adjustments became more frequent. We document that this macroeconomic transition was associated with a persistent decrease in the dispersion of real earnings and cyclical movements in higher-order moments of the distribution of earnings innovations. To understand this transition at the micro level, we estimate processes of regular wage adjustments within job spells. As the Argentine economy transitioned from low to high inflation, the monthly frequency of regular wage adjustments almost doubled, while the distribution of changes in regular wages morphed from having a mode close to zero and being positively skewed to having a positive mode and being more symmetric.

Keywords: Income Inequality, Income Volatility, Income Mobility, Wage Rigidity, Inflation.

JEL Classification: D31, E24, E31, J31.

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†University of Michigan. Email: jablanco@umich.edu.

‡CEDLAS and University of Buenos Aires. Email: bdiazdeastarloa@gmail.com.

§Columbia University. Email: ad3376@columbia.edu.

¶Columbia University, FRB Minneapolis, and CEPR. Email: c.moser@columbia.edu.

||University of Buenos Aires. Email: danilo.trupkin@fce.uba.ar.

1 Introduction

How are workers' fates tied to macroeconomic conditions? Who are the winners and losers as labor markets adjust to economic downturns and subsequent recoveries? And to what extent does the flexibility to adjust vary with macroeconomic conditions as well as throughout the workforce? The answers to these questions are of great importance for evaluating the welfare consequences of aggregate fluctuations and also for designing economic stabilization tools such as fiscal and monetary policy.

As part of the Global Income Dynamics Project, we address these questions by studying individual labor market outcomes in a large emerging-market economy. Using newly available administrative data, we analyze time trends and cross-sectional heterogeneity in earnings inequality, volatility, and mobility from 1996 to 2015 in Argentina.

This period was volatile for the Argentine macroeconomy. The country experienced several severe recessions and a sharp devaluation of its currency, which prompted a switch in the inflation regime. At the same time, there were substantial changes in the role of unions, the minimum wage, and other labor market institutions. The confluence of these events makes Argentina a particularly interesting setting to study worker-level labor market outcomes in the shadow of macroeconomic turbulence.

Our paper is the first to use administrative data from Argentina to document recent trends in earnings inequality, volatility, and mobility. We leverage newly available administrative data from Argentina's social security system, which comprise over 100 million job records over the period from 1996 to 2015. The large-scale administrative data provide a richer picture of the evolution of earnings inequality, volatility, and mobility than has been possible in previous studies.[1] Specifically, we are able to reliably compute the evolution of higher-order (e.g., third and fourth) standardized moments of Argentina's distribution of earnings and earnings innovations, akin to a recent study by Guvenen, Ozkan and Song (2014) based on 34 years of U.S. social security records. Since the administrative data cover only jobs in Argentina's formal sector, we also supplement our analysis with rich household survey data that allow us to validate our findings based on administrative records and also to compare labor market outcomes in Argentina's formal and informal sectors. In addition, a unique contribution of our paper is our leveraging of administrative data to measure the frequency and size of wage adjustments in Argentina during low- and high-inflation regimes, both in the aggregate and across subgroups of workers.

[1] Previous studies of the earnings distribution in Argentina have relied on household survey data. See, for example, Cruces and Gasparini (2009), Gasparini and Cruces (2010), and Alvaredo, Cruces and Gasparini (2018).

The first part of this paper implements a set of standardized measurement exercises related to earnings inequality, volatility, and mobility, using detailed administrative data on all formal, private sector jobs in Argentina. After nearly stagnant earnings from 1996 to 2001, the vast majority of workers saw a remarkable drop of over 20% in real terms amidst Argentina's economic crisis in 2001–2002. Following the crash, real earnings recovered quickly and reached new heights between 2002 and 2008, with more moderate growth thereafter, led by relatively more pronounced growth at the bottom of the distribution. These facts hold true among the bottom 90% of the formal sector earnings distribution, while real earnings above the 90th percentile fluctuated without significant net gains over this period. As a result, Argentina saw a marked decrease in earnings inequality among formal sector workers between 2002 and 2008, both within and across cohorts.

We then document cyclical movements in the dispersion, skewness, and kurtosis of earnings innovations in Argentina from 1996 to 2015, building on previous work by Guvenen et al. (2014) and Guvenen, Karahan, Ozkan and Song (2015). We find that lower-tail dispersion in 1-year earnings innovations is countercyclical (i.e., it is higher during recessions), while upper-tail dispersion is procyclical (i.e., it is lower during recessions); these findings are similar to patterns that have been documented for the U.S. This means that, in net, offsetting cyclical movements in the two tails of the distribution lead to muted cyclical movements in the overall dispersion in earnings innovations at business cycle frequency. In levels, the skewness of 1-year earnings innovations in Argentina is more positive than that for the U.S., while the kurtosis is of comparable levels. Over time, both the skewness and kurtosis of 1-year earnings innovations are strongly procyclical in Argentina, akin to those of the U.S.

A common view holds that cross-sectional earnings inequality is less concerning if accompanied by high rates of earnings mobility (meaning greater movement through the ranks of the earnings distribution) over time. Kopczuk, Saez and Song (2010) find that long-term mobility in the U.S. has increased overall but slightly decreased for men over the second half of the 20th century. Compared with recent evidence on earnings mobility in the U.S. (McKinney and Abowd, 2021), our findings document significantly higher 10-year earnings mobility among workers in the bottom quartile of the earnings distribution in Argentina. We find that both upward and downward mobility are higher for younger workers and comparable between men and women. Furthermore, mobility in Argentina has been approximately stable during the 2000s.

As part of our empirical investigation, we use rich household survey data to complement the administrative records and achieve two goals. First, we can validate our findings on earnings inequality and dynamics in Argentina's formal sector between the two—administrative and

household survey—datasets. We find that they show qualitatively similar patterns but have some important quantitative differences. Second, we can compare earnings inequality and dynamics between Argentina's formal and informal sectors. As is the case in other emerging economies, the informal sector constitutes an important part of Argentina's economy, with between 29% and 43 % of all employees in our sample working in informal (i.e., not covered by the social security system) jobs over the period we study. Here, we document significant differences in the distribution of earnings between formal and informal jobs, both in levels and also in time trends.[2]

The second part of this paper studies a particular aspect of the flexibility of labor market adjustments to macroeconomic conditions by quantifying nominal wage rigidities in Argentina. Frictions that prevent the adjustment of nominal wages are a core ingredient in many macroeconomic models of empirically realistic business cycle fluctuations. For instance, Christiano, Eichenbaum and Evans (2005) highlight staggered wage contracts as one of the most important features needed to match the observed dynamic effect of a monetary policy shock in a New Keynesian model. Similarly, Shimer (2004) shows that wage rigidity can solve the lack of propagation in the Mortensen-Pissarides search and matching model. In the international macro literature, Schmitt-Grohé and Uribe (2016) argue that wage rigidity can explain sharp differences in employment dynamics between fixed and floating exchange rates in a small-open-economy neoclassical model. Given the importance of wage rigidity in modern business cycle theories, extensive studies measure aggregate wages' business cycle properties. While business cycle moments of *aggregate* wages are well understood, our understanding of the nature of wage rigidity is incomplete without a set of facts about wage setting at the *micro* level.

Our analysis contributes to understanding wage rigidities by presenting facts about nominal wage setting under different inflation regimes. At a first glance of our data, individual wages appear to be changing almost every month, even when inflation is low and aggregate wages remain almost constant. On closer inspection, individual wages exhibit two clear patterns: either they revert to the exact previous nominal value after temporary deviations, or they fluctuate closely around a "regular" wage. Theory in the price-setting literature shows that aggregate price flexibility depends on the composition of price changes between those of a transitory or a permanent nature (see Eichenbaum, Jaimovich and Rebelo, 2011; Kehoe and Midrigan, 2015; Alvarez and Lippi, 2020). Motivated by this theory, we use methods developed in the pricing literature to construct regular wage changes. We construct regular wages using the Break Test proposed

[2]In this manner, we contribute to an emerging literature that compares administrative and household survey data in other emerging economies such as Brazil (Engbom, Gonzaga, Moser and Olivieri, 2021) and Mexico (Calderón, Cebreros, Fernández, Inguanzo, Jaume and Puggioni, 2021).

by Stevens (2020). This methodology detects breaks in the stochastic process of wages in non-Gaussian wage-setting models. We verify the validity of this methodology by calibrating and simulating a model that matches features of the wage-setting process in the actual data.

Our main finding pertains to the evolution of the frequency of regular wage changes. We find that in periods of low inflation (such as 1997-2001), the average monthly and annual frequencies are 0.09 and 0.64, respectively. Similar results have been found in other countries with low inflation (see, e.g., Grigsby, Hurst and Yildirmaz, 2019), which provides further support to our methodology for constructing regular wages. In contrast, during the period of high inflation (i.e., 2007-2015), the average annual frequency of wage change rises to 0.95. In addition, the transition from these two inflationary regimes encompasses other differences: the annual frequency of upward wage changes increases from an average of 0.44 to 0.90, while the frequency of decreases plummets from 0.2 to 0.05. Finally, the richness of the data allows us to study the frequency of wage adjustment for a wide set of workers. We find that in periods of low inflation, the frequency of wage changes falls with workers' ages and earnings ranks, and is largely heterogeneous across sectors. However, as inflation raises, the heterogeneity across workers becomes less pronounced.

Finally, we document a significant difference in the shape of the regular wage change distribution between low- and high-inflation regimes. During the low-inflation period, the distribution of regular wage changes (i) is asymmetric, with a missing mass of negative wage changes, and (ii) exhibits a large spike at positive-small changes. The pronounced asymmetry between positive and negative wage changes is consistent with previous studies analyzing the distribution of wage changes in low-inflation environments (see, e.g., Dickens, Goette, Groshen, Holden, Messina, Schweitzer, Turunen and Ward, 2007; Barattieri, Basu and Gottschalk, 2014; Grigsby et al., 2019). In contrast, during the high-inflation period, the wage change distribution is symmetric around a mean close to the annual inflation rate. The gap between the 50th and 10th percentiles of the change distribution is 22 log points, almost equal to the difference between the 90th and 50th percentiles (21 log points).

The paper is organized as follows. Section 2 describes the data. Section 3 provides the macroeconomic background in Argentina during the period of analysis. Section 4 presents a set of standardized statistics on earnings inequality, volatility, and mobility. Section 5 validates those findings by comparing administrative and household survey data and also studies the earnings distribution in Argentina's formal and informal sectors. Section 6 presents our results relating to nominal wage rigidity. Finally, Section 7 concludes.

2 Data

In this section, we introduce the administrative data we use to study earnings inequality and dynamics in Argentina. We also describe the selection criteria applied to select various samples, define the main variables, and present summary statistics. We complement our analysis using household survey data, which we use for data validation and comparisons of earnings inequality and dynamics in Argentina's formal and informal sectors. Finally, we briefly discuss other data sources that we use in our analysis.

2.1 Administrative Data

Data Description. Our primary data source consists of employer-employee matched panel data based on administrative records from Argentina's social security system, called *Sistema Integrado Previsional Argentino* (SIPA). Records come from sworn statements that employers must present by law each month to Argentina's tax authority, *Administración Federal de Ingresos Públicos* (AFIP). These records contain information about payroll for which employers pay social security contributions (i.e., that for formal workers). We work with a 3% random, anonymized subsample of employees in the private sector spanning the 1996–2015 period.[3]

Employees' information includes gross labor earnings, inclusive of all forms of monthly compensation that can trigger tax liabilities and social security contributions (i.e., base wage, overtime compensation, bonuses, severance payments). It also includes demographic characteristics such as gender, year of birth, and the province of the establishment where they work. Earnings information is top-coded to protect the privacy of employees.[4] However, statements do not include information about employees' education status. Information about employers includes their four-digit industry code.[5] Employees' anonymized unique identifiers and identifiers for each employer-employee match allow us to track individual workers and formal employment relationships over time.[6]

The dataset is representative of the formally employed population at private firms in all sec-

[3]The random sample is the *Registered Employment Longitudinal Sample* (RELS) compiled by the Ministry of Labor, Employment and Social Security of Argentina at a monthly frequency. The microdata and documentation are publicly available at http://www.trabajo.gob.ar/estadisticas/oede/mler.asp.

[4]The Ministry of Labor, Employment and Social Security documentation specifies that, for each month, earnings higher than the 98th percentile were replaced by a three-month moving average of gross wages aggregated within two-digit industries.

[5]To complete information about employers and employees, the Ministry of Labor, Employment and Social Security combines records from SIPA with employers' sector and type information from AFIP, and workers' gender and year of birth from Argentina's Social Security Agency (ANSES). The industry classification was developed by AFIP, closely following a correspondence with the ISIC Revision 4.

[6]Employers' identifiers are not included in the sample.

tors and regions and covering all types of contracts (e.g., full-time workers, internships, temporary workers). It contains data from about 130,000 workers in 1996 to 230,000 in 2015. With formal private employment accounting for roughly 30% to 40% of total employment over the period (including independent and self-employed workers), the sample amounts to about 1% of the employed population in any given year.

Sample Selection. To enhance harmonization and allow meaningful comparisons across countries in the project, we restrict the original dataset according to the following criteria. First, we focus on workers between 25 and 55 years old, a range within which most education choices are usually completed in Argentina and after which workers tend to leave the labor force for retirement.[7]

Second, we drop observations with earnings below a threshold to avoid observations from workers without a meaningful attachment to the labor force or with very low earnings, which could skew log-based statistics. Specifically, we discard observations with earnings below what a worker would earn if they were to work part-time for one quarter at the national minimum wage. In Argentina, the minimum wage is set as a monthly wage and is usually revised at the middle of the year. Maximum legal working hours are 48 hours per week, which in an average month amount to $52/12 \times 48 = 208$ hours. We compute the equivalent hourly minimum wage for Argentina as $y^h_{ts} \equiv y^m_{ts}/208$, where y^m_{ts} is the minimum wage in year t and month s. The annual average hourly minimum wage is then $y^h_t = \sum_{s=1}^{12} y^h_{ts}/12$. Finally, the threshold is chosen as part-time (24 hours) earnings for one quarter (13 weeks) at the national minimum wage, or $\underline{y}_t \equiv y^h_t \times 13 \times 24$. For future reference, we label the sample with age and minimum earnings restrictions as the *CS* sample.

In addition to age- and minimum earnings-related criteria, when computing longitudinal statistics, we apply two additional restrictions. First, we consider a subsample of workers for which we can compute one-year and five-year earnings changes; we call this the *LX* sample. Then, we further restrict the *LX* sample to observations for which we can compute a permanent earnings measure, as defined below; this limits the sample to workers in a given year who have been in the sample for the previous three consecutive years. We label the latter LX^+ sample.

Variable Construction. For our statistical analysis, we construct several measures of earnings for worker i in year t:

1. Raw real earnings in levels, y_{it}, and logs, $\log(y_{it})$. We compute real earnings from total

[7] Note that the minimum formal retirement age in Argentina is 65 for men and 60 for women.

annual worker compensation and our measure of CPI inflation.

2. Residualized log earnings, ε_{it}. This measure is the residual from a regression of log real earnings on a full set of age dummies, separately for each year and gender. It is intended to control for trends in earnings across workers at different stages of their life or business cycle.

3. Permanent earnings, P_{it-1}. They are defined as average earnings over the previous three years, $P_{it-1} = (\sum_{s=t-3}^{t-1} y_{is})/3$, where y_{is} can include earnings below $\underline{y}_s$ for at most one year.

4. Residualized permanent earnings, ε_{it}^P. These are computed from P_{it-1} similarly to ε_{it}.

5. One-year change in residualized log earnings, g_{it}^1. It is the one-year forward change in ε_{it}, $g_{it}^1 \equiv \Delta\varepsilon_{it} = \varepsilon_{it+1} - \varepsilon_{it}$, where earnings must be above $\underline{y}$ for both years.

6. Five-year change in residualized log earnings, g_{it}^5. It is the five-year forward change in ε_{it}, $g_{it}^5 \equiv \Delta^5\varepsilon_{it} = \varepsilon_{it+5} - \varepsilon_{it}$, where earnings must be above $\underline{y}$ for both years.

Summary Statistics. Table 1 presents sample sizes for our different sample selection criteria. After imposing restrictions on age and minimum earnings for cross-sectional analysis (the *CS* sample), we are left with around 70% of the sample. When we further restrict the sample for longitudinal analysis involving one- and five-year changes, the *LX* sample reduces to between 41% and 47%. The LX^+ sample, which reduces to observations between 1999 and 2010, includes between 34% and 38% of the original sample. The percentage of women remains almost identical after the cross-sectional restrictions and slightly decreases after selecting the sample to allow for the computation of one- and five-year changes and permanent earnings.

Table 2 reports summary statistics of the monthly real earnings distribution in the unrestricted sample. Average monthly real earnings (in 2018 AR$) increased by 34% over the sample period, from AR$11,725 to AR$15,673. There is wide dispersion in earnings, with the 5th and 99th percentiles of the distribution representing on average around 9% and 580% of the mean, respectively. As we will study in detail below, although there was an overall increase in real earnings over the period, growth was monotonically decreasing in percentiles of the earnings distribution. Real monthly earnings at the 5th percentile grew by 90% between 1996 and 2015, while earnings at the 95th and 99th percentiles increased in real terms by only 14.5% and 2.5%, respectively.

2.2 Household Survey Data

Data Description. We complement our analysis with rich household survey data covering both formal and informal employment in Argentina. The Permanent Household Survey (*Encuesta Per-*

Table 1: Employer-Employee Administrative Data Sample Selection and Size: Argentina, 1996–2015

Year	Original dataset		*CS* sample		*LX* sample		LX^+ sample	
	N	% Women	*N*	% Women	*N*	% Women	*N*	% Women
1996	134,430	27.0	97,197	26.5	55,413	25.2	-	-
2000	148,805	29.5	107,375	29.3	63,643	28.1	50,860	26.53
2005	173,522	29.9	123,375	29.8	80,897	28.0	58,545	27.68
2010	213,263	31.5	153,392	31.6	99,651	29.9	81,469	28.69
2015	229,876	32.3	167,595	32.8	-		-	-

Notes: This table reports the number of workers (*N*) and the fraction of women for the original random sample and under alternative sample selection criteria. The CS sample includes age and minimum earnings restrictions; the LX sample includes further restrictions to compute one- and five-year changes in earnings; the LX^+ sample includes still further restrictions to compute permanent earnings.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

Table 2: Monthly Labor Earnings Summary Statistics: Argentina, 1996–2015

Year	Mean	Std. Dev.	P5	P25	P50	P75	P95	P99
1996	11,725	16,975	828	3,764	7,415	13,949	35,017	74,876
2000	12,573	22,109	873	3,983	7,527	14,259	37,822	87,041
2005	11,762	17,772	1,239	4,583	8,565	13,401	31,142	67,819
2010	14,241	17,370	1,569	5,865	10,985	17,121	37,100	70,419
2015	15,673	18,794	1,570	6,569	12,597	19,175	40,093	76,745
%Δ, 1996–2015	33.7	-	89.6	74.5	69.9	37.5	14.5	2.5

Notes: This table reports monthly real earnings in 2018 AR$. P*x* indicates the *x*th percentile of the cross-sectional monthly labor earnings distribution for each year. The last row of the table computes the percentage growth rate of each column between 1996 and 2015.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

manente de Hogares or EPH) is Argentina's primary household survey collected by the National Institute of Statistics and Census (*Instituto Nacional de Estadística y Censos* or INDEC). It covers 31 large urban areas that represent more than 60% of the total population. Every year, the overall sample size is around 100,000 households, and the average response rate is roughly 90%, which is similar to that of the March Supplement of the U.S. Current Population Survey. The EPH questionnaire elicits responses pertaining to demographics (e.g., gender, level of education, age) and labor market outcomes (e.g., labor force status, hours worked, earnings, tenure, sector, occupation, and formality status). The EPH was conducted twice a year between 1995 and 2003 and has been conducted quarterly since 2003, with a rotating panel structure allowing households to be followed across two consecutive years.

The EPH distinguishes between informal and formal employees, which allows us to both validate our findings based on administrative data and also compare labor market outcomes across

the formal and informal sectors of Argentina. The definition of (in)formality follows standard proposals by the International Labour Organization, which classifies a worker as formal if his or her employer makes mandatory social security contributions; otherwise the worker is classified as informal.

Sample Selection. We apply selection criteria similar to those for the administrative data for Argentina's formal sector. Specifically, we keep women and men between the ages of 25 and 55 who are employed in a private sector job and earn at least half the current minimum wage. Finally, we aggregate multiple observations for the same individual within a year to the worker-year level as described in the next paragraph.

Variable Construction. Using the biannual (before 2003) or quarterly (after 2003) short-panel data, we first construct a dataset at the worker-year level by constructing residualized annual earnings based on an aggregation of the (one or two) available observations per worker in each year. Appendix A.1 describes the details of this procedure.

Summary Statistics. Appendix Table A.1 shows the number of observations in each year-quarter in the raw data. Appendix Table A.2 shows quarter-quarter combinations for the same individual within a given year based on the rotating panel structure of the EPH household survey data. Appendix Table A.3 shows sample sizes for each year when cumulatively applying our sample selection criteria.

2.3 Macroeconomic Variables

In our analysis, we use two additional data series, CPI inflation and the Argentine peso to U.S. dollar nominal exchange rate, which we obtained from INDEC and the Central Bank of Argentina.[8]

3 Background

This section provides a brief description of the macroeconomic context in Argentina during 1996–2015 and relevant institutional features of the labor market, especially those associated with wage setting, such as the role of unions and the minimum wage. To illustrate the macroeconomic context, Panel (a) of Figure 1 displays the cyclical component of real GDP, Panel (b) shows the evolu-

[8]Because of the manipulation of official inflation statistics, we use consumer price indices provided by national statistics before 2007 and the Central Bank of Argentina from 2007 onward.

tion of inflation, Panel (c) shows the nominal exchange rate, Panel (d) displays the unemployment rate, while Panel (e) displays the formality rate during the period of analysis.

3.1 Macroeconomic Context

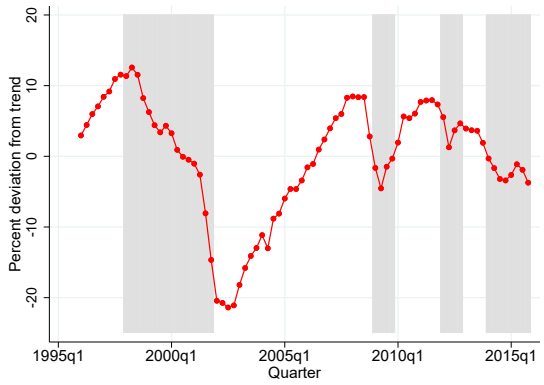
Our analysis below distinguishes two subperiods, 1996–2001 and 2002–2015. During the first subperiod, Argentina was under a currency board established by the Convertibility Plan, which pegged the Argentine peso to the U.S. dollar. By 1996, Argentina had stopped the hyperinflation of the early 1990s and had implemented a series of structural reforms. During this first period, the economy was characterized by low inflation rates, and even deflation. After a strong recovery starting in 1991, the economy was hit by a series of shocks in 1995 (the Mexican devaluation) and 1998–1999 (devaluations in east Asia, Russia, and later Brazil, Argentina's largest trade partner), which eventually pushed Argentina into a deep recession that culminated in the 2001–2002 crisis. Between 1998 and late 2001, real GDP fell by 15% and the unemployment rate increased from 12% to 20%, making this the largest crisis Argentina has experienced up to that point.

In 2002, Argentina abandoned the exchange rate peg, which raised the Argentine peso-U.S. dollar nominal exchange more than 200%. The nominal devaluation (incompletely) passed through to domestic prices, increasing the CPI by more than 40% in a year. Real wages fell by more than 20%, and the poverty rate reached a record high of 52% of the population.

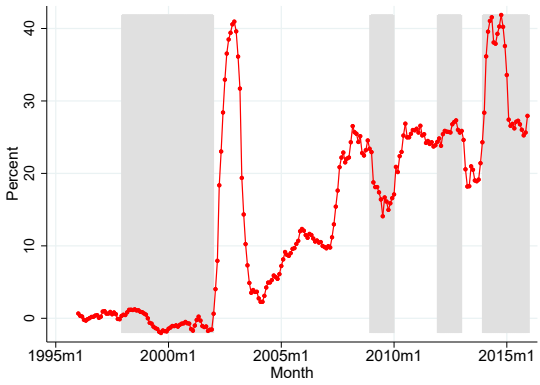
Following the crisis and devaluation, the economy recovered strongly, averaging 8% real GDP growth per year between 2004 and 2007. Changes in relative prices generated a switch in aggregate expenditure toward tradable, labor-intensive, import-substitutive sectors. The employment rate increased consistently, and by 2006, it was back to its 1998 levels. The unemployment rate decreased sharply and went below 10% by 2006.

After inflation stabilized in 2003–2004, inflationary pressures started mounting, fueled by a combination of growing aggregate demand for non-tradable goods and services, increased public spending (part of which was financed by central bank transfers), and nominal devaluations in 2009 and 2014. Between 2008 and 2015, monthly year-on-year inflation averaged 25%. After the 2008 global recession, Argentina was not able to attain high output growth rates. Eventually, the economy entered into stagflation: between 2011 and 2015, the economy was in a recession in roughly half of the quarters.

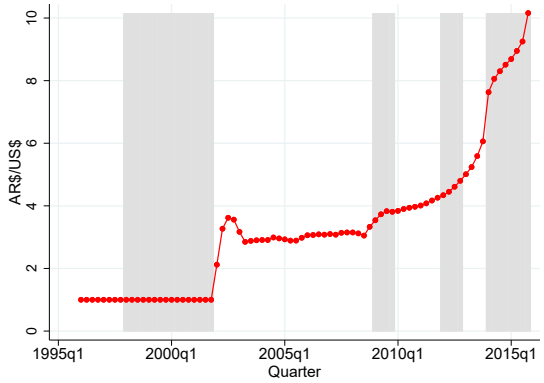
Figure 1: GDP, Inflation, Exchange Rate, Unemployment, and Formal Employment Rate in Argentina, 1996–2015



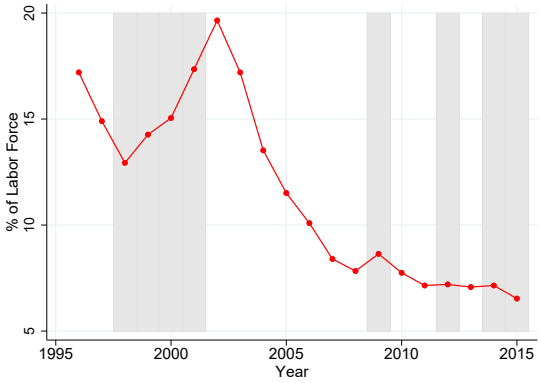
(a) Cyclical component of GDP



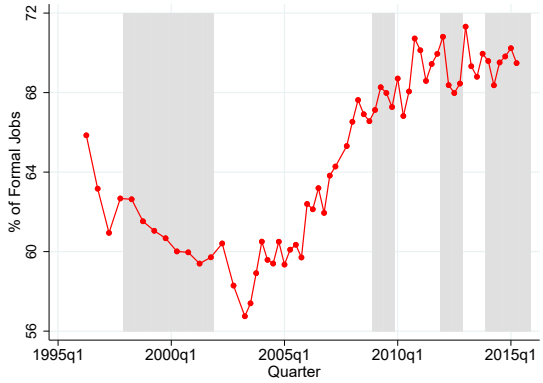
(b) Annualized inflation



(c) Nominal Exchange Rate



(d) Unemployment Rate



(e) Formal Employment Rate

Notes: Panels (a) to (e) show: (a) the deviation of quarterly real GDP from log linear trend, (b) the annual percentage change in the consumer price index, (c) the AR$ to US$ nominal exchange rate, (d) unemployment as a fraction of the labor force, and (e) the share of employment in the formal sector relative to total (formal and informal sector) employment. Shaded areas indicate recession periods.
Source: Authors' calculations based on INDEC, EPH, and Central Bank of Argentina.

3.2 Collective Bargaining Agreements and the Minimum Wage

In addition to the formal sector, Argentina has an informal sector, which represents over one-third of all employment. Wages are market based for informal workers, while in the formal sector, they are subject to labor regulations. Below, we briefly describe the role of two institutions that are essential to the process of wage setting in Argentina over the period we study: unions and the minimum wage.

Collective Bargaining Agreements. A fundamental aspect of wage setting in Argentina is the collective bargaining mechanism. Centralized unions and employers reach collective agreements with force of law, either at the sector or firm level. Agreements at the sector level apply to all formal labor relations associated with a particular sector, irrespective of whether employees have union affiliation. In contrast, firm-level agreements apply only to labor relations within the firm.[9] Once a collective agreement is signed, its rules prevail until they are explicitly modified by a new agreement, even if no new agreement is reached before the original one expires.

During the 1990s, unions' role in the wage setting process was reduced to a minimum. Most agreements were reached at the firm level and included clauses stipulating flexible working conditions rather than wage adjustment clauses. Price stability, a rigid minimum wage, and increasing unemployment discouraged unions from negotiating new agreements under very unfavorable conditions. In this way, unions preserved previously negotiated collective clauses (Palomino and Trajtemberg, 2006).

After the 2001–2002 crisis, the collective bargaining process was gradually re-established. First, in 2002, the government established a sequence of non-taxable lump-sum increases for wage earners in the private sector. In 2003, these were incorporated as updates to base wages established by previous agreements, effectively kick-starting collective bargaining between firms and unions.[10] Since 2004, collective bargaining has become more widespread, extending to virtually all sectors, and wages paid by firms gradually converged to those established in collective agreements. According to Palomino and Trajtemberg (2006), bargained wages represented around 50% of those effectively paid by firms in 2001, compared with 81% in 2006. To further illustrate this, Figure 2 shows the number of collective agreements renewals by year, which saw an unprecedented in-

[9] Specific groups of workers, such as those employed in the public sector and the agricultural and private education sectors, are excluded from the collective bargaining process in Argentina.

[10] Eventually, these wage adjustments flattened wage scales by reducing differentials among different categories of workers. Typically, collective bargaining contracts specify a scale of base wages for workers with different occupations and tenure. These scales define the wage over which workers pay taxes and social security contributions and what constitutes non-taxable labor income.

crease after 2003. While the number of agreements between 1991 and 2002 averaged 177 per year, it reached 348 in 2004 and peaked at 2,038 in 2010. As employment grew during the period, the number of private, non-agricultural workers covered by collective agreements increased substantially, from 3 to 5 million between 2003 and 2010 (Ministerio de Trabajo, Empleo y Seguridad Social, 2011).[11] A recovery based on labor-intensive sectors and the need to protect purchasing power against rising inflation explain part of this trend. Moreover, governments in this period relied on political support from unions and favored the conditions for this development.

Minimum Wage. In Argentina, the minimum wage is set by the Employment, Productivity and Minimum Wage Council (the Council from hereon), whose role is to bring together representatives of workers, employers, and the government to discuss broad issues related to labor relations and set the national minimum wage. Between 1993 and 2003, the *Council* was mostly inactive and the minimum wage was fixed at AR$200. During 2003 and 2004, the government unilaterally raised the minimum wage, which increased by 90% from 2002 to 2004 (see Figure 2). In 2004, the *Council* became active again, and since then, it has set new levels for the minimum wage with an approximately annual frequency, increasing wage floors in collective bargaining between unions and employers.[12] The latter tended to favor the weakest unions, granting their workers a higher wage floor, while stimulating the negotiation of new wage scales for unions with greater bargaining power. Between 2004 and 2015, the minimum wage increased by around 1,225% nominally and by 56% in real terms.

4 Earnings Inequality and Dynamics in Argentina

This section describes our main results regarding the evolution of earnings inequality, earnings volatility, and earnings mobility in Argentina during the 1996-2015 period.

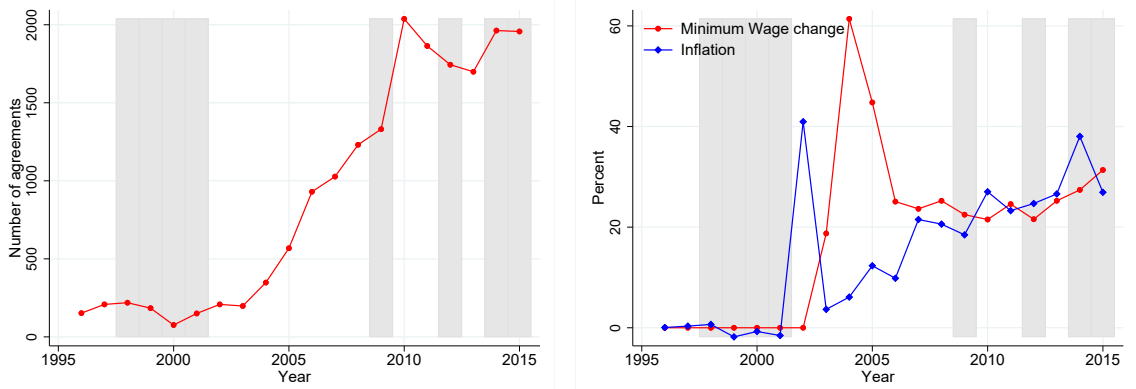
4.1 Earnings Inequality

We first document the evolution of different percentiles of the earnings distribution. Then, we describe the implications of this evolution for overall earnings inequality. Finally, we present results regarding the concentration of earnings at the top of the distribution.

[11] The fraction of workers covered by collective agreements changed only slightly, however, from around 82% in 2002 to 85% in 2009.

[12] See Casanova, Jiménez and Jiménez (2015) for a discussion of the enforcement of the minimum wage in Argentina after 2003.

Figure 2: Collective Bargaining Agreements, Minimum Wage Changes, and Inflation, 1996–2015



(a) Collective Bargaining Agreements

(b) Minimum Wage Changes and Inflation

Notes: This figure plots the evolution over the 1996–2015 period of the annual number of collective bargaining agreements in panel (a) and of the annual percentage change of the minimum wage and the consumer price index in panel (b).
Source: Ministry of Employment, Labor and Social Security of Argentina, INDEC, and Central Bank of Argentina.

The Evolution of the Earnings Distribution. Panels (a) and (b) of Figure 3 present the evolution of percentiles of the earnings distribution of men and women, respectively, normalized by their value in 1996.[13] Over the sample period, there was an overall increase in real earnings across the entire earnings distribution for both men and women. To illustrate this trend, median log real earnings were 56 and 45 log points higher for men and women, respectively, in 2015 relative to 1996. However, the magnitude of the increase was not homogeneous across the distribution. Instead, the size of the increase was monotonically decreasing in percentiles of the earnings distribution. While the 10th percentile of men's distribution increased by 69 log points, the 90th percentile increased by only 23 log points. Similar trends hold for women. The only exception to this pattern is the dynamics at the top of the earnings distribution, illustrated in Panels (c) and (d) of Figure 3 for men and women, respectively. Not only were the long-run gains experienced at the top the lowest among the reported percentiles, but some percentiles experienced small net gains, or even losses, between 1996 and 2015. Examples of such small gains or losses include the 99th and 99.9th percentiles of the distribution for men.

In addition to these long-run trends, Figure 3 shows significant fluctuations at the business cycle frequency, particularly around the 2001-2002 crisis. In the years before the crisis, there was an increase in real earnings, which was more pronounced for women at the bottom of the distribution and all workers at the top of the distribution.[14] However, given the large pass-through

[13] Appendix Figure A.1 shows similar results for the entire population.

[14] Using household survey data, Cruces (2005) finds that the impact of fluctuations in total household income during 1995–2002 was three times higher among households in the bottom quintile of the income distribution compared with

of the 2002 nominal devaluation to domestic prices, real earnings fell by more than 20 log points for the vast majority of workers. The only exception to this aggregate decline was the earnings dynamics of workers at the very top of the distribution—those above the 99.9th percentile—which exhibited resilience against the crisis and the increase in inflation. Following the crisis, there was a heterogeneous recovery of real earnings: the bottom of the earnings distribution of both men and women reached the pre-devaluation level of earnings much faster than the top of the distribution.

Blanco, Drenik and Zaratiegui (2020) analyze the labor market around the 2001–2002 crisis and highlight how labor mobility and statutory earnings floors set by unions were important in generating this heterogeneous recovery during the subsequent years. During the recessions between 2007 and 2015, the decline in real earnings was much less pronounced, and the effects on workers' earnings were limited to a slowdown in growth rates.

The Evolution of Earnings Inequality. As a result of the faster earnings growth at the bottom of the distribution, Argentina has experienced a large decline in inequality since 2002. Panels (a) and (b) of Figure 4 show the dynamics of two measures of log earnings inequality for men and women, respectively, the difference between the 90th and 10th percentiles and the standard deviation, scaled by a factor of 2.56, which corresponds to the P90-P10 differential for a Gaussian distribution. First, in terms of the level of inequality, the earnings distribution for women has been consistently less unequal than the distribution for men. Second, inequality started to decrease sharply after 2002 for both groups of workers. During the 2002-2008 period, the P90-P10 differential decreased from 2.90 to 2.43 for men and from 2.74 to 2.31 for women. Since then, inequality has mildly and similarly increased for both men and women.[15]

Panels (c) and (d) of Figure 4 show the contribution of top and bottom inequality as measured by the P90-P50 and P50-P10 differences, respectively, to the aggregate dynamics of inequality. For men, there was a similar decline in top and bottom inequality of 28 and 23 log points, respectively, between 2002 and 2008 when inequality decreased. By contrast, for women, the main contributor to the decline in inequality during the same period was top inequality, which decreased by 26 log points. While, top inequality since 2008 has remained stable or even decreased, bottom inequality has been steadily increasing, especially for men.[16]

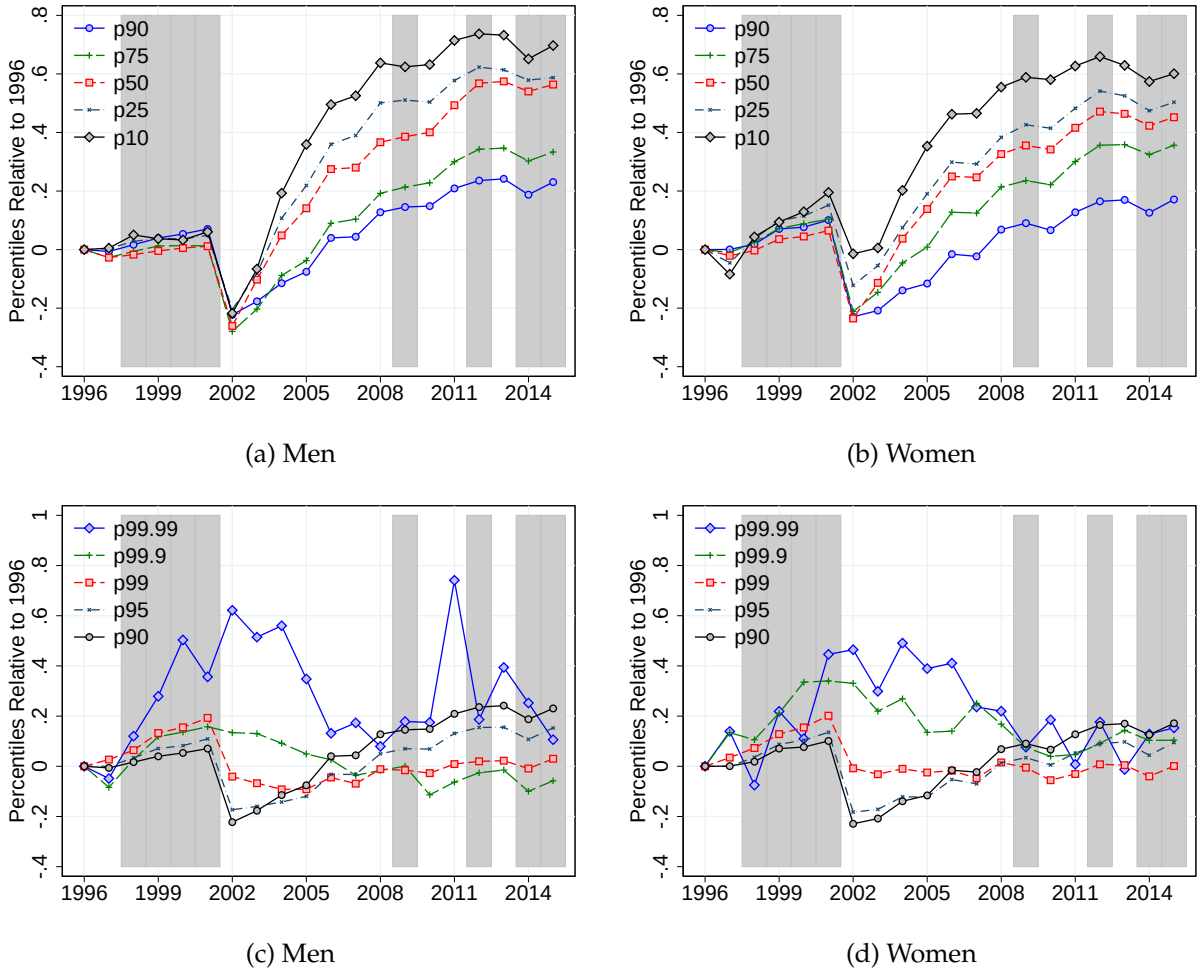
Cruces and Gasparini (2009) highlight four forces behind the reduction in earnings inequality

those in the top quintile, even during periods of positive GDP growth between 1996 and 1998.

[15] Figure A.6 shows the evolution of the Gini coefficient for the overall population, which followed dynamics similar to the previous measures of inequality, albeit with a more pronounced increase in inequality between 1996 and 2002.

[16] Appendix Figure A.2 presents similar dynamics for residual earnings after controlling for age, indicating that results are not driven by changes in the age composition of the population.

Figure 3: Change of Percentiles of the Log Real Earnings Distribution



(a) Men

(b) Women

(c) Men

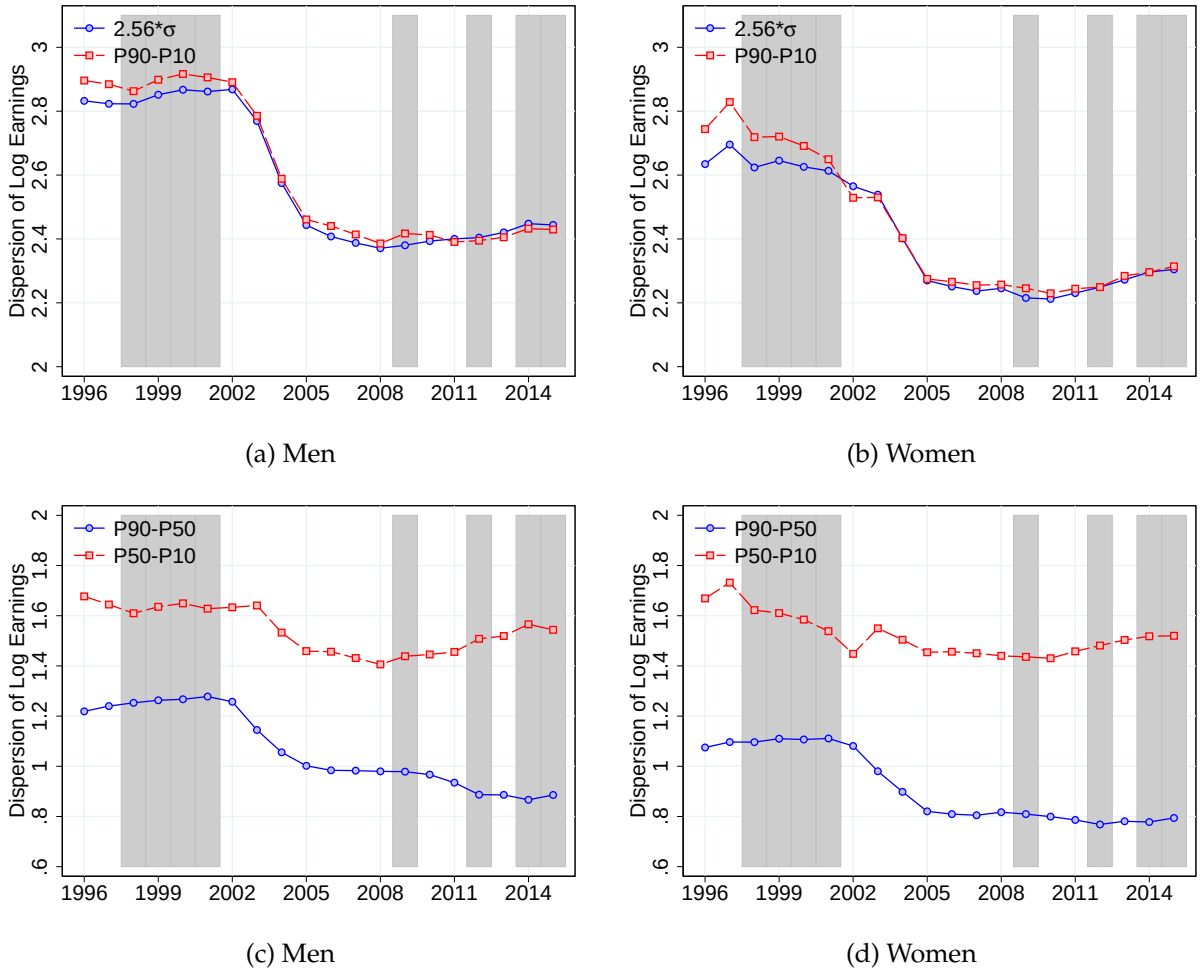
(d) Women

Notes: Using raw log earnings and the *CS* sample, Figure 3 plots the following variables against time: (a) Men: P10, P25, P50, P75, P90; (b) Women: P10, P25, P50, P75, P90; (c) Men: P90, P95, P99, P99.9, P99.99; (c) Women: P90, P95, P99, P99.9, P99.99. All percentiles are normalized to 0 in the first available year. Shaded areas indicate recessions.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

during 2003-2007: first, the recovery of labor demand, which induced upward pressure on nominal wages and earnings growth of the previously unemployed; second, changes in relative prices favoring labor-intensive industries, who were protected from imports following the devaluation; third, the potential role of decreasing technology adoption, which could have reduced earnings inequality by inducing less substitution of unskilled labor; and fourth, the aforementioned establishment of non-taxable lump-sum increases in formal workers' salaries by the government.

Initial and Life-Cycle Earnings Inequality. Previous literature has documented that earnings inequality differs significantly over the life cycle (see, e.g., Deaton and Paxson, 1994; Storesletten,

Figure 4: Earnings Inequality



(a) Men

(b) Women

(c) Men

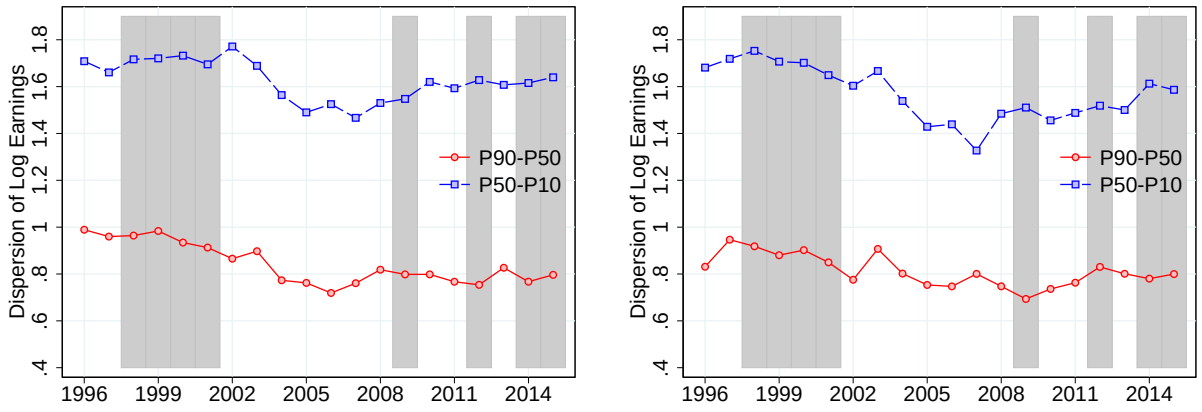
(d) Women

Notes: Using raw log earnings and the *CS* sample, Figure 4 plots the following variables against time: (a) Men: P90-10 and 2.56*SD of log earnings, (b) Women: P90-10 and 2.56*SD of log earnings, (c) Men: P90-50 and P50-10, (d) Women: P90-50 and P50-10. Shaded areas indicate recessions. 2.56*SD corresponds to the P90-10 differential for a Gaussian distribution.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

Telmer and Yaron, 2004). Figure 5 reports the evolution of top and bottom inequality for 25-year-old workers. Inequality among young workers followed dynamics similar to those as in the overall population: inequality consistently decreased until 2008, particularly at the bottom, and then increased until the end of the sample. The only difference is that the decline in inequality started before 2002, especially for the decline in top inequality. Another pattern worth highlighting is that while younger workers' earnings have lower average dispersion at the top of the distribution (e.g., top-tail inequality measured by the log P90/P50 earnings percentile ratio was 0.84 for 25-year-old men vs. 1.07 for all men), they exhibit slightly higher dispersion at the bottom of the distribution

(e.g., bottom-tail inequality measured by the log P50/P10 earnings percentile ratio was 1.63 for 25-year-old men vs. 1.54 for all men).

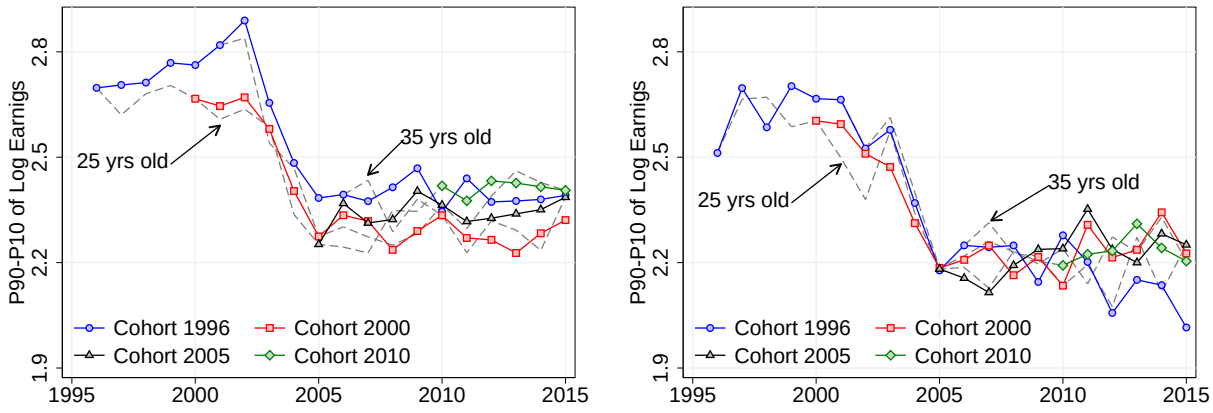
Figure 5: Initial Earnings Inequality among 25-Year-Olds



(a) Men (b) Women

Notes: Using raw log earnings and the *CS* sample, Figure 5 plots the following variables against time: (a) Men: P90-50 and P50-10 at age 25, (b) Women: P90-50 and P50-10 at age 25. Shaded areas indicate recessions.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

Figure 6: Life-Cycle Earnings Inequality Across Cohorts



(a) Men (b) Women

Notes: Using raw log earnings and the *CS* sample, Figure 6 plots the following variables against time: (a) Men: P90-10 over the life cycle for all available cohorts, (b) Women: P90-10 over the life cycle for all available cohorts.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

In Figure 6, we report the evolution of the log earnings P90-P10 differential for four different cohorts: workers who turned 25 years old in 1996, 2000, 2005, and 2010. The gray dashed lines show the evolution of log earnings dispersion for 25-, 30-, and 35-year-old workers. The overall

pattern is dominated by the aggregate decline in inequality precipitated by the 2001-2002 crisis. Since 2005, earnings inequality for men has been increasing with each additional cohort. For women, there are no large differences across the most recent cohorts.

Top Earnings Inequality. Figure A.3 in the Appendix plots the log complementary cumulative distribution function of the earnings distribution against log earnings for workers within the top 1% of the earnings distributions in 1996 and 2015. The close-to-linear relationship found in the data indicates that a Pareto distribution approximates well the right tail of the earnings distribution in Argentina. The same figure also reports estimates of the slope of the relationship between these variables, which is equal to (the negative of) the shape parameter of the Pareto distribution. Two patterns emerge. First, the earnings distribution for men is more fat-tailed than the distribution for women, as captured by the lower shape parameter in 1996 and 2015. Second, over time, the Pareto tail became thinner for both men and women.

Despite the overall decline in inequality at the top of the earnings distribution, there is substantial heterogeneity within the top 1%. Panels (a) and (b) of Figure A.5 plot the evolution of earnings shares by quintiles and by selected percentiles, respectively. Broadly, the share of earnings received by the first four quintiles increased from 1996 to 2015, at the expense of a decline of 7.7 percentage points of the top quintile's earnings share. While the earnings share received by the top 10% experienced a similar decline, the change in earnings shares received by those at the very top was remarkably different. For example, the earnings share received by the top 1% declined by only 2.5 percentage points, and the earnings share of those above the top 0.1% and 0.01% remained virtually constant throughout the entire period.

Consistent with the patterns we show in Figure A.5, Alvaredo (2010) estimates, based on personal income tax returns, that the share of income excluding capital gains that accrues to the top 0.1% increased from 4.3% in 1997 to 7% in 2004, and that of the 0.01% almost doubled from 1.4% to 2.5% over the same period. He associates this increase with the employment of high-income individuals in export-oriented sectors, which benefited from the real depreciation of the Argentine peso following the country's currency devaluation in 2002.

4.2 Earnings Dynamics

A standard life-cycle model with incomplete markets predicts that idiosyncratic earnings risk is an important determinant of consumption and savings decisions. In what follows, we document the dynamics of the distribution of earnings *changes*. More specifically, we report the evolution

of the dispersion and higher moments of the distribution of the one-year change in log residual earnings, g^1_{it}.[17]

Dynamics over Time. Figure 7 shows the evolution of the P90-P50 and P50-P10 gaps of the distribution of one-year residualized log earnings changes, which intend to capture a measure of earnings risk. The first fact to notice is that Argentina's level of earnings risk is higher than the measured risk in more advanced economies. For example, Guvenen et al. (2014) report the same measures for men in the U.S., which fluctuate mostly within the $[0.40 - 0.55]$ range. Instead, in Argentina, the top and bottom inequality of g^1_{it} exceeds that upper bound, reaching levels above 0.7. Despite these differences in levels, earnings dynamics in Argentina share patterns over time similar to those of the relative to the U.S. Over the period of analysis, overall dispersion of one-year changes (i.e., the log P90/P10 gap) decreased by 0.38 and 0.29 log points per year for men and women, respectively. Also, top and bottom inequality exhibited a negative co-movement during the business cycle, with positive (negative) shocks becoming less (more) likely during recessions.

Panel (a) of Figure 7 plots the dynamics of the Kelley skewness—a measure of symmetry—of the one-year residualized log earnings change distribution, defined as $[(P90 - P50) - (P50 - P10)]/[P90 - P10]$. Consistent with the fact that in recessions, large negative shocks become more prevalent, the figure shows a procyclical measure of skewness, similar to what Guvenen et al. (2014) find in the U.S. Such procyclicality of skewness is more pronounced for men than for women. As highlighted by Hoffmann and Malacrino (2019), this cyclical pattern can be explained by changes in employment time (e.g., due to countercyclical unemployment risk). Additionally, in Section 6, we analyze an additional source of negative skewness in recessions: the asymmetric distribution of 12-month changes in nominal monthly earnings.[18] The large shift from a negative to a positive skewness around 2002 can be explained by the slow and infrequent adjustment of nominal wages to the inflation shock experienced after the devaluation.

Panel (b) of Figure 7 plots the dynamics of the Crow-Siddiqui kurtosis—a measure of "tailedness"—of the distribution of one-year residualized log earnings changes, defined as $(P97.5 - P2.5)/(P75 - P25)$. This measure is presented relative to that corresponding to the Normal distribution. First, for both men and women, the distribution of earnings changes exhibits much fatter tails than a Normal distribution, as was previously documented by Guvenen et al. (2014) and Guvenen et al. (2015) for the U.S. Second, we find a secular increase in the kurtosis, which was temporarily

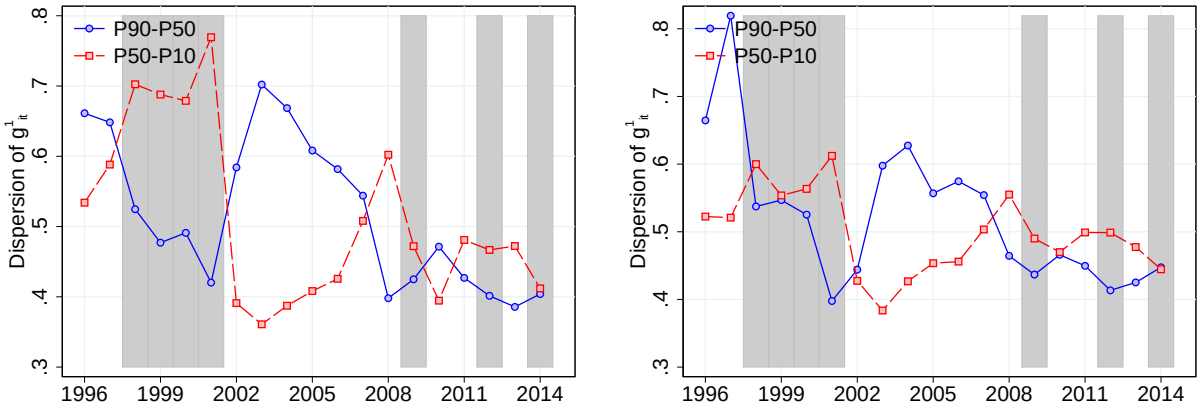
[17] In Appendix A.2, we report similar qualitative patterns for five-year changes in log residual earnings, denoted by g^5_{it}.

[18] Such asymmetry is observed only in the low-inflation period (before 2002), which can explain the lower fluctuation of skewness in the high-inflation period (after 2007).

interrupted around the end of the 2002 crisis.

To summarize, the facts shown in Figure 7 point to significant deviations between the empirical distribution of earnings changes and a Normal distribution.[19]

Figure 7: Dispersion of 1-Year Log Earnings Changes



(a) Men

(b) Women

Notes: Using residual one-year earnings changes and the *LS* sample, Figure 7 plots the following variables against time: (a) Men: P90-50 and P50-10 differentials, (b) Women: P90-50 and P50-10 differentials. Shaded areas are recessions.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

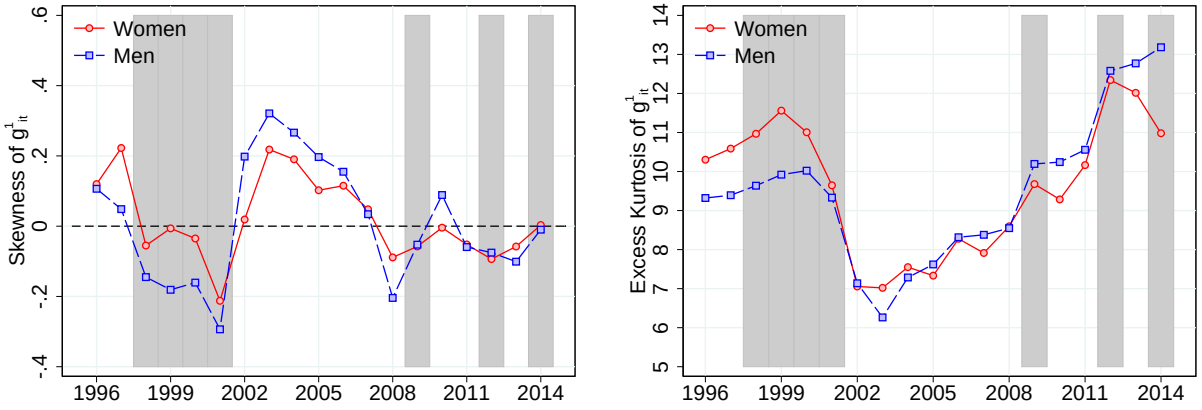
Dynamics by Age and Earnings Rank. Next, we provide facts about the distribution of one-year earnings changes by age, earnings rank, and gender. To do so, we group workers into three age groups (25–34, 35–44, and 45–55 years) and permanent earnings percentiles over the last three years.

We find that the dispersion of earnings changes is decreasing in age conditional on earnings—see Panels (a) and (b) of Figure 9 for results for men and women, respectively. We also find a *U*-shaped pattern of dispersion by earnings conditional on age. While the decline in permanent earnings at the bottom of the distribution is gradual, the increase in earnings occurs above the 95th percentile and is steep. The overall pattern is similar across gender groups, except for a higher dispersion for men at the bottom of the permanent earnings distribution, irrespective of age.

Panels (c) and (d) of Figure 9 present the Kelley skewness of one-year earnings changes. We find a more symmetric distribution for men: skewness is mostly positive but close to zero. Also,

[19] Figures A.11 and A.12 in the Appendix plot the empirical log-densities of one- and five-year earnings growth changes. Deviations from normality are evident: the distributions exhibit non-zero skewness and are leptokurtic (i.e., a more pronounced "peak" around zero changes and fatter tails).

Figure 8: Skewness and Kurtosis of One-Year Log Earnings Changes



(a) Kelley Skewness

(b) Excess Crow-Siddiqui Kurtosis

Notes: Using residual one-year earnings changes and the *LS* sample, Figure 8 plots the following variables against time: (a) Men and Women: Kelley skewness, (b) Men and Women: Excess Crow-Siddiqui kurtosis calculated as $\frac{P97.5-P2.5}{P75-P25} - 2.91$, 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 indicate recessions.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

differences in skewness across earnings and age groups among men are small. In contrast, skewness among women is much more heterogeneous across the earnings distribution: it fluctuates in the $[-0.15, 0.15]$ range, which is much wider than the range of fluctuations for men of $[-0.05, 0.10]$. Such fluctuations also follow a *U*-shaped pattern across the earnings distribution, especially those for young women: for women, skewness is positive at the bottom third of the distribution, negative in the second third, and closer to zero for women in the top third.

Regarding the Crow-Siddiqui kurtosis of earnings changes, Panels (e) and (f) of Figure 9 show an inverted *U*-shape across the permanent earnings distribution. The degree of heterogeneity across the distribution is much more pronounced for men than for women. For the former, there is a steeper increase in kurtosis for older workers at the bottom third of the distribution. For men in the middle and top of the distribution, kurtosis is highest among the youngest workers. We also observe an increase at the bottom of the distribution for women across all age groups, albeit one that is smaller in magnitude. In addition, the decline is more gradual and observed mostly among younger women.

Figure A.13 in the Appendix presents results for the distribution of five-year earnings changes by age, earnings, and gender. The overall patterns are similar, but with three main differences. First, as expected, the level of earnings volatility is higher across the earnings distribution and age groups. Second, the distribution of "persistent" earnings shocks exhibits negative skewness also

for men. Finally, the distribution of changes over a five-year horizon has thinner tails than the distribution of 1-year changes.

4.3 Mobility

In Figure 10, we analyze how earnings dynamics have affected earnings mobility over the life cycle in Argentina. We consider the average rank-rank mobility of permanent earnings over a 10-year period and look at two age brackets, 25-34 and 35-44, for both men and women. Consistent with the compression in the earnings distribution we have documented so far, we see upward (downward) rank mobility below (above) the 40th percentile of the permanent earnings distribution. Those at the lower end of the distribution exhibit higher mobility. For instance, on average, workers at the 10th percentile of the permanent earnings distribution manage to transition to between the 25th and 30th percentiles after ten years. Women seem to exhibit slightly higher mobility than men and younger workers show higher mobility than their older counterparts for both genders, especially at the extremes of the distribution.[20]

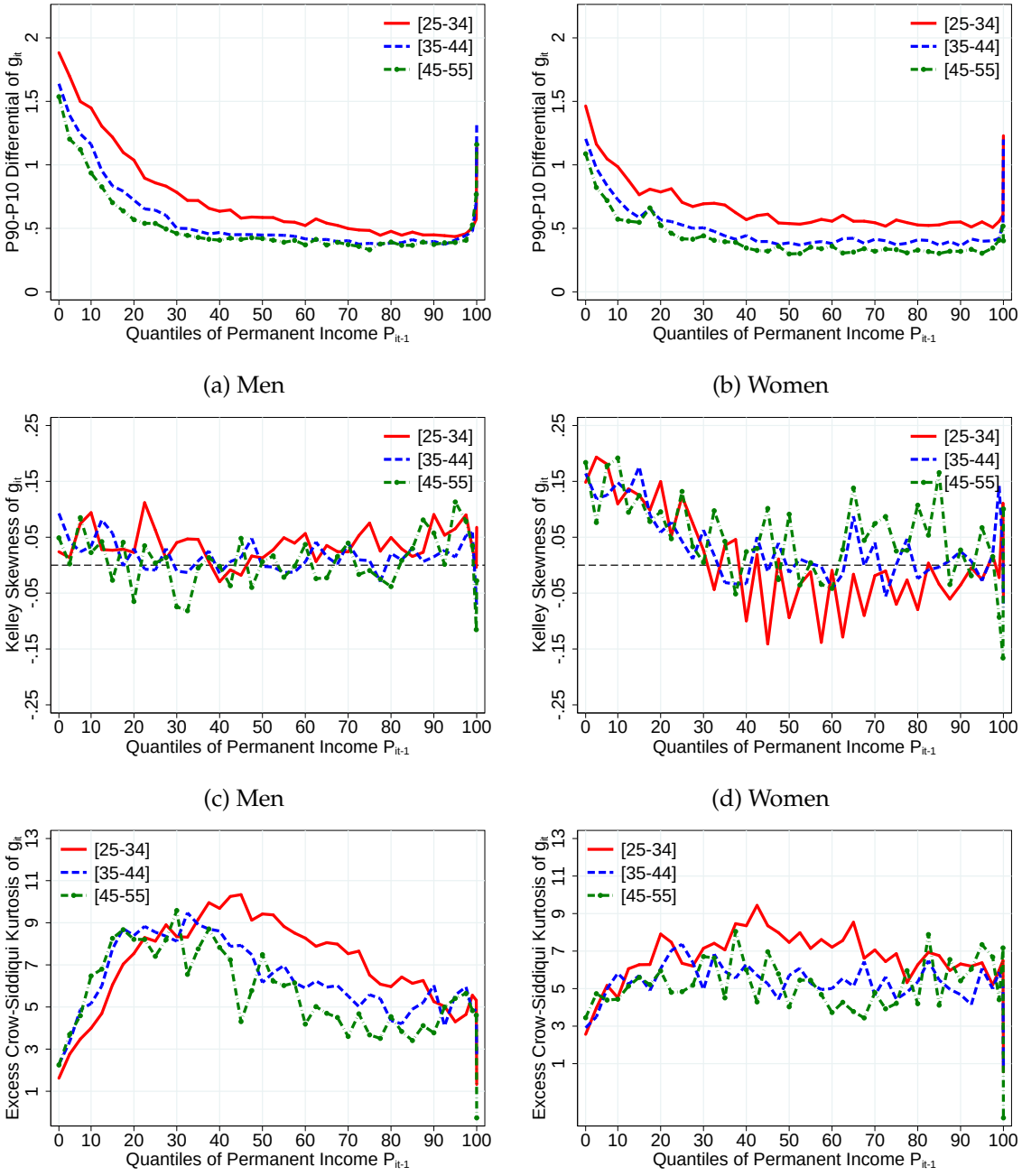
Figure 11 further compares mobility patterns over time, looking at 10-year changes in 2000 and 2005. Mobility patterns seem to be very stable for both men and women in Argentina over this period. Finally, Figures A.16 and A.17 in the Appendix show that these mobility patterns are similar in the short run when looking at a five-year horizon.

5 Comparing Data Sources and Economic Sectors

While the SIPA administrative data have several advantages in measuring labor market outcomes, they naturally miss a significant share of Argentina's informal labor market. This section compares the administrative data from SIPA with independent household survey data from the EPH. We validate cross-sectional statistics in both samples, highlighting similarities and differences between the two data sources. Using the EPH household survey data only, we also compare earnings inequality and dynamics in Argentina's formal and informal sectors over this period.

[20] In the Appendix, we look at five-year mobility and confirm that mobility falls monotonically with age when we include an additional age group: those between 45 to 55 years of age.

Figure 9: Dispersion, Skewness and Kurtosis of One-Year Log Earnings Changes



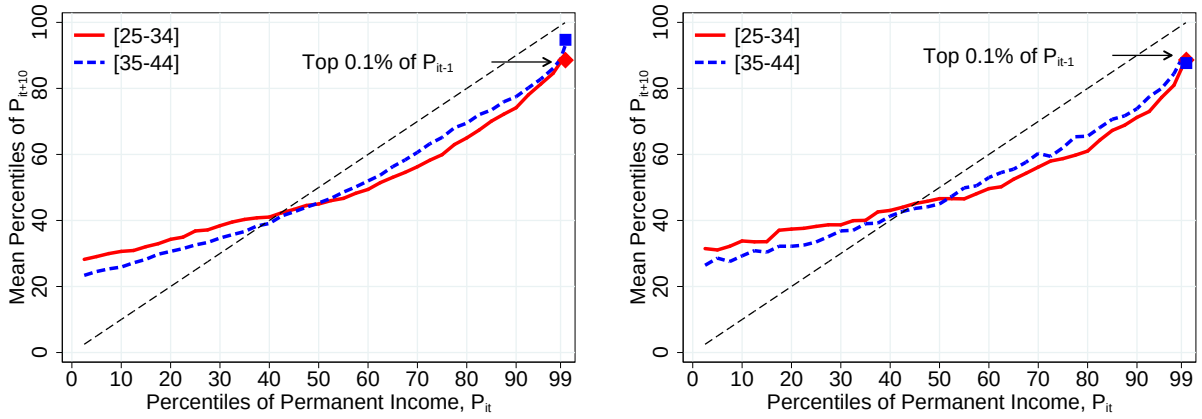
(a) Men (b) Women

(c) Men (d) Women

(e) Men (f) Women

Notes: Using residual one-year earnings changes and the LS^{+} sample, Figure 9 plots the following variables against permanent earnings quantile groups for the three age groups: (a) Men: P90-10, (b) Women: P90-10, (c) Men: Kelley skewness, (d) Women: Kelley skewness, (e) Men: Excess Crow-Siddiqui kurtosis, (f) Women: Excess Crow-Siddiqui kurtosis. Excess Crow-Siddiqui kurtosis is calculated as $\frac{P97.5-P2.5}{P75-P25} - 2.91$, 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. *Source:* Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

Figure 10: Evolution of 10-Year Mobility Over the Life Cycle



(a) Men

(b) Women

Notes: Figure 10 plots average rank-rank mobility over a 10-year period by showing average rank of permanent earnings in $t + 10$ as a function of the permanent earnings rank in t. Results are reported as the average mobility during the period of analysis (1996-2015) and for two age groups defined in period t (25-34 and 35-44).
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

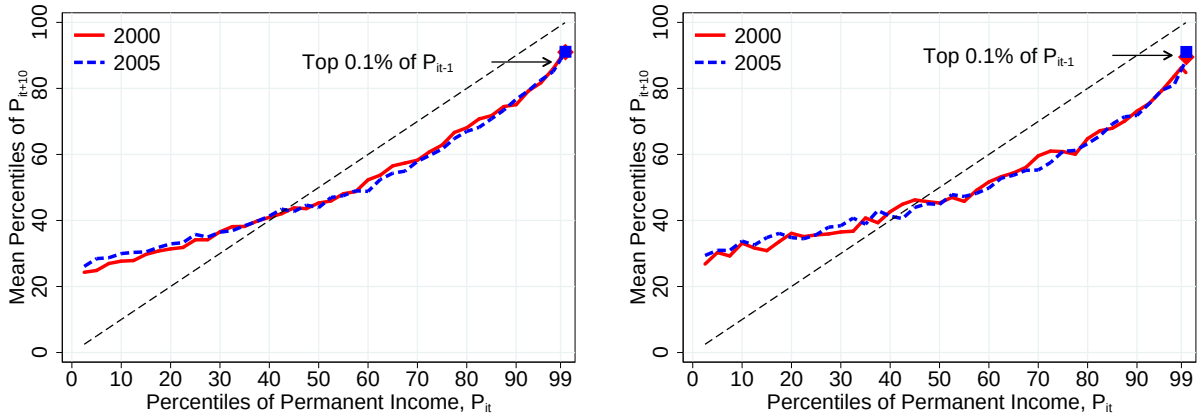
5.1 Comparing the Formal Sector between Administrative and Household Survey Data

A characteristic feature of the earnings distribution during Argentina's economic crisis was the sharp inflation spike surrounding the country's devaluation in January 2002. We have already shown that this spike in the general price level resulted in a concurrent drop in real wages in Argentina's formal sector. In Figure 12, we confirm a similar drop in real earnings for workers at all percentiles in Argentina's formal sector in 2002. To do so, we use administrative data from SIPA in panel (a) and household survey data from EPH in panel (b). Over the 15 years following Argentina's devaluation in 2002, real earnings among workers in the formal sector recovered in both SIPA and EPH.

However, the speed and magnitude of recovery are more pronounced in SIPA than EPH, particularly over the period from 2002 to 2008. This is especially true for workers at the bottom of the formal sector's earnings distribution. For example, the P50 grows by around 50 log points between 2002 and 2017 in the EPH household survey data, compared with a more pronounced 80 log points growth over the same period in the SIPA administrative data. Relative to 2002, real earnings growth is understated across all percentiles in EPH compared with SIPA, although the very bottom percentiles (P5 and P10) grew especially fast in SIPA compared with EPH.

As a result, panels (c) and (d) of Figure 12 show that overall earnings inequality measured by

Figure 11: Evolution of 10-Year Mobility Over Time



(a) Men

(b) Women

Notes: Figure 11 plots average rank-rank mobility over a 10-year period by showing average rank of permanent earnings in $t + 10$ as a function of the permanent earnings rank in t. Results are reported for $t = 2000$ and $t = 2005$.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

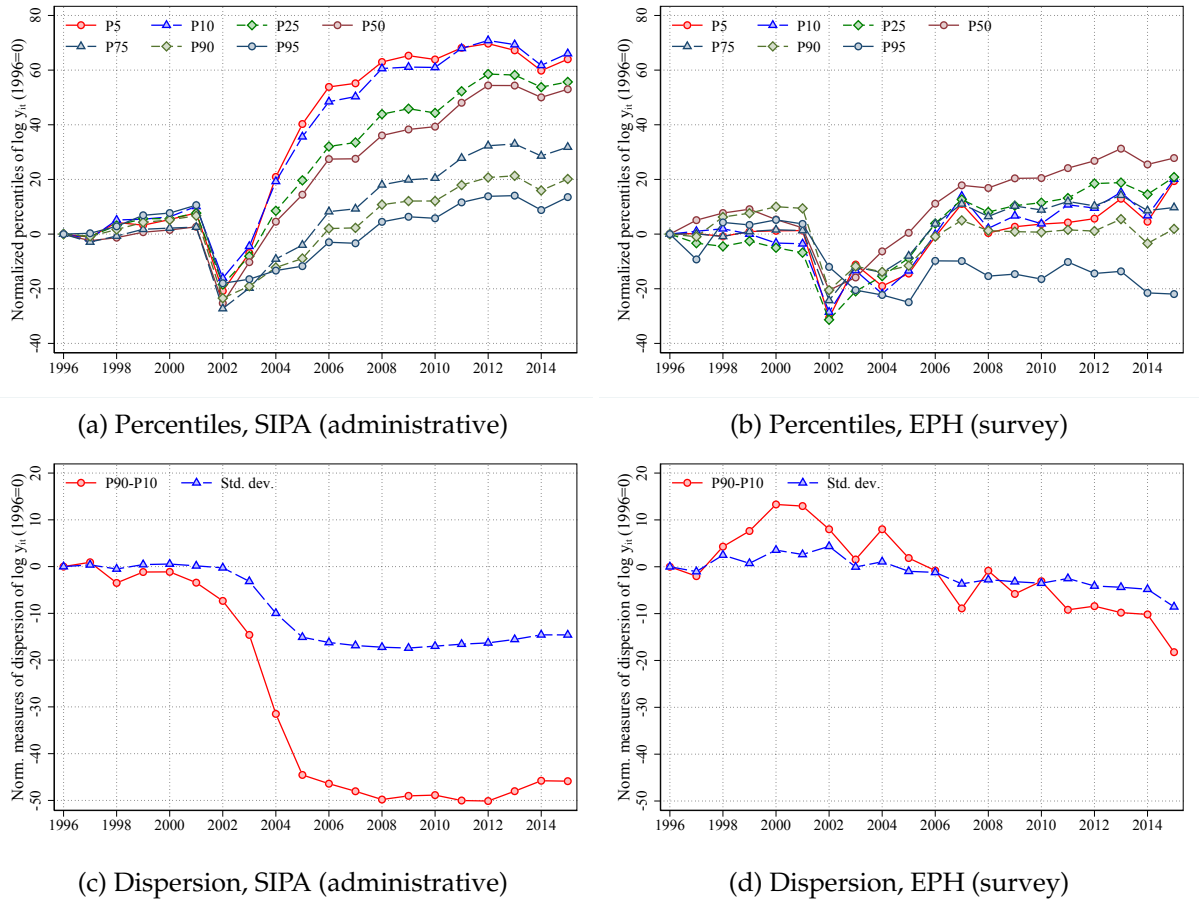
the P90-P10 log percentile ratio or the standard deviation of log earnings has declined in both the SIPA administrative data and the EPH household survey data between 2002 and 2017. However, the magnitude of the decline in earnings inequality is somewhat more pronounced in SIPA than EPH by both inequality measures. For example, the standard deviation of log earnings declined by around 15 log points between 2002 and 2017 in SIPA but by only around 7 log points in EPH.

5.2 Comparing the Formal and Informal Sectors in Household Survey Data

There are many differences between Argentina's formal and informal sectors. Chief among them is that informal workers are not covered by formal labor institutions such as the minimum wage, collective bargaining agreements, employment protection, and social security benefits. This raises the important question: How do labor market outcomes compare for workers in Argentina's formal versus informal sectors?

To answer this question, Figure 13 replicates the same set of standardized statistics of the distribution of earnings in Argentina separately for workers in the formal and informal sectors. Panels (a) and (b) of the figure compare the evolution of various percentiles of the earnings distribution from 1996 to 2017. Both sectors saw approximately stagnant earnings from 1996 to 2001, followed by a sharp drop in real earnings due to the inflation spike in 2002. In subsequent years, an interesting pattern emerges. Workers in the lower 75% of the earnings distribution in the formal sector recover significantly faster from the crisis compared with those in the informal sector. Through

Figure 12: Normalized Percentiles and Dispersion of Log Earnings, SIPA and EPH



(a) Percentiles, SIPA (administrative)

(b) Percentiles, EPH (survey)

(c) Dispersion, SIPA (administrative)

(d) Dispersion, EPH (survey)

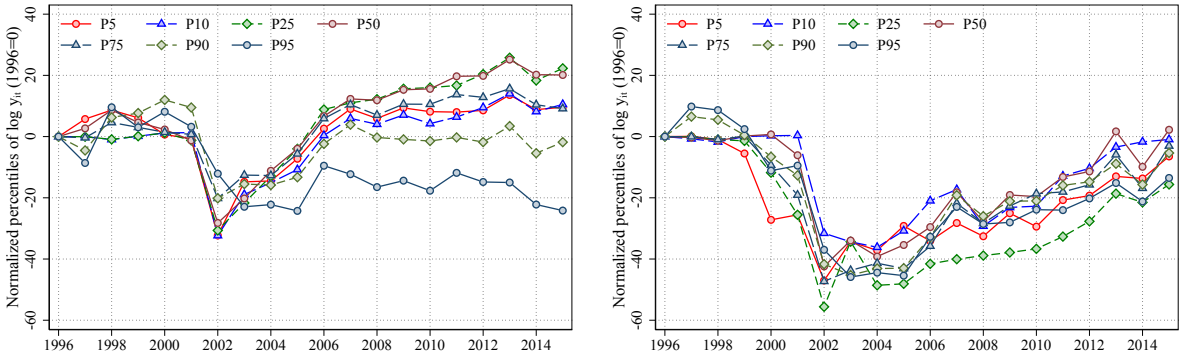
Notes: Figure 12 shows percentiles of the earnings distribution (Panels (a) and (b)) and measures of earnings dispersion (Panels (c) and (d)), using administrative data from SIPA (Panels (a) and (c)) and household survey data from EPH (Panels (b) and (d)) for Argentina.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina) and EPH, 1996–2015.

slower growth of earnings in the informal sector, only around ten years after the inflation spike do earnings of workers in the informal sector catch up.

As a result of these dynamics, panels (c) and (d) of Figure 13 show a significant decline in earnings dispersion—measured by either the log P90/P10 ratio or the standard deviation of log earnings—starting in 2002 both in the formal sector and also in the informal sector of Argentina. However, the decline in earnings dispersion occurred more quickly in the formal sector than in the informal sector between 2002 and 2008.

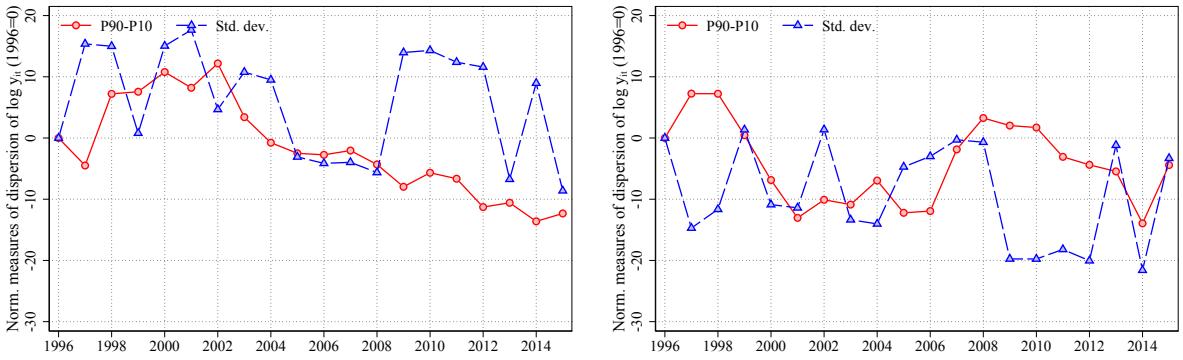
These observations are consistent with the role of the minimum wage and of unions, which have a direct effect only on workers in the formal sector.

Figure 13: Normalized Percentiles and Dispersion of Log Earnings, Formal and Informal Sectors



(a) Percentiles, formal sector

(b) Percentiles, informal sector



(c) Dispersion, formal sector

(d) Dispersion, informal sector

Notes: Figure 13 shows percentiles of the earnings distribution (Panels (a) and (b)) and measures of earnings dispersion (Panels (c) and (d)) for workers in Argentina's formal sector (Panels (a) and (c)) and informal sector (Panels (b) and (d)), based on household survey data from EPH.
Source: EPH, 1996–2015.

6 Wage Setting under Low and High Inflation

In this section, we document a series of facts pertaining to wage dynamics across workers in Argentina under low- and high-inflation settings. We first describe how we construct regular wage changes for each worker. We then describe how we evaluated the validity of these measures using a statistical model that reproduces Argentina's micro-wage behaviors. Lastly, we report and discuss the moments generated by our empirical approach.

6.1 Measurement

In the following analysis, we restrict our attention to total monthly labor compensation—henceforth referred to as "wages"—of workers between 25 and 55 years old in the private sector. Before we

measure nominal wage rigidity in our data, we need to address four measurement challenges associated with administrative wage data in Argentina.

First, since SIPA collects data on workers at a monthly frequency, we do not know the exact day their job spells start or end. Owing to this time aggregation problem, we omit the first and last wage of each job spell. Additionally, the last month of the job spell may include severance payments, so a worker's wage in the last month of a job spell is not necessarily comparable with previous wages. Second, the SIPA dataset features outliers that are incongruent with Argentine labor market policies. Following criteria similar to those in Section 2, we define outliers as the wages of workers who earn less than half of the monthly minimum wage. We drop monthly observations with wages below this threshold. Third, observed wages exhibit slight variations (i.e., cents) in total value (e.g., AR$2,012.75 versus AR$2,013.15) across months, which we discard by rounding monthly earnings to the nearest integer.

The fourth, and most significant, measurement challenge is the presence of transitory deviations from a modal or permanent wage. Theory in the price-setting literature shows that aggregate price flexibility depends on the composition of price changes between those of a transitory or a permanent nature (see Eichenbaum et al., 2011; Kehoe and Midrigan, 2015; Alvarez and Lippi, 2020). In particular, Kehoe and Midrigan (2015) show that aggregate price flexibility depends mainly on price changes that do not revert to their previous nominal value. Intuitively, transitory deviations in prices matter less for aggregate price rigidity as prices revert to their previous value, while the same is not true for permanent changes. For this reason, we distinguish between total wages and "regular" wages and present facts about the latter.

Transitory wage changes typically take the form of small deviations around a permanent wage or significant deviations in particular months of the year. These small, transitory fluctuations in wages can result from changes in the intensive margin of labor supply, small regular bonuses, workers' commissions, and other temporary economic phenomena. In Argentina, there is an additional relevant source of transitory wage changes: the 13th salary. This 13th salary is established by law, equals 50% of the highest wage earned over the previous semester, and is split into two equal payments disbursed in June and December. In addition to end-of-year bonuses and vacation payments, the 13th salary generates significant transitory fluctuations in wages across particular months of the year.

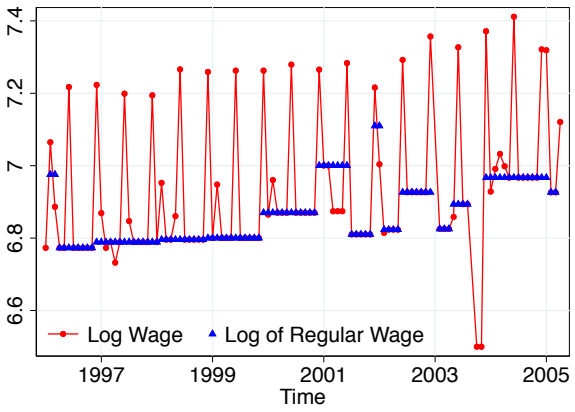
To illustrate how we measure a worker's regular wage, panels (a) and (b) of Figure 14 show the log wage (red lines) of two workers—whom we call Diana and Mario—from our sample. Each has varying experiences in the labor market. Following our previous description, we start the

measurement exercise by first dropping the first and last month of all job spells. As the figures show, Diana changed jobs in March of 1998, so we drop wages earned in March and April to construct the regular wage. Second, we drop any outliers from their reported wage series. Mario's wages are below half of the minimum wage in two months, and there is a large spike in Diana's last wage, so we drop those three observations as well.

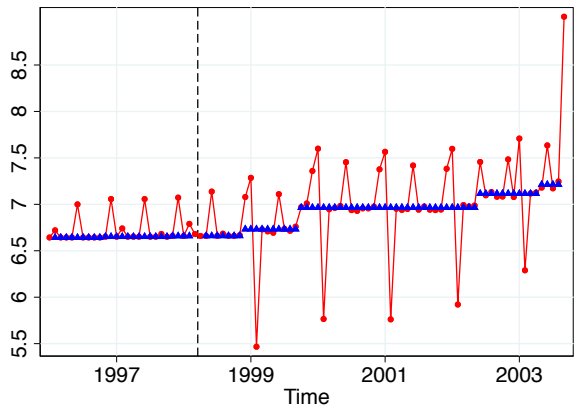
Notice that the repeated temporary wage increase across the two samples is the wage increase in June and December due to payment of the 13th salary. Although the 13th salary is commonly paid in June and December, there are instances in which, for administrative reasons, they are paid in adjacent months. Finally, observe that in Diana's second job spell, only 7% of wages are repeated, but wages clearly fluctuate around persistent levels. This pattern underlines the importance of filtering out transitory and persistent components of a given wage series. Next, we describe the methodology to purge wages from their transitory components—the result of which we refer to as the *regular wage*.

Figure 14: Two Examples: Evolution of Wages and Regular Wages

(a) Example 1: Mario (Data)



(b) Example 2: Diana (Data)



Notes: Panels (a) and (b) of Figure 14 plot the evolution of the log wage (red line with dots) and the log regular wage (blue line with triangles) for two workers in our sample with fictitious names. The black dashed vertical lines mark job changes.
Source: SIPA, 1996–2015, and simulations.

Overview. We construct regular wages within job spells using the Break Test proposed by Stevens (2020), which is an adaptation of the Kolmogorov-Smirnov test of the equality of two distributions. The basic idea behind this methodology is to split a wage series into two contiguous subsamples and test whether those subsamples were drawn from the same distribution. The methodology will identify changes in the regular wage series—henceforth referred to as "breaks"—whenever

differences between observed wage series before and after a potential break are sufficiently large.

This methodology requires the specification of a threshold value, denoted by $\mathcal{K}$, that determines whether differences in subsamples of wages are large enough to reject the null hypothesis of no break in the series. As there are no standardized critical values to test for this null hypothesis, this parameter can be determined only via estimation and simulation of a structural model of total and regular wage setting. Therefore, we proceed in three steps. In the first step, we estimate a statistical model for total and regular wages. This model reproduces the behavior of total wages in the data and provides the underlying frequency of regular wage changes. The second step finds the value of $\mathcal{K}$ that matches the model's (known) frequency of regular wage changes. Finally, we apply the Break Test to the data using the parameter value obtained in the second step.

A Statistical Model for Total and Regular Wages. The statistical model for total wages is defined at the job-spell level. Total wages are the sum of two components, a transitory wage w_t^T and a regular wage w_t^R, so that $w_t = w_t^T + w_t^R$. The transitory component captures small deviations or significant but short-lived deviations around a regular wage. The evolution of the regular wage follows a model that combines elements of a fixed cost model (Barro, 1972) and a Taylor model (Taylor, 1980) with unit root shocks to the optimal static wage. We now describe the mathematical formulation for an individual worker.[21]

Time is discrete and denoted by t. We normalized time so that the second month of a job spell corresponds to $t = 0$. Let w_t^* be a worker's target nominal wage that follows a discrete-time random walk with drift,

$$w_t^* = w_{t-1}^* + \pi_t - \sigma_\epsilon \eta_t,$$

where $\eta_t \overset{iid}{\sim} \mathcal{N}(0, \sigma_\eta)$ with its initial value normalized to zero, i.e., $w_0^* = 0$. Here, π_t captures the monthly wage inflation rate, which we construct in two steps. First, we extract monthly seasonality from observed wage-inflation series using a linear regression with calendar-month dummies. Second, we regress these seasonally adjusted changes in wages on a set of age, sector, and gender dummies in addition to time fixed effects. We then recover π_t as the predicted time fixed effects from this specification.

With the target wage in hand, we construct the wage gap as $\tilde{w}_t^R = w_t^R - w_t^*$. We assume that the regular wage is changed whenever the wage gap hits an upper or lower trigger or if the last

[21] See Caballero and Engel (1993) for the original formulation of defining the probability of adjustment using an optimal static target and its application to producer-level employment. See Alvarez, Lippi and Paciello (2011) for a micro-foundation in a price-setting context and Baley and Blanco (Forthcoming) for capital producer-level investment.

regular wage adjustment occurred more than T periods before. Under these assumptions, the joint stochastic process of the wage gap and the time elapsed since the last adjustment of the regular wage, denoted by a, follows

$$z_t \equiv \tilde{w}^R_{t-1} - \pi_t + \sigma_\epsilon \eta_t,$$
$$(\tilde{w}^R_t, a_t) = \begin{cases} (0,0) & \text{if } a_{t-1}+1 \geq T \text{ or } z_t \notin [\tilde{w}^-, \tilde{w}^+] \\ (z_t, a_{t-1}+1) & \text{otherwise} \end{cases}$$

Here, z_t is an auxiliary variable and $\tilde{w}^-$ and $\tilde{w}^+$ denote the lower and upper bounds of the wage gap that trigger an adjustment of the regular wage, respectively. We assume that the initial regular wage is equal to the target nominal wage; thus, $(\tilde{w}^R_0, a_0) = (0,0)$.

Fluctuations in the wage gap come from variations in the nominal target or wage shocks η_t. During periods of adjustment in the regular wage, $\tilde{w}^R_t - z_t$ captures the regular wage change. Thus,

$$w^R_t = \begin{cases} w^R_{t-1} + \tilde{w}^R_t - z_t & \text{if } a_{t-1}+1 \geq T \text{ or } z_t \notin [\tilde{w}^-, \tilde{w}^+] \\ w^R_{t-1} & \text{otherwise} \end{cases}.$$

The transitory component of total wages is modeled as the sum of random transitory deviations across months, denoted by γ_t, and another random deviation that captures the payment of the 13th salary, denoted by ϕ_t. Formally, $w^T_t = \gamma_t + \phi_t$, with

$$\gamma_t \sim \begin{cases} \mathcal{N}(0, \sigma_\gamma) & \text{with probability } \beta \\ 0 & \text{with probability } 1-\beta \end{cases},$$

and ϕ_t is drawn from a Normal distribution with mean m_ϕ and variance σ_ϕ in June and December and is zero otherwise.

Model Estimation. We use the simulated method of moments (SMM) to estimate the parameters of the stochastic process of (w^R_t, w^T_t). We match moments of the wage-change distribution at the two-digits sectoral level to account for the pervasive heterogeneity in wage behavior across sectors. Table 3 reports the estimation results (from rows 1 to 14) for the manufacturing and trade sectors and the average across sectors weighted by sectoral employment. Tables A.4 to A.7 in the Appendix report the same statistics for all the sectors in the economy.

The set of targeted moments includes the monthly and annual frequencies of wage changes and moments of the distributions of one-month and one-year wage changes. Intuitively, moments of the one-month wage change distribution discipline the dispersion and frequency of transitory

innovations of total wages, while moments about the distribution of one-year wage changes inform mostly parameters affecting the regular wage. We select the one-year moments suggested by the theory in Baley and Blanco (Forthcoming) as sufficient statistics for aggregate wage flexibility (see Corollary three). More specifically, we choose moments reflecting the size (i.e., frequency, mean, and standard deviation of one-year wage changes) and dispersion (i.e., the third-order coefficient of variation) of wage changes. Intuitively, the size of wage changes identifies the variance of permanent worker-level shocks and the total wage change frequency due to Taylor or fixed cost adjustments. The dispersion of wage changes identifies the composition of the wage change frequency due to wages hitting the adjustment trigger or reaching the maximal date before adjustment.

The statistical model is able to generate the wage-setting patterns observed in the data within sectors. The outcome of the estimation reveals a highly asymmetric adjustment policy toward wage increases for the regular wage. Finally, note that despite the fact that the frequency of total wage changes is 80% in the data (see the row labeled "Share zero 1-month Δw"), the frequency of regular wage changes is around 10% in the model.

Regular Wage Construction. In the last step of the measurement exercise, we apply the Break Test to simulated data from the estimated model to compute the model-implied frequency of regular wage changes. We relegate a formal description of the Break Test algorithm to Appendix B.1 and present the main intuition here. The method follows an iterative approach. First, it starts by assuming that there is no break in the wage series within a job spell. Under this assumption, it computes the maximum distance across two sub-series defined by all possible breaks (i.e., by all the dates in the series). If that maximum distance is larger than the threshold $\mathcal{K}$, then the method adds a new break at the date in which the distance is maximized. The method continues these iterations within each resulting sub-series until the maximum distance across all breaks is less than $\mathcal{K}$. Once all the breaks have been identified, we construct the regular wage as the median wage in between breaks and the frequency of regular wage changes as the fraction of regular wages that changed between $t-1$ and t. Finally, we calibrate $\mathcal{K}$ to match the (known) monthly frequency of wage changes in the model.

Table 3 reports the calibrated values for $\mathcal{K}$. The estimated $\mathcal{K}$ ranges from 0.38 to 0.51 across sectors, with a mean of 0.47 across sectors. For comparison, Stevens (2020) recovers $\mathcal{K} = 0.61$ from weekly data on grocery store prices. By construction, the Break Test generates the same model-implied frequency as regular wage changes. The last two rows evaluate the accuracy of the Break Test. If in the model there is no break in period t, the test correctly identifies no change in regular

wages with a probability of at least 0.9. As we show below, most wage changes are concentrated in June and December, two months with particularly large transitory shocks due to the payment of the 13th salary. For this reason, the method cannot always accurately identify the exact date of the break. Intuitively, there is no useful information for the test if a break occurs during months of large transitory shocks. Therefore, the last row of Table 3 reports the probability of correctly identifying changes in regular wages in a two-month window around an actual change, which is equal to 0.81 across sectors.

Table 3: Estimated Threshold Values and Break Test Evaluation

	Manufacturing	Retail	Sector Average
Moments (data,model):			
Mean of 1-yr Δw	(0.20, 0.20)	(0.22, 0.23)	(0.21, 0.21)
Std. of 1-yr Δw	(0.23, 0.24)	(0.20, 0.21)	(0.22, 0.22)
CV(3) of 1-yr Δw	(4.06, 4.14)	(2.38, 2.41)	(3.46, 3.37)
Std. of 1-mo Δw	(0.19, 0.19)	(0.14, 0.13)	(0.17, 0.17)
Mean of 1-mo Δw in Jun/Dec	(0.35, 0.35)	(0.30, 0.30)	(0.30, 0.30)
Std. of 1-mo Δw in Jun/Dec	(0.21, 0.21)	(0.20, 0.20)	(0.21, 0.21)
Share of 1-yr $\Delta w = 0$	(0.02, 0.02)	(0.03, 0.03)	(0.03, 0.03)
Share of 1-mo $\Delta w = 0$	(0.15, 0.15)	(0.24, 0.24)	(0.23, 0.22)
Share of 1-mo $\Delta w > 0$	(0.47, 0.45)	(0.44, 0.41)	(0.43, 0.42)
Parameters:			
$(T, \tilde{w}^-, \tilde{w}^+)$	(26, -0.20, 1.5)	(30, -0.22, 1.5)	(29, -0.20, 1.5)
σ_η	0.06	0.06	0.06
(m_ϕ, σ_ϕ)	(0.38, 0.03)	(0.36, 0.04)	(0.35, 0.06)
(σ_γ, β)	(0.15, 0.58)	(0.11, 0.46)	(0.14, 0.49)
Threshold and break test evaluation:			
Threshold value $\mathcal{K}$	0.47	0.49	0.47
$\Pr(w_t^R \neq w_{t-1}^R)$ (model,break test)	(0.12, 0.12)	(0.11, 0.11)	(0.13, 0.13)
Pr(no break in t | no break t)	0.91	0.93	0.91
Pr(break between $t-2, t+2$ | break t)	0.76	0.85	0.81

Notes: The table presents moments used in and parameter estimates from the SMM estimation. Δw denotes wage changes. The first block of rows (i.e., rows 1 to 9) describes the wage change moments in the data and in the model. The second block of rows (i.e., rows 10 to 13) describes the estimated parameters. The last block of rows (i.e., rows 14 to 17) describes the threshold value $\mathcal{K}$ across sectors and some statistics to evaluate the validity of the methodology. We truncate the wage change distribution at the 2nd and 98th percentiles in the data and in the model. CV(3) denotes the third order generalized coefficient of variation, i.e., $CV(3) = E[\Delta w^3]/E[\Delta w]^3$. The last column shows the average results across sectors weighted by the number of workers in each sector.
Source: SIPA, 1996–2015, and simulations.

Panels (a) and (b) of Figure 14 show the log regular wage (blue lines) for Diana and Mario. Inspection of the figures, together with the results of the structural model, suggests that while the break test is not perfect, it captures well the theoretical notion of a regular wage in the data and in the simulated data.

Robustness. In the next subsection, we provide a set of facts that rely on the Break Test for the construction of regular wages. Here, we highlight the advantages of this test over three other methods commonly used in the literature (see Stevens, 2020, for a similar discussion using price data). In particular, we construct series of regular wages following three alternative methods proposed by Nakamura and Steinsson (2008), Kehoe and Midrigan (2015), and Blanco (2020). Based on model simulation and inspection of the raw data, we find that the Break Test performs better in constructing series of regular wages—Figure A.18 in Appendix B.2 shows two examples of the Break Test algorithm successfully recovering true regular wages in simulated data. The main intuition why this is the case is that the Break Test does not change the regular wage after small deviations around a stable value—see Figures A.19 and A.21 in Appendix B.2, which reproduce Figure 14 under all four methods. In addition, we have further analyzed the robustness of our results by computing different critical $\mathcal{K}$ values for periods of high and low average inflation. More specifically, we split job spells according to their start date into two samples: jobs that started before January 2002 and those that started after. Those samples correspond to periods of low and high inflation, respectively. Then, we repeated the same steps described above to each of the two samples. While there are considerable differences in the estimated moments and parameters across periods, we do not find a significant difference in the calibrated critical $\mathcal{K}$ values across samples. The reason for this result is that there is no significant change in the stochastic process for transitory shocks across periods.

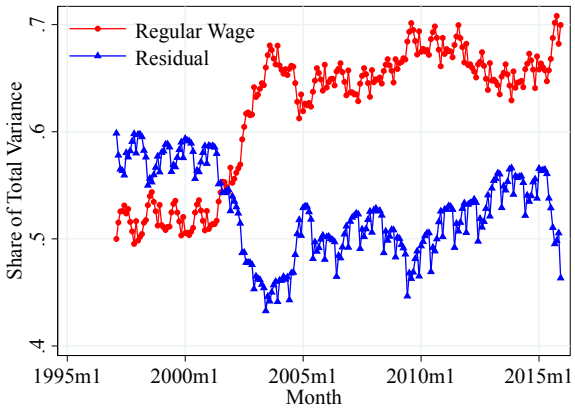
The Relevance of Regular Wages. Before documenting our main results, here we show that the dynamics of regular wages capture a significant fraction of the volatility of total wages. Using $w_t = w_t^T + w_t^R$, we can decompose the variance of total wages w_t as follows:

$$\underbrace{var(w_t)}_{=0.48} = \underbrace{var(w_t^R)}_{=0.44} + \underbrace{var(w_t^T)}_{=0.03} + \underbrace{2covar(w_t^R, w_t^T)}_{=0.01}.$$

This decomposition shows that almost 92% of the dispersion in total wages across workers and years is due to the dispersion in their regular wages. Around 6% of the remaining variation stems from the dispersion in transitory wages, while the covariance term captures the roughly 2% remaining variation. Figure 15 presents a similar variance decomposition for 12-month changes in the total wage, $\Delta w_t \equiv w_t - w_{t-12}$, and reports the contribution of the variance of the regular and transitory components of wage changes to the overall variance of Δw_t. In periods of low inflation (i.e., between 1996 and 2002), changes in the regular and transitory wage account for 52% and 56% of the overall variation, respectively, with a negative covariance component equal to -9.3%. Dur-

ing the period of increasing inflation after 2002, the contribution of regular wage changes increases to 66%, while that of changes in transitory wages declines to 51%, with a negative covariance term equal to -16.7%. Thus, we conclude that regular wages capture an important component of workers' earnings and their changes, especially in times of high inflation.

Figure 15: Variance Decomposition of 12-Month Wage Changes



Notes: Figure 15 presents the variance decomposition of $\Delta w_t \equiv w_t - w_{t-12}$ over time. Regular wage corresponds to $var(\Delta w_t^R)/var(\Delta w_t)$ and Residual corresponds to $var(\Delta w_t - \Delta w_t^R)/var(\Delta w_t)$.
Source: SIPA, 1996–2015, and simulations.

6.2 Results

This section presents and discusses the main results. We first report the frequency of regular wage changes for the aggregate data under low and high inflation. We then discuss the results across different groups of workers by age, gender, earnings, and sector.

6.2.1 Aggregates

We next provide evidence of the process of regular wage adjustment for the overall population of workers. We present results for the entire period from 1996 to 2015 but also report summary statistics for two subperiods. The first subperiod is from 1997 to 2001, with low annual inflation rates of -0.3% on average. The second subperiod is from 2007 to 2015, with high annual inflation rates of 24.3% on average. We study these periods to focus on the two clear inflation regimes in Argentina while omitting the transition period originated by the 2002 devaluation and the subsequent adjustment of relative prices.

Frequency of Changes in Regular Wages. Figure 16, panel (a) displays the annual frequency of regular wage changes—that is, the share of workers who experienced at least one regular wage change between $t-12$ and t. Panel (b) shows the 12-month moving average of the monthly frequency of wage changes. We find that the frequency of wage changes increases with inflation and is procyclical. For the low-inflation period, the average annual (monthly) frequency is 0.64 (0.09). In the same vein, using administrative payroll data for the U.S. during the 2008-2016 period, Grigsby et al. (2019) measure a similar average annual frequency of 0.65, while Sigurdsson and Sigurdardottir (2016) find a mean monthly frequency of (base) wage change of 0.13 using administrative data from Iceland during 1998-2010. During the high-inflation period in Argentina, the average annual frequency of wage change increases to 0.95. Finally, Table A.8 in the Appendix reports the correlation of the frequency of wage changes with inflation, which was 0.67 during the entire sample. However, this correlation is different across inflation regimes: in the low-inflation regime, the correlation was 0.16, while in the high-inflation regime, it was 0.66. This evidence shows strong state dependence of the wage-setting mechanism.[22]

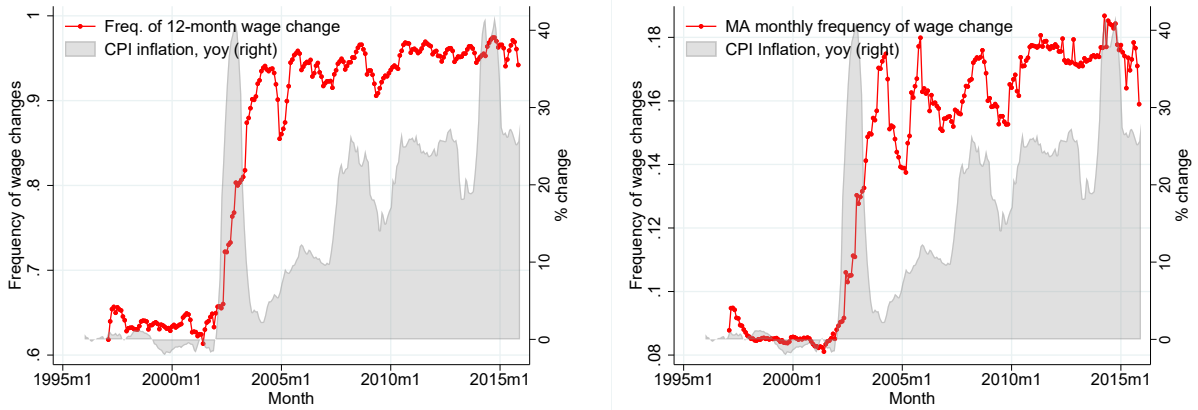
Changes in Regular Wages within Job Spells. Despite this sizeable annual frequency of wage changes, it is not the case that in periods of high inflation workers' wages are constantly updated, as the monthly frequency of wage changes increases from 0.09 to only 0.17 across subperiods. To further illustrate this point, Figure A.22 plots the average fraction of months within a year and job spell that experienced a regular wage change relative to the previous month. Before 2002, the average job spell experienced a wage change in 7.5% of the months. For a spell that lasted 12 months, this corresponds to slightly less than a single wage change per year. After 2002, this fraction increased to 14.4%, which means that a worker who kept the same job for 12 months experienced on average slightly less than two wage changes per year.

Seasonality of Changes in Regular Wages. In addition to affecting how often workers experience wage changes, the level of inflation is associated with different seasonal patterns. Figure A.23 plots the average frequency of regular wage changes by calendar month for low- and high-inflation periods. There are no large seasonal patterns in times of low and stable inflation, except for December, when the average monthly frequency of wage changes is 0.14 (relative to an average of 0.08). This pattern—combined with the fact that workers experienced a single wage change during the year and union bargaining was dormant in this period, as discussed in Section 3—means that the nature of wage changes responded to idiosyncratic motives at the worker or firm level.

[22] Sigurdsson and Sigurdardottir (2016) also find evidence of state dependence of the wage-setting process in Iceland with respect to cumulative inflation and unemployment.

Instead, sharper seasonal patterns emerge in times of high inflation, when the monthly frequency of wage changes spikes to 0.35 in June and December, relative to an average of 0.17. This stronger time dependence is consistent with the fact that as inflation increased, unions (i) started playing a more significant role in the adjustment of wages and (ii) were able to negotiate two wage scales within the same contract, with one scale for each semester in the year. As a consequence, wage changes became more synchronized and concentrated in July and December.[23]

Figure 16: Frequency of Regular Wage Changes



(a) 12-month changes

(b) Monthly changes

Notes: Panels (a) and (b) of Figure 16 show the annual frequency of regular wage changes and the 12-month moving-average of the monthly frequency of regular wage changes. The shaded area shows the annual percentage change in the consumer price index.

Direction of Changes in Regular Wages. Panel (a) of Figure 17 shows the annual frequency of wage increases, while Panel (b) shows the annual frequency of wage decreases. We find that the frequency of upward (downward) wage changes significantly increases (falls) with inflation, from an average of 0.44 (0.20) during the low-inflation period to an average of 0.90 (0.05) during the high-inflation period. As expected, at high inflation levels, regular wage increases become the norm, while wage cuts become very rare.

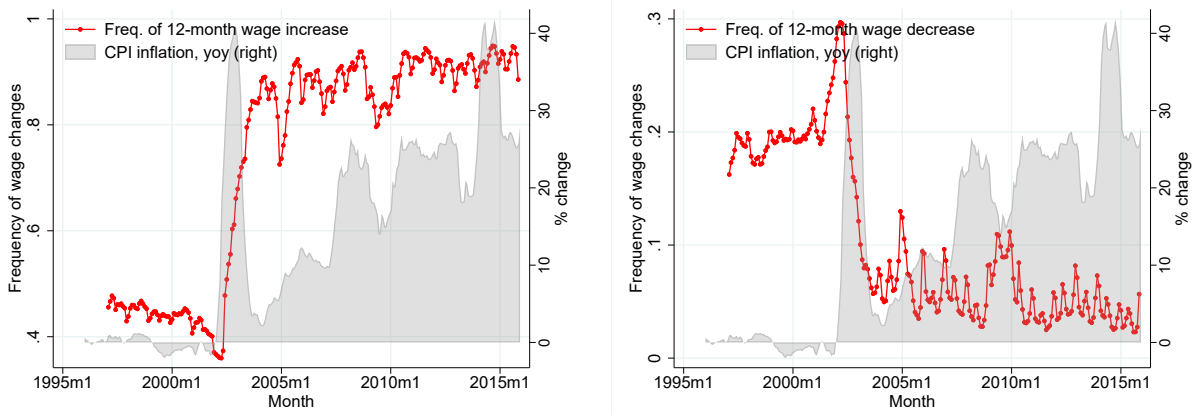
In addition to the co-movement with inflation, these series seem to respond to the business cycle. This co-movement is particularly true during the slowdown in economic activity in 1998 that precipitated the large recession in 2001-2002, when the frequency of wage increases fell from a peak of 0.47 in March 1997 to 0.36 in April 2002. During that same period, the frequency of wage

[23] Sigurdsson and Sigurdardottir (2016) find a similar time-dependence pattern for Iceland, with half of the wage increases concentrated in January becayse of union settlements, while the remaining wage changes were distributed over the year.

decreases sharply rose from 0.17 to 0.29.

Figure A.24 in the Appendix reports the evolution of the 12-month average change in regular wages, conditional on experiencing a wage increase or cut. Conditional on a positive (negative) regular wage change occurring in the previous 12 months during the low-inflation period, the average annual wage increase was 13.4% (20.2%). During the high-inflation period, the average positive wage growth increased to 30.2% and closely followed the inflation dynamics, while the average negative wage growth remained virtually unaffected and constant throughout the entire period.

Figure 17: Frequency of 12-Month Upward and Downward Regular Wage Changes



(a) Increases

(b) Decreases

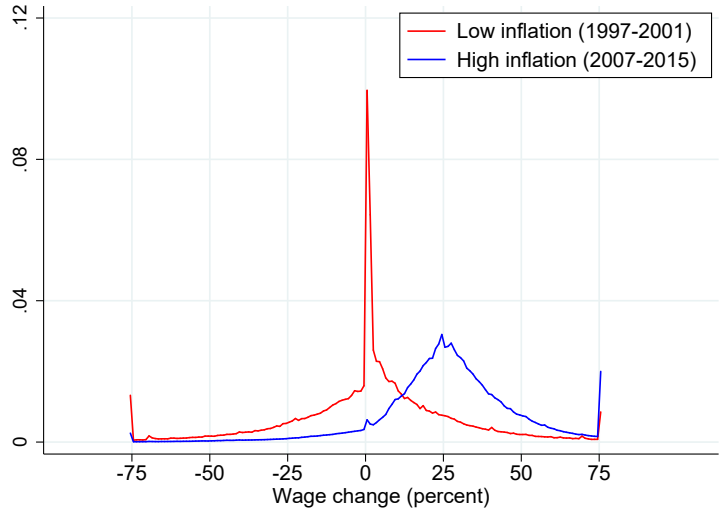
Notes: Panels (a) and (b) of Figure 17 show the frequency of 12-month upward and downward regular wage changes. The shaded area shows the annual percent change in the consumer price index.

Distribution of Changes in Regular Wages. The previous literature has documented that in economies with low inflation, the distribution of regular wage changes (i) is asymmetric, with a missing mass of negative wage changes, and (ii) exhibits a large spike at positive-small changes (see, e.g., Barattieri et al., 2014; Grigsby et al., 2019). Figure 18 displays the distribution of 12-month non-zero regular wage changes across inflation regimes.[24] During the low-inflation period, we find patterns similar to those described in the previous literature. First, there is a large spike at zero (omitted from the figure) as 36% of workers do not experience a wage change between $t-12$ and t. Second, the distribution is asymmetric: the distribution concentrated 24% of the observations in the $[-25\%, 0\%)$ range of wage changes, while 48% of the observations fell in the

[24]This exercise is fundamentally different from the statistics presented in the first part of our analysis, which were based on one-year differences in annualized (residual) earnings. Here, we compute year-on-year changes in regular wages based on monthly earnings. Figure A.20 in the Appendix illustrates these differences.

$(0\%, 25\%]$ range. We also find that during the high-inflation regime, the average wage change was similar to the average inflation rate of the period (25%). Also, at higher levels of inflation, the distribution became much more symmetric: the difference between the mass of workers in the $[0\%, 25\%)$ range of regular wage changes and the mass in the $(25\%, 50\%]$ range was only 4 percentage points (p.p.), much smaller than the difference of 24 p.p. during the period of low inflation. Thus, higher inflation allows for a higher prevalence of wage cuts in *real* terms.

Figure 18: Distribution of 12-Month Regular Wage Changes across Inflation Regimes

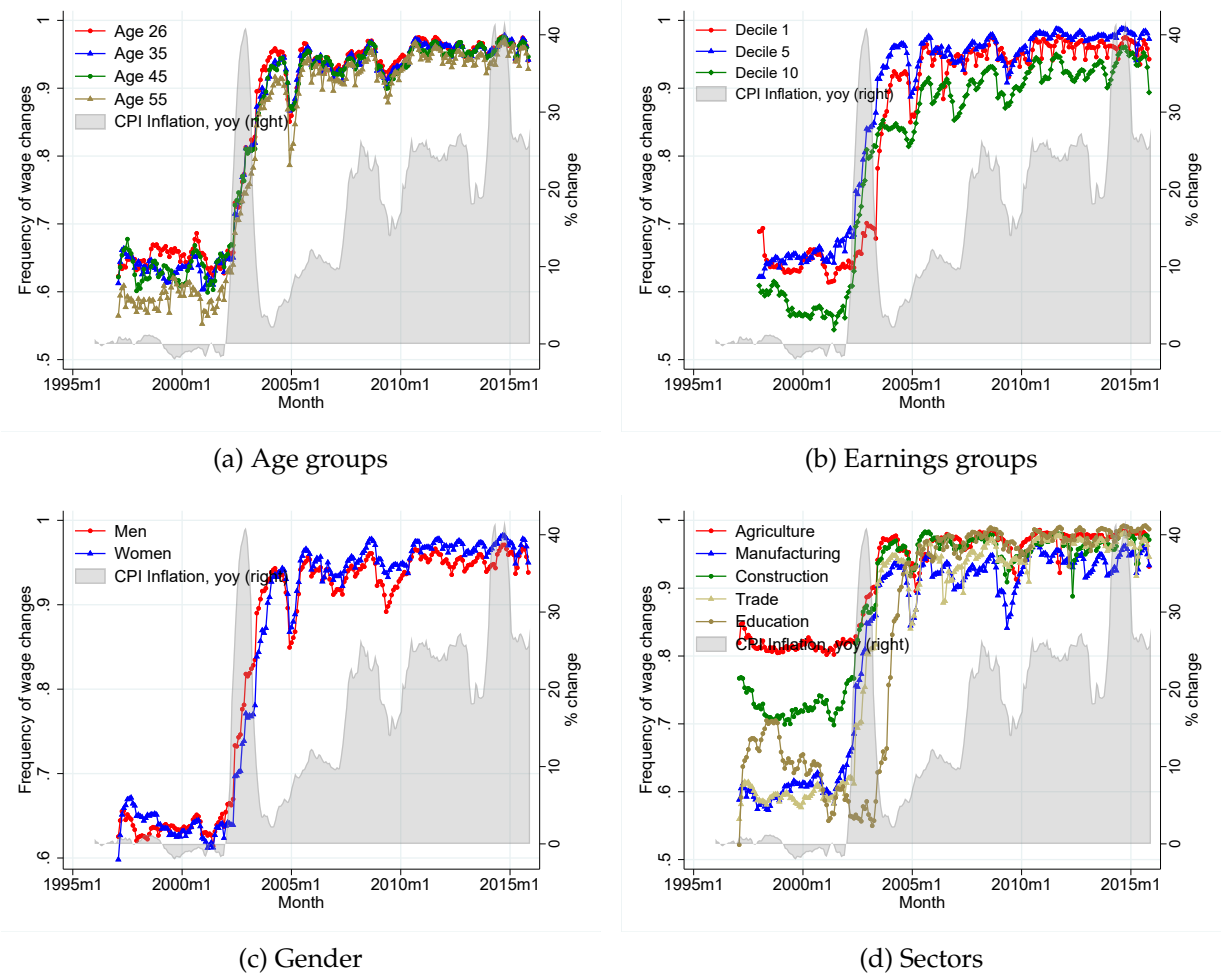


Notes: Figure 18 plots the distribution of 12-month regular wage changes under low- and high-inflation regimes (1997-2001 and 2007-2015, respectively).

6.2.2 Heterogeneity across Workers

The literature that studies price setting has documented considerable heterogeneity in the frequency of price changes across goods (see, e.g., Bils and Klenow, 2004; Nakamura and Steinsson, 2008). Next, we show that while the broad aggregate patterns are prevalent in the overall population, there is also significant heterogeneity in wage adjustment processes across different groups of workers. Figure 19 plots the 12-month frequency of regular wage changes by age, earnings, gender, and sector. In the Online Appendix, Figure A.25 plots the evolution of the average 12-month regular wage increases, and Table A.8 presents summary statistics for similar splits of the population during the low and high inflation regimes (the 1997-2001 and 2007-2015 subperiods, respectively).

Figure 19: Frequency of 12-Month Regular Wage Changes by Groups of Workers



(a) Age groups

(b) Earnings groups

(c) Gender

(d) Sectors

Notes: Figure 19 plots the annual frequency of regular wage changes for the following groups of workers: (a) ages 26, 35, 45 and 55; (b) earnings deciles 1, 5 and 10; (c) women and men; and (d) agricultural, manufacturing, construction, trade, and education sectors. The shaded area shows the annual percentage change in the consumer price index.

Heterogeneity by Age. We present results for four groups of workers at different points of their lifecycle: workers who are 26, 35, 45, and 55 years old.[25] Several interesting patterns are worth noting. Regardless of the inflation regime, we find that the frequency of wage changes falls with age, especially during the low-inflation period. During this period, the annual frequency was 0.65 for the youngest workers and 0.59 for the oldest workers. However, with high inflation, these differences almost vanish—the frequencies of wage changes increased to 0.95 and 0.94 for these workers.

We also find that, regardless of the inflation regime, average wage increases fall with age. For example, during the low-inflation period, the average regular wage increases for these four groups

[25]Since we focus on the frequency of 12-month wage changes and restrict the sample to workers who are between 25 and 55 years old, for the youngest group, we report results for workers who are 26 years old.

of workers were: 15.6%, 14%, 12.5%, and 11.7%. In contrast, there are no similar differences across groups in the average regular wage decrease.

Heterogeneity by Earnings. To analyze the process of regular wage changes by earnings, in each month, we first sort workers according to their average monthly earnings in the preceding 24 months. Then, we group workers by deciles of this earnings measure. Our first finding is that the frequency of wage changes falls with earnings: throughout the entire period, the average annual frequency of regular wage changes for workers in the first and last decile was 0.85 and 0.81, respectively. This difference was more pronounced in the low-inflation period, when the gap in the frequency between workers in the 2nd and 10th deciles was 11 p.p. This gap persisted in the high-inflation period, although smaller in magnitude (4 p.p.). In addition, the co-movement between the annual frequency of regular wage changes and inflation also differs across the earnings distribution: in both the low- and high-inflation periods, the correlation between these variables is increasing in earnings.

Workers at the top of the earnings distribution not only had more rigid wages but also experienced wage increases at a lower rate. During the low-inflation period, the probability of a wage increase conditional on a wage change was 0.64 for workers above the median of the earnings distribution, 10 p.p. lower than the probability of a wage increase for workers at the bottom half of the distribution. This difference completely vanished in the high-inflation regime.

Regarding the average size of wage changes, we find an inverted *U*-shape pattern for average wage increases, especially during the low-inflation regime. According to this pattern, workers in the 1st, 3rd, and 10th earnings decile experienced average wage increases of 12.9%, 7.5%, and 17.1%. A relatively similar pattern is found for the average wage decrease, albeit with a more compressed differential and in the low-inflation period only.

Heterogeneity by Gender. Differences in the wage-setting mechanism between men and women are among the smallest found in the heterogeneity analysis. The average frequency and size of wage changes are virtually the same. There are only two noteworthy differences. First, the probability of an increase conditional on a wage change was higher for women in the low-inflation period (0.74 vs. 0.67 for men). During the same period, the frequency of wage changes for men exhibited a larger correlation with inflation than the one for women (0.53 and -0.12, respectively).

Heterogeneity by Sector. Although trade unions' presence is ubiquitous in the Argentine labor market, we find substantial heterogeneity in wage-setting processes across sectors. In the interest of space, we present results for a subset of industries representing the degree of potential

heterogeneity: agriculture, manufacturing, construction, trade, and education (these sectors capture 57% of formal employment). The most considerable differences in the frequency of regular wage changes manifested in the period of low inflation, when the gap in this measure between the sector with the most flexible wages (agriculture) and the least flexible one (trade) averaged 23 p.p. It is also evident from Figure 19 that a large fraction of this heterogeneity vanished as the economy transitioned into the high-inflation regime. Similarly, the conditional probability of a wage increase exhibits similar differences across sectors. While 79% of wage changes in the agriculture sector were positive between 1997 and 2001, only 58% were positive in the construction sector. Finally, sectoral heterogeneity goes beyond differences in levels during periods of low and high inflation. While some sectors exhibited a large co-movement between the frequency of wage changes and inflation (e.g., a correlation of 0.7 in the manufacturing sector), in others, this relationship is more muted (e.g., a correlation of 0.55 in the Education sector).[26]

Table A.8 in the Appendix shows the average wage increase by sector, which also exhibits large differences across sectors: while the average increase in the agriculture sector between 1997 and 2001 was 7.1%, the average increase in the Construction sector was 19.6%. As is consistent with results for other workers' groupings, sectoral heterogeneity in the average wage decrease is much smaller (the widest gap between sectors is 2.5 p.p.). However, we do not find any clear relationship between the frequency of wage changes and the size of the increase. For example, the average increase in the construction and education sectors was similar—19.6% and 19.9%, respectively—but the respective frequencies of wage changes were 0.72 and 0.64.

7 Conclusion

This paper analyzes earnings inequality and dynamics for the formal private sector in Argentina between 1996 and 2015. We document nearly stagnant earnings from 1996 to 2001 and a significant drop in the mean and dispersion of earnings during the 2001–2002 crisis. While earnings levels recovered after 2003, dispersion remained low during the remaining period. The evolution of earnings inequality coincides with a greater prevalence of centralized wage-setting mechanisms and a significant increases in the minimum wage, among other things. We also document novel facts on wage setting during Argentina's transition from a low- to a high-inflation regime. We find

[26]The latter result highlights the importance of the nature of the labor market for wage setting. Since the education sector operates in an arguably less competitive market, as the government is a large employer in the sector, workers' wages are more insulated from the macroeconomic environment. Figure 19 illustrates this point by showing the frequency of wage changes during the 2002 devaluation and subsequent spike in inflation. The sizeable fiscal deficit that originated during the recession prevented the government from adjusting nominal wages at a similar pace in the private sector, creating a large negative effect on the real wages of education workers.

that during the high-inflation regime, the frequency of regular wage changes strongly increased, while exhibiting significant heterogeneity across population subgroups. An interesting avenue for future research is to study the causes of such heterogeneity as well as its macroeconomic consequences.

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APPENDIX FOR ONLINE PUBLICATION

A Data Appendix

A.1 Description of Household Survey Data (EPH)

Additional Details on Variable Construction. We first create a dataset at the worker-year level by estimating residual annual earnings based on an aggregation of the (one or two) available observations per worker in each year.[27] Therefore, depending on the individual's appearances in a year, two-quater or only one-quarter information is used to annualize earnings. We create a variable that identifies the quarter-quarter combinations for individuals within a given calendar year. There are nine possible quarter-quarter combinations:

[Q1,Q2], [Q2, Q3], [Q3,Q4], [Q1, Q4], [Q2, Q4], [Q1,.], [Q2,.], [Q3,.], [Q4,.],

where "Q1", "Q2", "Q3", and "Q4" represent the four quarters of a year and "." represents no matching quarter in the current calendar year.

Next, we transform reported nominal earnings in real terms and in multiples of the prevailing minimum wage. In doing so, we drop observations with average earnings below a threshold—namely, half the current minimum wage.[28] We then annualize the individual earnings, keeping in mind that the variable of earnings in the quarter of the dataset (*labor_income*) corresponds to monthly earnings. Annualize differently if individual appears two times or one time in a year. If a given individual appears in two quarters within the same calendar year, then we compute mean real earnings from formal employment as

$$\text{Mean real formal earnings across quarters} \times \text{Number of quarters working as formal} \times 6.$$

If a given individual appears in only one quarter within a given calendar year, then we compute mean real earnings from formal employment as

$$\text{Mean real formal earnings in the quarter} \times 12.$$

We collapse the data to the individual-year level data with annualized earnings. Note that this means that all quarter-pair observations for a given individual will be collapsed to one observation per calendar year. Sample weights in the survey for up to two quarters are averaged to yield a yearly individual sample weight. Age is rounded up if it changes during the two quarter observations. The collapsed data contain around 70% of the number of observations compared with before, as shown in the last column of Table A.3.

Finally, we construct earnings residuals by estimating the following earnings equation for all individuals i of gender $G(i) = g$ and age $A(i,t)$ who appeared in a quarter-quarter combination ("season") $S(i,t)$ in year t separately by gender and year, taking into account yearly individual sample weights:

$$\varepsilon_{it} = \log y_{it} - \alpha_{gt} - \sum_{A'} \beta_{gtA'} \, \mathbf{1}[A(i,t) = A'] - \sum_{S'} \gamma_{gtS'} \, \mathbf{1}[S(i,t) = S'],$$

where ε_{it} denotes the earnings residual of interest, $\log y_{it}$ is log earnings, α_{gt} is a gender-year-specific intercept, $\beta_{gtA'}$ is a gender-year-age-specific coefficient on the age indicator $\mathbf{1}[A(i,t) = A']$, and $\gamma_{gtS'}$ is a gender-year-season-specific coefficient on the season indicator $\mathbf{1}[S(i,t) = S']$.

[27] We also tried an alternative procedure in which the data is treated at the worker-quarter-year level. Under this alternative procedure, if the same individual appears in two quarters in a year, we treat him or her as two distinct individuals. In this case, only one observation per worker-year is used to annualize earnings.

[28] This accounts for very few observations, as seen in the second-to-last column of table A.3.

Additional Summary Statistics. Table A.1 shows the number of observations in each year-quarter in the raw data.

Table A.1: Number of Observations by Year-Quarter Combination

Year	Q1	Q2	Q3	Q4	Total
1996	0	26,498	0	25,288	51,786
1997	0	26,330	0	26,430	52,760
1998	0	25,874	0	24,326	50,200
1999	0	22,264	0	22,333	44,597
2000	0	20,073	0	19,927	40,000
2001	0	19,648	0	19,365	39,013
2002	0	18,467	0	17,184	35,651
2003	0	12,514	11,102	11,440	35,056
2004	10,904	11,888	12,095	11,836	46,723
2005	11,874	12,048	12,473	12,389	48,784
2006	11,874	12,761	16,526	16,256	57,417
2007	15,959	16,078	0	15,761	47,798
2008	16,124	15,953	15,932	16,042	64,051
2009	15,388	15,491	15,746	15,593	62,218
2010	15,167	15,523	15,867	15,375	61,932
2011	14,952	15,554	15,469	15,199	61,174
2012	14,607	15,051	14,883	14,467	59,008
2013	14,195	14,529	14,717	14,716	58,157
2014	15,013	16,102	16,035	15,992	63,142
2015	15,762	16,045	0	0	31,807

Notes: This table shows the number of observations in each quarter (Q1–Q4) and year of the EPH household survey data.
Source: EPH, 1996–2015.

Table A.2 shows quarter-quarter combinations for the same individual within a given year, based on the rotating panel structure of the EPH household survey data.

Finally, Table A.3 shows the number of observations as we cumulatively apply our selection criteria starting from the raw data.

Table A.2: Number of Observations by Panelized Year-Quarter-Quarter Combination

Year	Q1,Q2	Q2,Q3	Q3,Q4	Q2,Q4	Q1,Q4	Q1,.	Q2,.	Q3,.	Q4,.	Total
1996	0	0	0	28,288	0	0	12,354	0	11,144	51,786
1997	0	0	0	29,286	0	0	11,687	0	11,787	52,760
1998	0	0	0	26,658	0	0	12,545	0	10,997	50,200
1999	0	0	0	25,790	0	0	9,369	0	9,438	44,597
2000	0	0	0	21,996	0	0	9,075	0	8,929	40,000
2001	0	0	0	20,970	0	0	9,163	0	8,880	39,013
2002	0	0	0	18,696	0	0	9,119	0	7,836	35,651
2003	0	0	8,678	0	0	0	12,514	6,763	7,101	35,056
2004	8,502	9,668	9,454	0	3,936	4,685	2,803	2,534	5,141	46,723
2005	9,356	9,678	10,104	0	4,264	5,064	2,531	2,582	5,205	48,784
2006	9,692	10,290	13,296	0	4,468	4,794	2,770	4,733	7,374	57,417
2007	12,660	0	0	0	5,718	6,770	9,748	0	12,902	47,798
2008	12,968	12,250	12,760	0	5,748	6,766	3,344	3,427	6,788	64,051
2009	12,098	12,046	12,530	0	5,688	6,495	3,419	3,458	6,484	62,218
2010	11,808	12,346	12,516	0	5,384	6,571	3,446	3,436	6,425	61,932
2011	11,846	12,426	12,156	0	5,410	6,324	3,418	3,178	6,416	61,174
2012	11,522	12,232	11,554	0	5,556	6,068	3,174	2,990	5,912	59,008
2013	11,254	11,674	11,522	0	5,208	5,964	3,065	3,119	6,351	58,157
2014	12,198	12,500	12,620	0	5,558	6,135	3,753	3,475	6,903	63,142
2015	12,362	0	0	0	0	9,581	9,864	0	0	31,807

Notes: This table shows the number of observations in each quarter-quarter (Q1–Q4 mixed with Q1–Q4) and year of the EPH household survey data. There is double counting in the first five columns for quarter pairs—indeed, the number of observations in these columns are all even.
Source: EPH, 1996–2015.

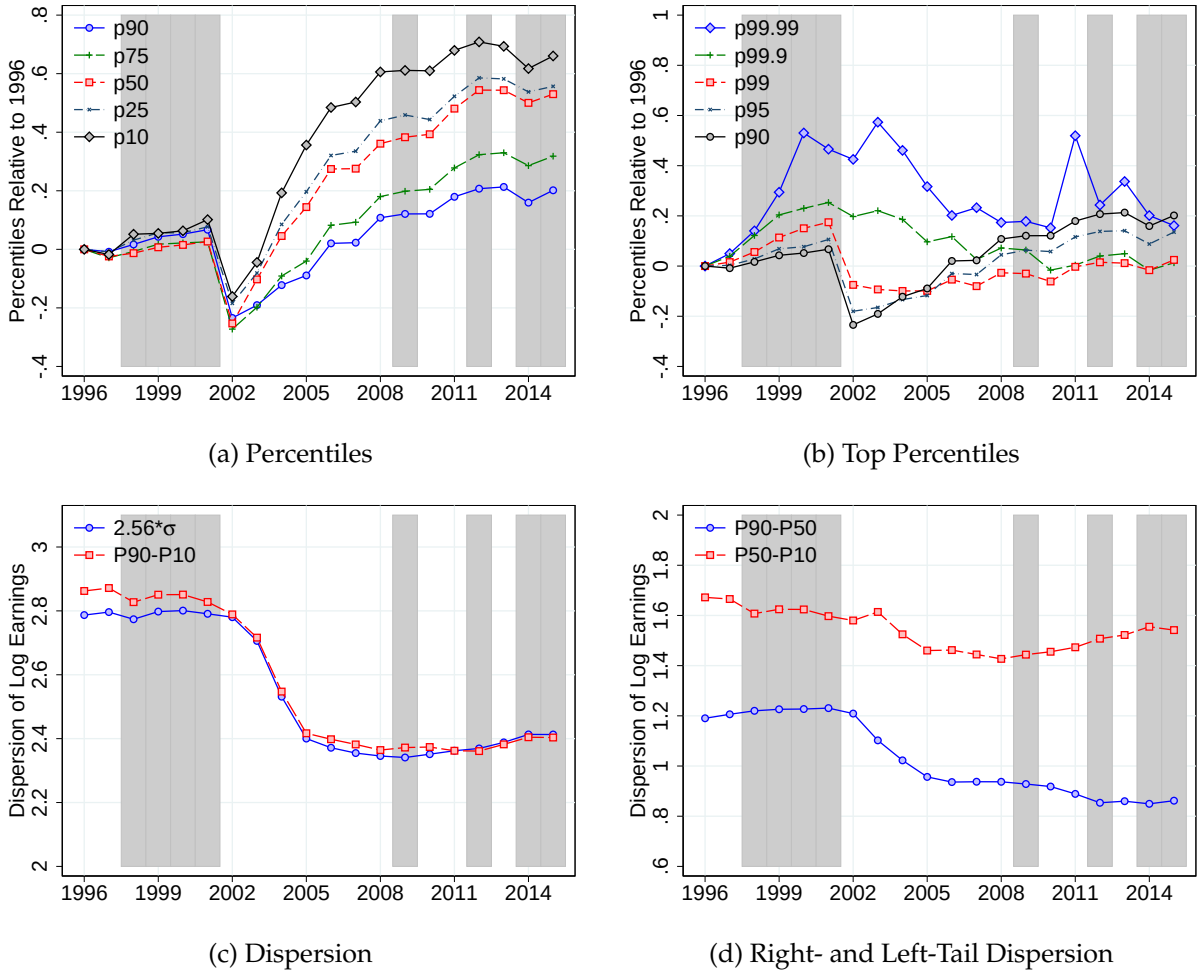
Table A.3: Number of Observations Subject to Cumulative Selection Criteria

		Quarterly employment in formal private private sector job											
Year	Raw data	Q1,Q2	Q2,Q3	Q3,Q4	Q2,Q4	Q1,Q4	Q1,.	Q2,.	Q3,.	Q4,.	Formal	Threshold	Collapsed
1996	51,786	0	0	0	9,038	0	0	3,096	0	2,602	14,736	14,687	10,180
1997	52,760	0	0	0	9,272	0	0	2,855	0	2,766	14,893	14,869	10,241
1998	50,200	0	0	0	8,940	0	0	2,979	0	2,624	14,543	14,502	10,046
1999	44,597	0	0	0	8,512	0	0	2,282	0	2,168	12,962	12,933	8,684
2000	40,000	0	0	0	7,202	0	0	2,165	0	2,102	11,469	11,445	7,849
2001	39,013	0	0	0	6,880	0	0	2,213	0	2,056	11,149	11,081	7,661
2002	35,651	0	0	0	5,788	0	0	2,026	0	1,479	9,293	9,250	6,367
2003	35,056	0	0	2,868	0	0	0	2,878	1,728	1,816	9,290	9,020	7,630
2004	46,723	2,916	3,332	3,232	0	1,310	1,170	651	553	1,395	14,559	14,138	8,873
2005	48,784	3,300	3,418	3,596	0	1,614	1,375	548	632	1,389	15,872	15,345	9,559
2006	57,417	3,682	3,876	5,136	0	1,756	1,419	702	1,278	2,166	20,015	19,345	12,345
2007	47,798	4,980	0	0	0	2,284	2,102	3,137	0	4,259	16,762	16,147	12,633
2008	64,051	5,262	4,974	5,116	0	2,286	2,227	1,004	954	2,248	24,071	23,120	14,624
2009	62,218	4,846	4,920	5,084	0	2,308	2,105	963	1,007	2,098	23,331	22,284	14,058
2010	61,932	4,626	4,974	5,168	0	2,288	2,179	1,019	1,067	2,195	23,516	22,567	14,346
2011	61,174	4,876	5,210	5,154	0	2,320	2,150	1,081	960	2,165	23,916	23,002	14,527
2012	59,008	4,780	5,024	4,894	0	2,256	2,150	943	943	1,992	22,982	22,182	13,984
2013	58,157	4,836	4,660	4,770	0	2,230	2,051	913	982	2,211	22,653	21,909	13,905
2014	63,142	5,004	5,138	5,132	0	2,362	2,101	1,138	1,100	2,358	24,333	23,460	14,943
2015	31,807	5,268	0	0	0	0	3,375	3,432	0	0	12,075	11,707	9,142

Notes: This table shows the number of observations of the EPH household survey data satisfying cumulative sample selection criteria, starting with the raw data and ending with the collapsed sample.
Source: EPH, 1996–2015.

A.2 Figures

Figure A.1: Distribution of Earnings in the Population



(a) Percentiles

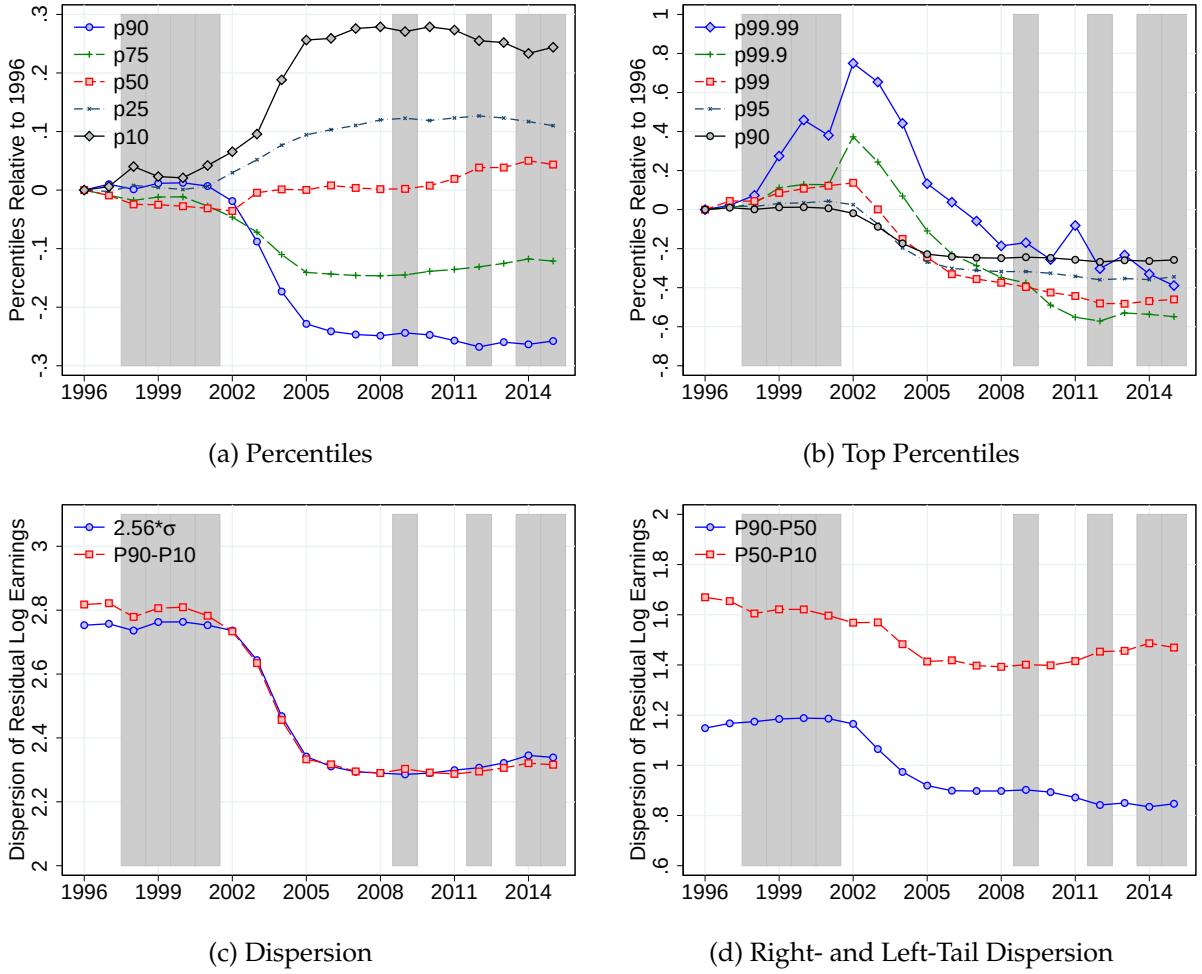
(b) Top Percentiles

(c) Dispersion

(d) Right- and Left-Tail Dispersion

Notes: Using raw log earnings and the *CS* sample, Figure A.1 plots the following variables against time for the overall population: (a) P10, P25, P50, P75, P90; (b) P90, P95, P99, P99.9, P99.99; (c) P90-10 and 2.56*SD of log income; (d) P90-50 and P50-10. All percentiles are normalized to 0 in the first available year. Shaded areas indicate recessions. 2.56*SD corresponds to P90-10 differential for a Gaussian distribution.

Figure A.2: Distribution of Residual Earnings in the Population After Controlling for Age



(a) Percentiles

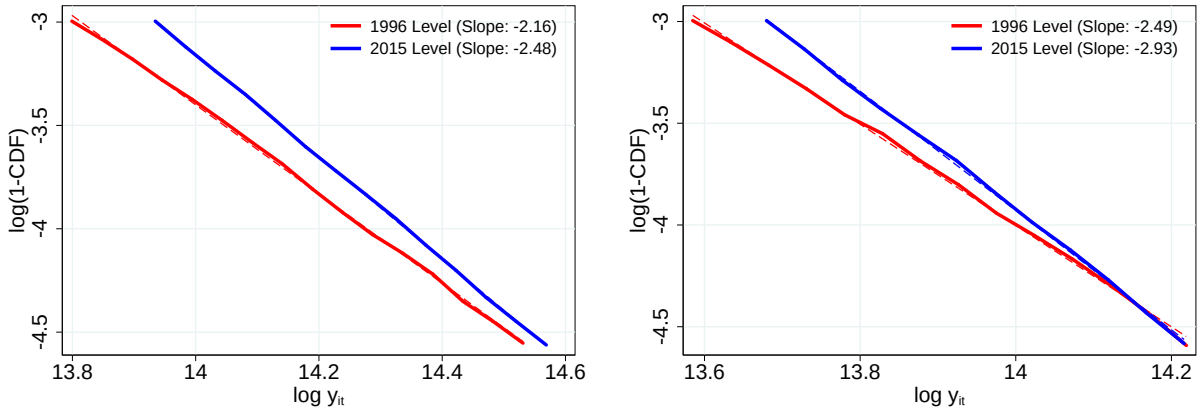
(b) Top Percentiles

(c) Dispersion

(d) Right- and Left-Tail Dispersion

Notes: Using residual log earnings and the *CS* sample, Figure A.2 plots the following variables against time for the overall population: (a) P10, P25, P50, P75, P90; (b) P90, P95, P99, P99.9, P99.99; (c) P90-10 and 2.56*SD of residual log earnings; (d) P90-50 and P50-10. All percentiles are normalized to 0 in the first available year. Residual log earnings are computed as the residual from a regression of log real earnings on a full set of age dummies, separately for each year and gender. Shaded areas indicate recessions. 2.56*SD corresponds to P90-10 differential for a Gaussian distribution.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

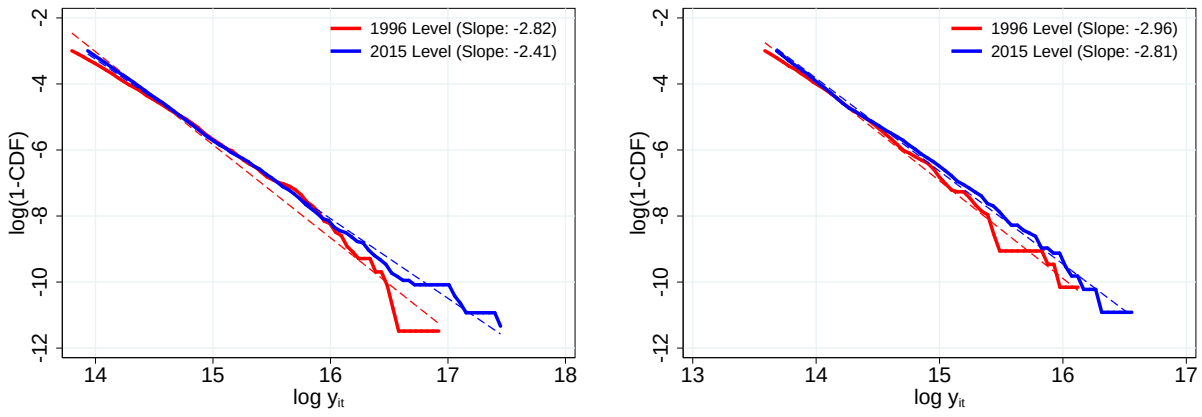
Figure A.3: Top Income Inequality: Pareto Tail at Top 1%



(a) Men (b) Women

Notes: Using raw log earnings and the top 1% of the *CS* sample, Figure A.3 shows the log empirical density $(\log(1 - CDF))$ of log earnings and the linear fit in 1996 and 2015. This is a log-log plot, and the slope of the regression line gives the Pareto tail index of the earnings distribution.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

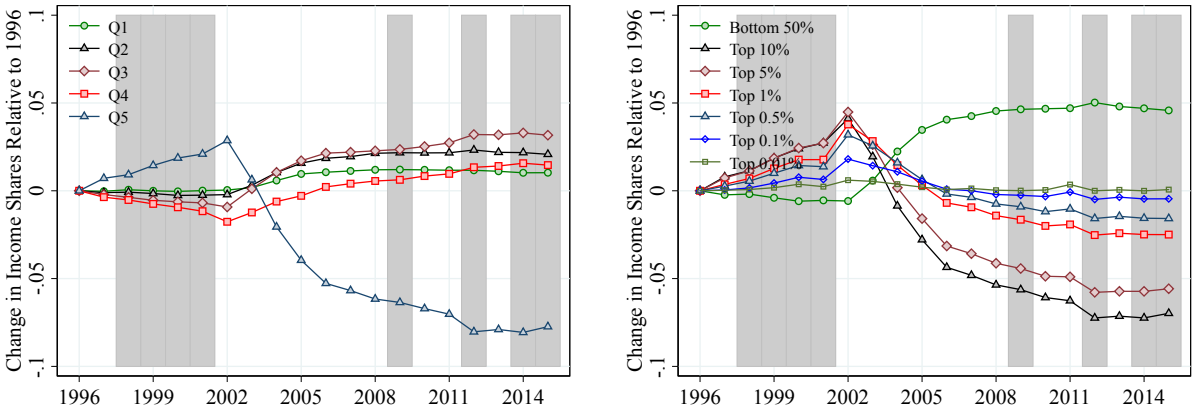
Figure A.4: Top Income Inequality: Pareto Tail at Top 5%



(a) Men (b) Women

Notes: Using raw log earnings and the top 5% of the *CS* sample, Figure A.4 shows the log empirical density $(\log(1 - CDF))$ of log earnings and the linear fit in 1996 and 2015. This is a log-log plot, and the slope of the regression line gives the Pareto tail index of the earnings distribution.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

Figure A.5: Changes in Income Shares Relative to 1996

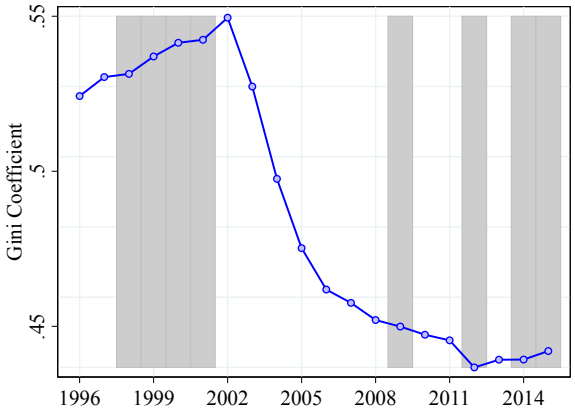


(a) Income Shares of Quintiles

(b) Selected Income Shares

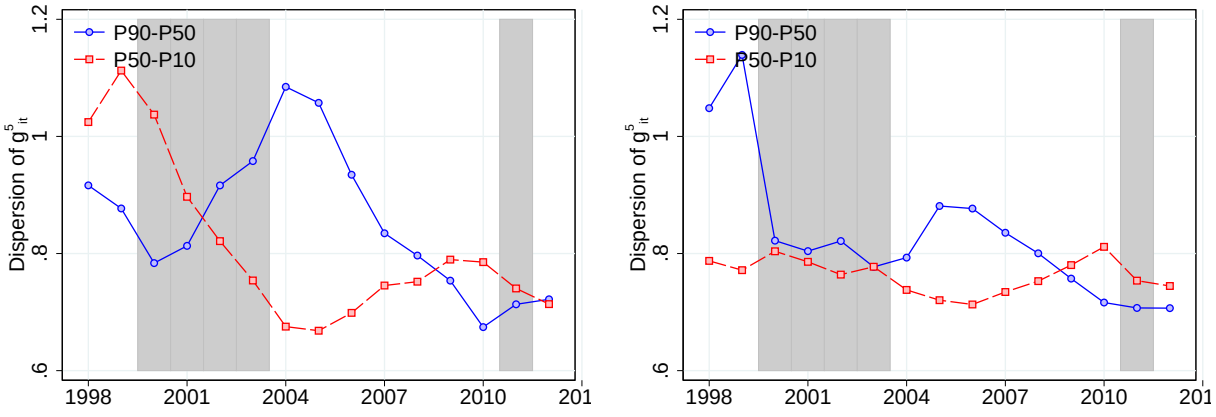
Notes: Using raw earnings in levels and the *CS* sample, Figure A.5 plots the following variables against time for the overall population: (a) the share of aggregate income going to each quintile, (b) the share of aggregate income going to the bottom 50%, and top 10%, 5%, 1%, 0.5%, 0.1%, 0.01%. All income shares are normalized to 0 in the first available year. Shaded areas indicate recessions.

Figure A.6: Gini Coefficient



Notes: Using raw earnings in levels and the *CS* sample, Figure A.6 plots the Gini coefficient against time. Shaded areas indicate recessions.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

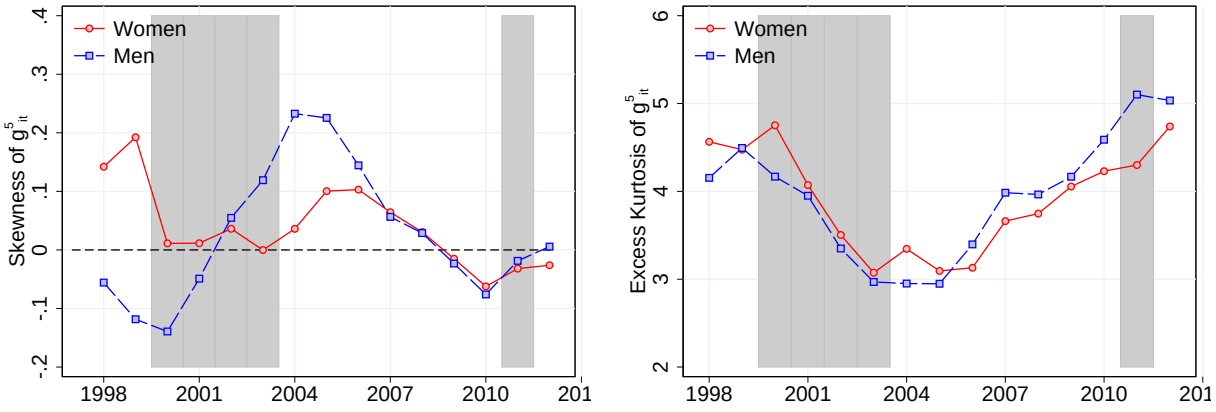
Figure A.7: Dispersion of Five-Years Log Earnings Changes



(a) Men (b) Women

Notes: Using residual five-year earnings changes and the *LS* sample, Figure A.7 plots the following variables against time : (a) Men: P90-10 differential; (b) Women: P90-10 differential. Shaded areas indicate recessions.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

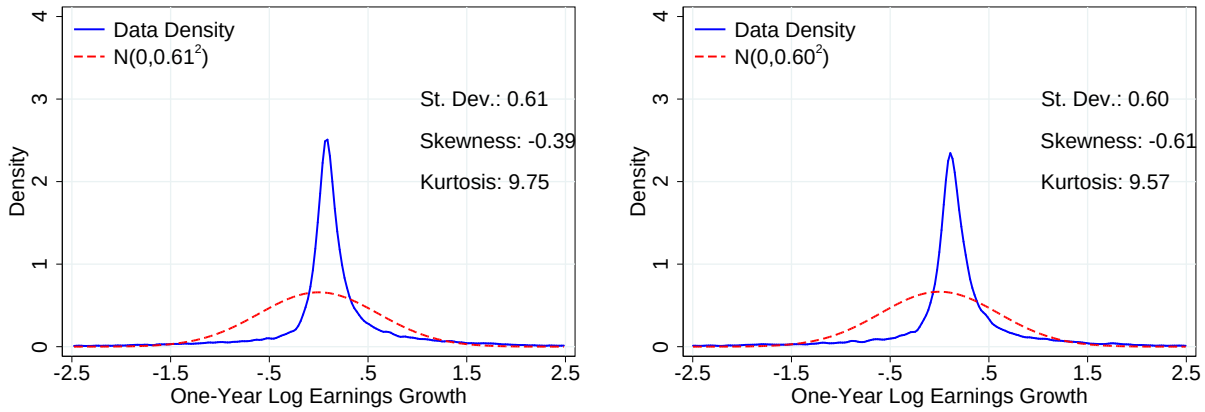
Figure A.8: Skewness and Kurtosis of Five-Year Log Earnings Changes



(a) Kelley Skewness (b) Excess Crow-Siddiqui Kurtosis

Notes: Using residual five-year earnings changes and the *LS* sample, Figure A.8 plots the following variables against time: (a) Men and Women: Kelly skewness; (b) Men and Women: Excess Crow-Siddiqui kurtosis calculated as $\frac{P97.5-P2.5}{P75-P25} - 2.91$ 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 indicate recessions.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

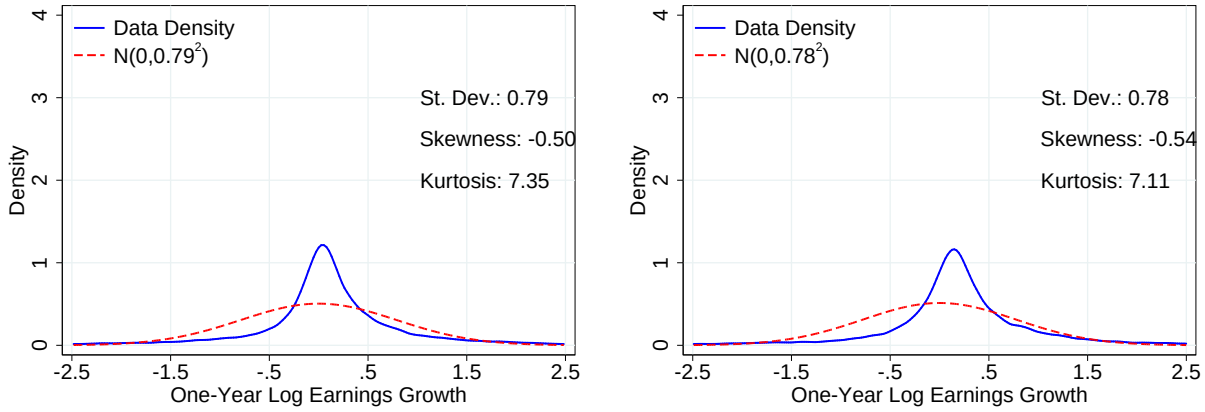
Figure A.9: Empirical Densities of One-Year Earnings Growth



(a) Men (b) Women

Notes: Figure A.9 shows the log-density of one-year log residual earnings growth for men and women for 2005.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

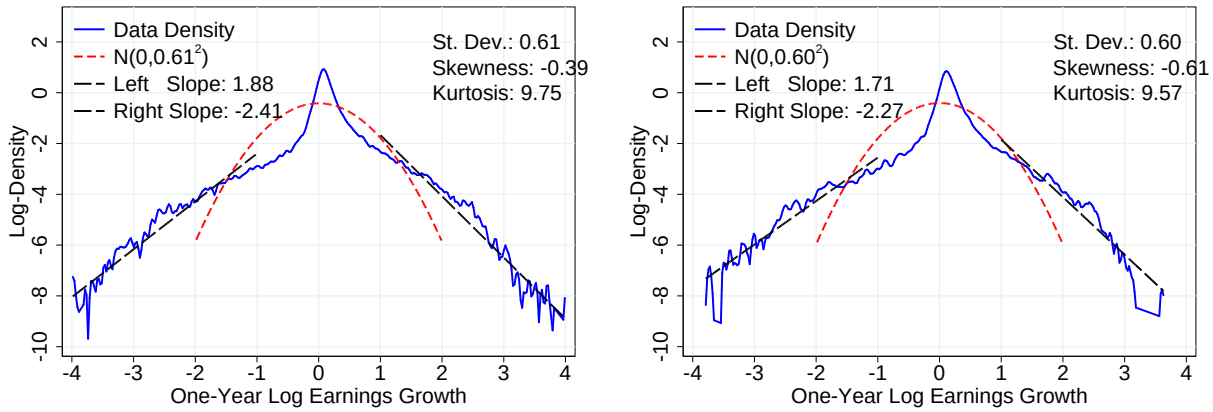
Figure A.10: Empirical Densities of Five-Year Earnings Growth



(a) Men (b) Women

Notes: Figure A.10 shows the log-density of five-year log residual earnings growth for men and women for 2005.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

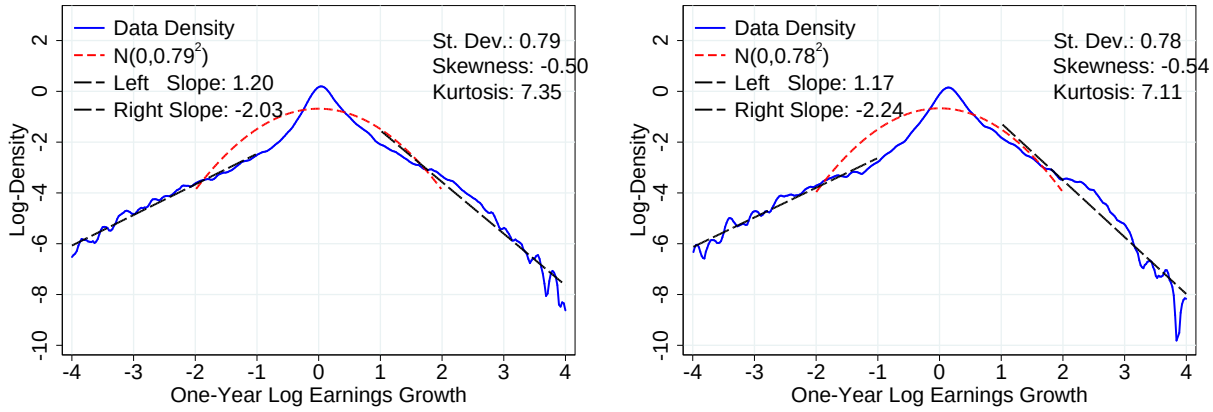
Figure A.11: Empirical Log-Densities of One-Year Earnings Growth



(a) Men (b) Women

Notes: Figure A.11 shows the log-density of one-year log residual earnings growth for men and women for 2005.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

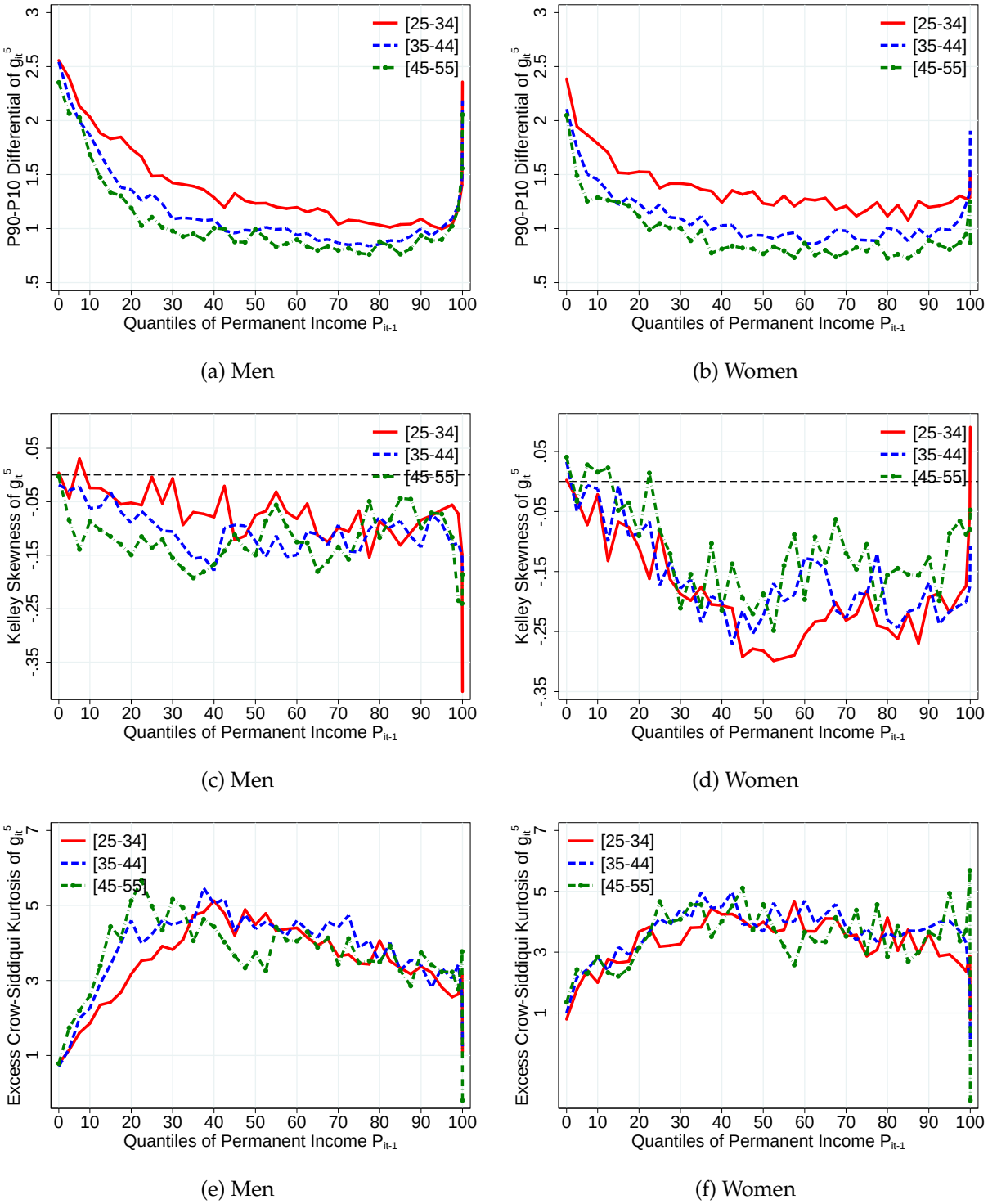
Figure A.12: Empirical Log-Densities of Five-Year Earnings Growth



(a) Men (b) Women

Notes: Figure A.12 shows the log-density of five-year log residual earnings growth for men and women for 2005.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

Figure A.13: Dispersion, Skewness and Kurtosis of Five-Year Log Earnings Changes



(a) Men

(b) Women

(c) Men

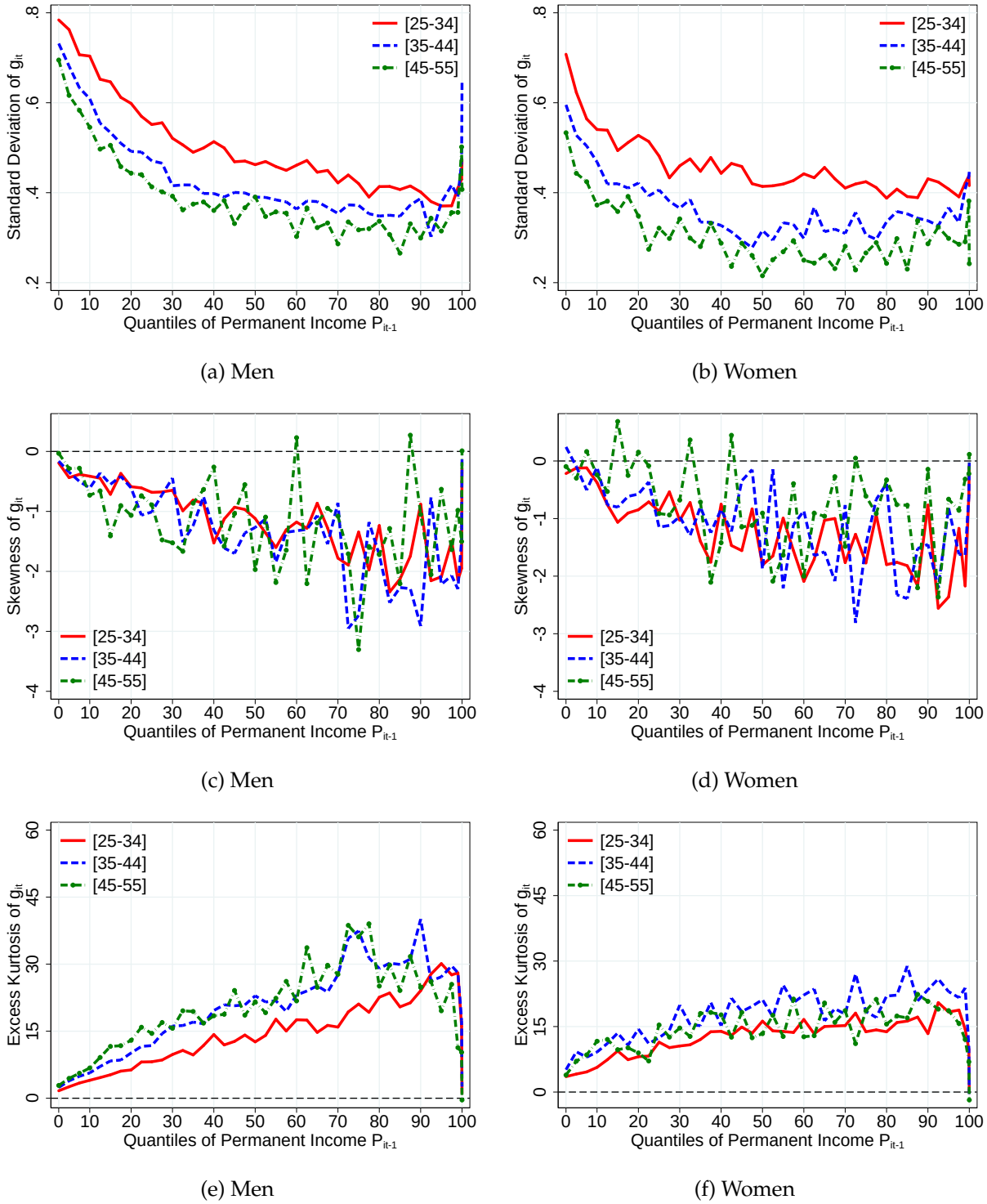
(d) Women

(e) Men

(f) Women

Notes: Using residual five-year earnings changes and the LS^+ sample, Figure A.13 plots the following variables against permanent income quantile groups for the three age groups: (a) Men: P90-10; (b) Women: P90-10; (c) Men: Kelley Skewness; (d) Women: Kelley Skewness; (e) Men: Excess Crow-Siddiqui kurtosis; (f) Women: Excess Crow-Siddiqui kurtosis. Excess Crow-Siddiqui kurtosis calculated as $\frac{P97.5-P2.5}{P75-P25} - 2.91$ 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.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

Figure A.14: Standardized Moments of One-Year Log Earnings Changes



(a) Men

(b) Women

(c) Men

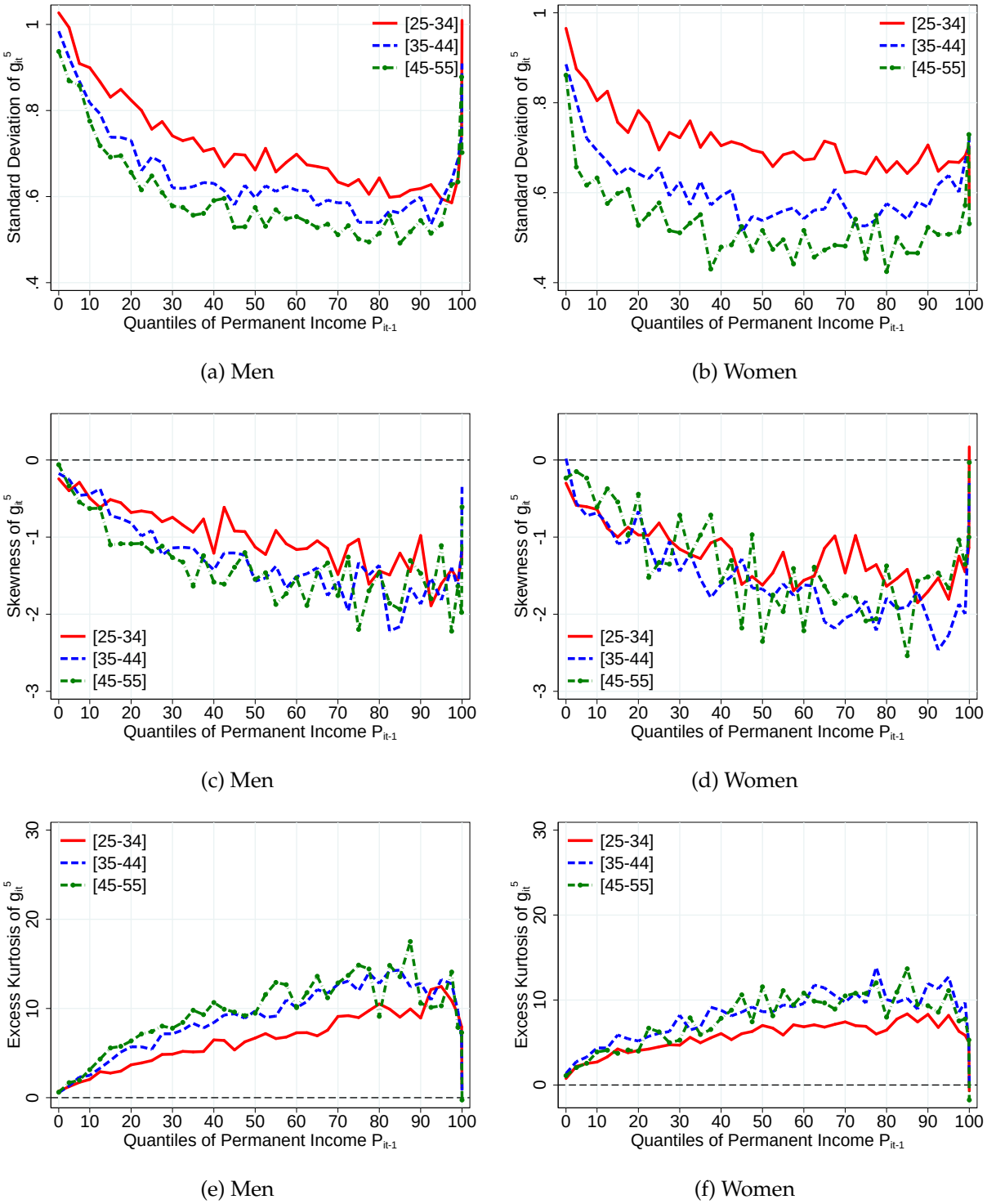
(d) Women

(e) Men

(f) Women

Notes: Using residual one-year earnings changes and the LS^{+} sample, Figure A.14 plots the following variables against permanent income quantile groups for the three age groups: (a) Men: Standard deviation; (b) Women: Standard deviation; (c) Men: Skewness; (d) Women: Skewness; (e) Men: Kurtosis; (f) Women: Kurtosis.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

Figure A.15: Standardized Moments of Five-Year Log Earnings Changes



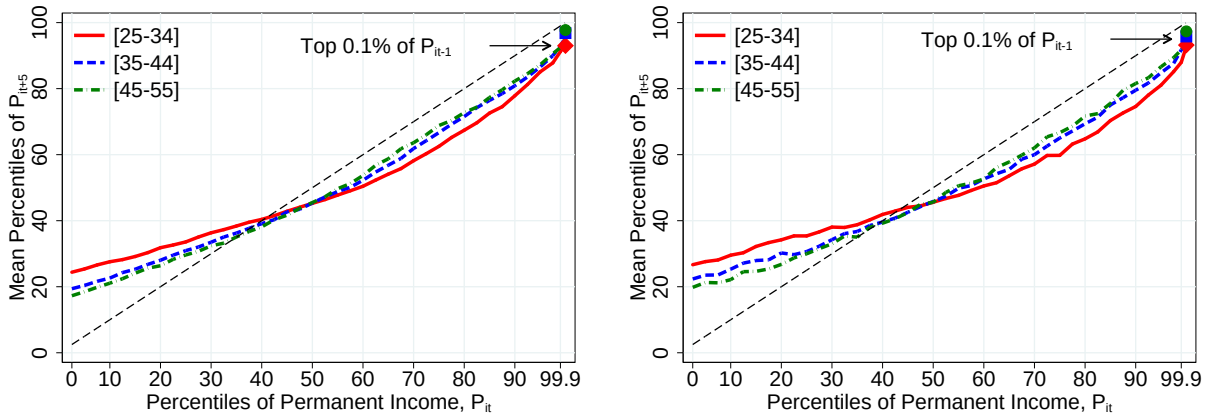
(a) Men (b) Women

(c) Men (d) Women

(e) Men (f) Women

Notes: Using residual five-year earnings changes and the LS^+ sample, Figure A.15 plots the following variables against permanent income quantile groups for the three age groups: (a) Men: Standard deviation; (b) Women: Standard deviation; (c) Men: Skewness; (d) Women: Skewness; (e) Men: Kurtosis; (f) Women: Kurtosis.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

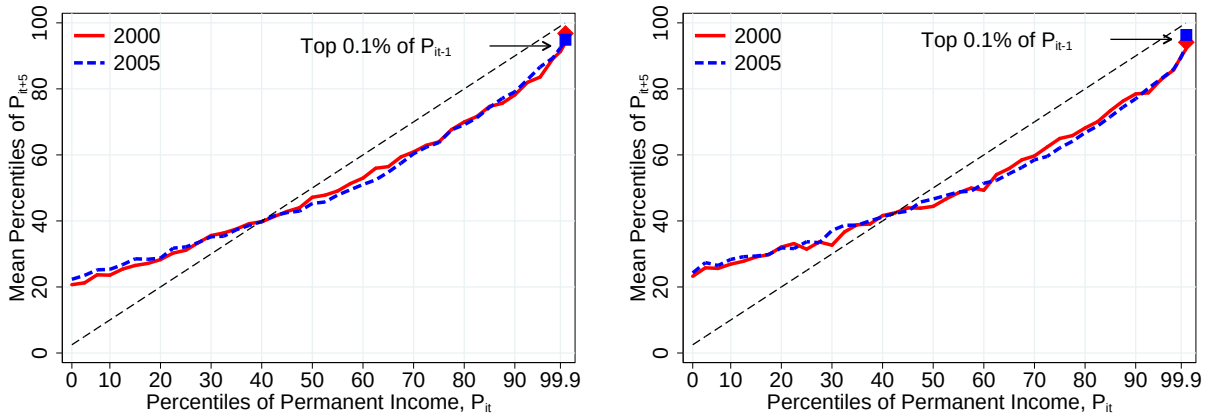
Figure A.16: Evolution of Five-Year Mobility over the Life Cycle



(a) Men (b) Women

Notes: Figure A.16 plots average rank-rank mobility over a five-year period by showing average rank of permanent income in $t+5$ as a function of the permanent income rank in t. Results are reported as the average mobility during the period of analysis (i.e., 1996-2015) and for three age groups defined in period t ($25-34$, $35-44$, and $45-55$).
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

Figure A.17: Evolution of Five-Year Mobility over Time



(a) Men (b) Women

Notes: Figure A.17 plots average rank-rank mobility over a five-year period by showing average rank of permanent income in $t+5$ as a function of the permanent income rank in t. Results are reported for $t=2000$ and $t=2005$.
Source: Registered Employment Longitudinal Sample (Ministry of Employment and Labor of Argentina), 1996–2015.

B Model Appendix

B.1 Methods to Construct Regular Wages

This section describes the methods to construct regular wages, including the Break Test algorithm. We focus on the methods proposed by Nakamura and Steinsson (2008), Kehoe and Midrigan (2015), Stevens (2020), and Blanco (2020). Let $\{w_{jt}\}_{t=0}^{T_j}$ be the monthly wage in job spell j with a duration given by T_j. For simplicity, from now on, we suppress the job spell identifier.

Stevens (2020) Method. The method constructs an increasing sequence of breaks $\{\tau_s\}_{s=0}^{m}$, with $\tau_0 = 0$ and $\tau_m = T$. It depends on two parameters: $\mathcal{L}$ and $\mathcal{K}$. The minimum T to apply the method to construct the regular wage within a job spell is described by $\mathcal{L}$, and $\mathcal{K}$ describes the minimum of the maximum distances to add new breaks.

The method works as follows:

1. Drop all spells with $T \leq \mathcal{L}$.
2. Set $m = 1$.
3. For each $\{\{w_t\}_{t=\tau_i}^{\tau_{i+1}}\}_{i=0}^{m}$, compute the following statistics:

$$S_i = \sqrt{\tau_{i+1} - \tau_i + 1} \max_{\tau_i \leq t \leq \tau_{i+1}} \left[\frac{t - \tau_i}{\tau_{i+1} - \tau_i + 1} \frac{\tau_{i+1} + 1 - t}{\tau_{i+1} - \tau_i + 1} D_t \right],$$
$$D(t) = \sup_w |F_{\tau_i,t}(w) - F_{t+1,\tau_{i+1}}(w)|.$$

   Here, $F_{j,h+1}(w)$ is the empirical cumulative distribution functions of the sample $\{w_t\}_{t=j}^{h+1}$; that is, $F_{j,h+1}(w) = \frac{1}{h-j} \sum_{t=j}^{h+1} \mathbb{I}(w_t \leq w)$, where $\mathbb{I}(\cdot)$ denotes the indicator function.

4. If $S_i \leq \mathcal{K}$ for all i, stop and compute the regular wage as

$$w_t^r = \text{median}\left\{w_t : \tau_i \leq t \leq \tau_{i+1} \text{ for some } i+1\right\}.$$

5. For every i such that $S_i \leq \mathcal{K}$, add a new break at

$$\arg \max_{\tau_i \leq t \leq t_{i+1}} \sqrt{\frac{t - \tau_i}{\tau_{i+1} - \tau_i + 1} \frac{\tau_{i+1} + 1 - t}{\tau_{i+1} - \tau_i + 1} D_t}.$$

   Increase m by the new number of new breaks and go to step 3.

Nakamura and Steinsson (2008) Method. The method removes inverse V-shape wage changes. Since the method was original designed for V-shaped wage changes, we modify it to detect the inverse pattern. This method depends on three parameters: $\mathcal{J}_{NS}$, $\mathcal{L}_{NS}$, and $\mathcal{K}_{NS}$. The number of periods for the wage to return to the regular wage is described by $\mathcal{J}_{NS}$, and $\mathcal{L}_{NS}$ and $\mathcal{K}_{NS}$ describe the prevalence of the regular wages.

The method works as follows:

1. If $w_{t-1}^r = w_t$, then $w_t^r = w_t$.

2. If $w_t < w^r_{t-1}$, then $w^r_t = w_t$.

3. If $w^r_{t-1} \in \{w_{t+1}, \ldots, w_{t+J}\}$ and $w_{t+j} \geq w^r_{t-1}\ \forall j \leq \mathcal{J}_{NS}$, then $w^r_t = w^r_{t-1}$.

4. If $\{w_t, \ldots, w_{t+L}\}$ has $\mathcal{K}_{NS}$ or more elements, $w^r_t = w_t$.

5. Set $w^{\min}_t = \min\{w_t, \ldots, w_{it+L}\}$, $k^{\min}_t =$ first-time-min$\{w_t, \ldots, w_{t+L}\}$,
$$\text{If } w^{\min}_t = \min\{w_{k^{\min}_t}, \ldots, w_{k^{\min}_t+L}\}, \text{ then } w^r_t = w^{\min}_t$$

6. Set $w^r_t = w_t$.

In the first time period, the method begins at step 4.

Kehoe and Midrigan (2015) Method. The method constructs the regular wage as the running mode of the original series. This method depends on three parameters: $\mathcal{L}_{KM}$, $\mathcal{C}_{KM}$, and $\mathcal{A}_{KM}$. The length of rolling window periods to construct the mode is described by $\mathcal{L}_{KM}$, $\mathcal{C}_{KM}$ describes the number of periods to use the running modes, and $\mathcal{A}_{KM}$ describes the number of non-missing wages to compute the mode.

The method works as follows:

1. Construct $h_t = \sum_{j=-\mathcal{L}_{KM}}^{\mathcal{L}_{KM}} \mathbb{I}(w_{t+j} \text{ non missing})/(2\mathcal{L}_{KM})$ for all $t \in [1 + \mathcal{L}_{KM}, T - \mathcal{L}_{KM}]$.

2. Set $f_t = \sum_{j=-\mathcal{L}_{KM}}^{\mathcal{L}_{KM}} \mathbb{I}(w_{t+j} \text{ non missing}, w_{t+j} = w^m_t)/(2\mathcal{L}_{KM})$, where
$$w^m_t = \begin{cases} mode\{w_{t-\mathcal{L}_{KM}}, \ldots, w_{t+\mathcal{L}_{KM}}\} & \text{If } h_t \geq \mathcal{A}_{KM} \\ . & \text{Otherwise} \end{cases}.$$

3. Define w^r_t with the recursive algorithm
   (a) Set $w^r_{\mathcal{L}_{KM}+1} = w^m_{\mathcal{L}_{KM}+1}$ if $w^m_{\mathcal{L}_{KM}+1}$ is not missing or set $w^r_{\mathcal{L}_{KM}+1} = w_{\mathcal{L}_{KM}+1}$ otherwise.
   (b) For $t \in [\mathcal{L}_{KM} + 2, T - \mathcal{L}_{KM}]$
$$w^r_t = \begin{cases} w^m_t & \text{if } w^m_t \neq . \text{ and } f_t > c \text{ and } w_t = w^m_t \\ w^r_{t-1} & w^m_t = . \text{ or } f_t \leq c \text{ or } w_t \neq w^m_t \end{cases}.$$

4. Repeat the following algorithm 5 times:
$$w^r_{\{\mathcal{R}\cap\mathcal{C}\}-1} = w_{\{\mathcal{R}\cap\mathcal{C}\}} \text{ and } w^r_{\{\mathcal{R}\cap\mathcal{P}\}} = w_{\{\mathcal{R}\cap\mathcal{P}\}-1}.$$
   Here, $\mathcal{R}$ denotes periods of regular wage changes:
$$\mathcal{R} = \{t : w^r_{it} \neq w^r_{it-1} \ \&\ w^r_{it-1} \neq . \ \&\ w^r_{it} \neq .\};$$
   $\mathcal{C}$ denotes periods with regular wages:
$$\mathcal{C} = \{t : w^r_{it} = w_{it} \ \&\ w^r_{it} \neq . \ \&\ w_{it} \neq .\};$$
   and $\mathcal{P}$ denotes the periods where the last wage was regular:
$$\mathcal{P}_1 = \{t : w^r_{t-1} = w_{t-1} \ \&\ w^r_{t-1} \neq 0 \ \&\ w_{t-1} \neq 0\},$$
$$\mathcal{P} = \mathcal{P}_1/(\mathcal{P}_1 \cap \mathcal{R} \cap \mathcal{C}).$$

Blanco (2020) Method. The method drops wage changes with two properties: (i) wage changes preceded and followed by the same wage and (ii) inverse V-shaped wage changes. This method depends on three parameters: $\mathcal{K}_B$, $\mathcal{P}_B$, and $\mathcal{E}_B$. Here, $\mathcal{K}_B$ describes the number of periods to drop wages changes for wages when they are preceded and followed by the same wage, $\mathcal{P}_B$ denotes ignored small wage changes, and $\mathcal{E}_B$ denotes the minimum size to drop an inverse V-shape wage change.

The method works as follows:

1. Set $K = 1$.

2. Construct $\mathcal{F}$ and $\mathcal{Z}$

$$\mathcal{F}_K = \left\{ t : |\sum_{j=0}^{K} \Delta w_{t+j}| < \mathcal{P}_B \right\} \quad , \quad \mathcal{Z}_K = \left\{ t : |\sum_{j=0}^{K} \Delta w_{t-j}| < \mathcal{P}_B \right\}.$$

   Observe that $t^* \in \mathcal{F}_K \iff t^* + K \in \mathcal{F}_K$.

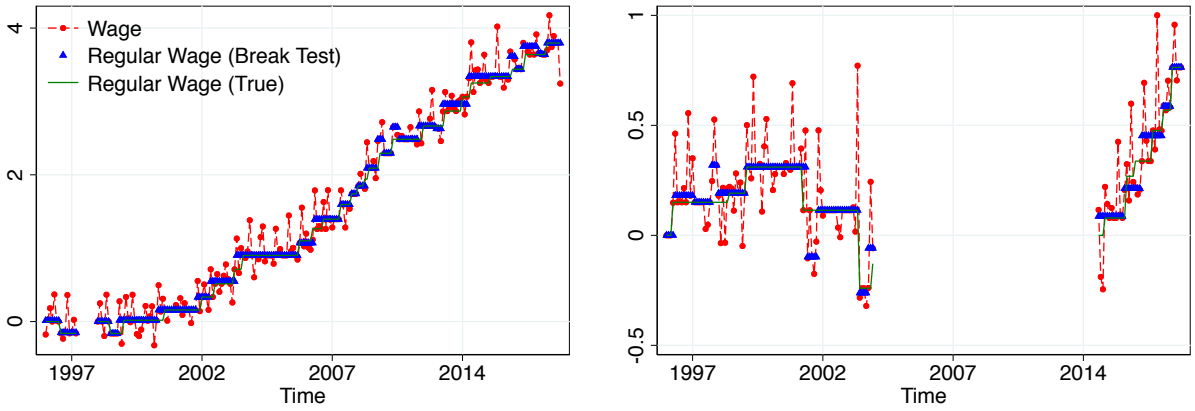
3. Replace $\Delta w_t = 0$ for all dates between t^* and $t^* + K$, where $t^* \in \mathcal{F}_K$. If $K < \mathcal{K}_B$, go to step 1 and set $K = K + 1$. If $K = \mathcal{K}_B$, go to step 3.

4. Replace Δw_t if $\Delta w_t > \mathcal{E}_B$ and $\Delta w_{i,t+1} < -\mathcal{E}_B$.

B.2 Additional Results

Figure A.18: Two Sample Paths of Wages and Regular Wages

(a) Sample Path 1 (b) Sample Path 2



Notes: Panels (a) and (b) plot the evolution of the (log) wage (red line with dots), the simulated (log) regular wage (green dashed line), and the regular wage (blue triangle) recovered with the Break Test for two workers in our sample.

Table A.4: Estimated Threshold Values and Break Test Evaluation, Sectors 1–4

	Sectors			
	1	2	3	4
Moments (data,model):				
Mean of 1-yr Δw	(0.19, 0.18)	(0.17, 0.14)	(0.24, 0.27)	(0.20, 0.20)
Std. of 1-yr Δw	(0.20, 0.20)	(0.67, 0.42)	(0.26, 0.29)	(0.23, 0.24)
CV(3) of 1-yr Δw	(3.78, 3.39)	(39.73, 25.66)	(3.59, 3.43)	(4.06, 4.14)
Std. of 1-mo Δw	(0.17, 0.18)	(0.69, 0.35)	(0.24, 0.23)	(0.19, 0.19)
Mean of 1-mo Δw in Jun/Dec	(0.21, 0.21)	(0.34, 0.32)	(0.31, 0.31)	(0.35, 0.35)
Std. of 1-mo Δw in Jun/Dec	(0.21, 0.24)	(0.62, 0.54)	(0.24, 0.23)	(0.21, 0.21)
Share of 1-yr $\Delta w = 0$	(0.04, 0.04)	(0.02, 0.00)	(0.02, 0.00)	(0.02, 0.02)
Share of 1-mo $\Delta w = 0$	(0.43, 0.39)	(0.12, 0.12)	(0.14, 0.14)	(0.15, 0.15)
Share of 1-mo $\Delta w > 0$	(0.32, 0.34)	(0.46, 0.46)	(0.46, 0.47)	(0.47, 0.45)
Parameters:				
$(T, \tilde{w}^-, \tilde{w}^+)$	(36,-0.11,1.5)	(31,-0.12,1.1)	(3,-0.83,1.5)	(26,-0.20,1.5)
σ_η	0.02	0.09	0.07	0.06
(m_ϕ, σ_ϕ)	(0.30 , 0.17)	(0.34 , 0.45)	(0.32 , 0.08)	(0.38 , 0.03)
(σ_γ, β)	(0.18 , 0.28)	(0.30 , 0.58)	(0.20 , 0.51)	(0.15 , 0.58)
Threshold and break test evaluation:				
Threshold value $\mathcal{K}$	0.42	0.39	0.38	0.47
Pr($w_t^R \neq w_{t-1}^R$)	(0.17, 0.17)	(0.21, 0.23)	(0.34, 0.33)	(0.12, 0.12)
Pr(no break in t | no break t)	0.90	0.82	0.72	0.91
Pr(break between $t \pm 2$ | break t)	0.89	0.78	0.85	0.76

Notes: The table presents selected moments of the wage data in the SMM estimation for sectors 1 (i.e., agriculture), 2 (i.e., fishing), 3 (i.e., minining), and 4 (i.e., manufacturing). Δw denotes wage changes. The first block of rows (i.e., rows 1 to 9) describes the wage change moments in the data and in the model. The second block of rows (i.e., rows 10 to 13) describes the estimated parameters. The last block of rows (i.e., rows 14 to 17) describes the value of $\mathcal{K}$ across sectors and some statistics to evaluate the validity of the methodology. We truncate the wage change distribution at the 2nd and 98th percentiles in the data and in the model. CV(3) denotes the third order generalized coefficient of variation, i.e., $CV(3) = E[\Delta w^3]/E[\Delta w]^3$. The last column shows the average results across sectors weighted by the number of workers in each sector.
Source: SIPA, 1996–2015, and simulations.

Table A.5: Estimated Threshold Values and Break Test Evaluation, 5–8

	Sectors			
	5	6	7	8
Moments (data,model):				
Mean of 1-yr Δw	(0.20, 0.20)	(0.22, 0.22)	(0.22, 0.23)	(0.22, 0.22)
Std. of 1-yr Δw	(0.24, 0.26)	(0.26, 0.24)	(0.20, 0.21)	(0.20, 0.20)
CV(3) of 1-yr Δw	(4.65, 4.93)	(4.14, 3.68)	(2.38, 2.41)	(2.62, 2.55)
Std. of 1-mo Δw	(0.27, 0.24)	(0.19, 0.20)	(0.14, 0.13)	(0.13, 0.13)
Mean of 1-mo Δw in Jun/Dec	(0.34, 0.33)	(0.31, 0.31)	(0.30, 0.30)	(0.30, 0.30)
Std. of 1-mo Δw in Jun/Dec	(0.26, 0.25)	(0.21, 0.23)	(0.20, 0.20)	(0.19, 0.19)
Share of 1-yr $\Delta w = 0$	(0.02, 0.02)	(0.02, 0.01)	(0.03, 0.03)	(0.03, 0.03)
Share of 1-mo $\Delta w = 0$	(0.14, 0.14)	(0.14, 0.16)	(0.24, 0.24)	(0.24, 0.23)
Share of 1-mo $\Delta w > 0$	(0.46, 0.45)	(0.47, 0.45)	(0.44, 0.41)	(0.44, 0.42)
Parameters:				
$(T, \tilde{w}^-, \tilde{w}^+)$	(25, -0.20, 1.5)	(36, -0.18, 1.5)	(30, -0.22, 1.5)	(29, -0.21, 1.5)
σ_η	0.03	0.09	0.06	0.06
(m_ϕ, σ_ϕ)	(0.36, 0.05)	(0.33, 0.09)	(0.36, 0.04)	(0.35, 0.06)
(σ_γ, β)	(0.19, 0.60)	(0.17, 0.54)	(0.11, 0.46)	(0.10, 0.47)
Threshold and break test evaluation:				
Threshold value $\mathcal{K}$	0.50	0.41	0.49	0.49
$\Pr(w_t^R \neq w_{t-1}^R)$	(0.10, 0.10)	(0.17, 0.17)	(0.11, 0.11)	(0.11, 0.12)
Pr(no break in t | no break t)	0.92	0.87	0.93	0.93
Pr(break between $t \pm 2$ | break t)	0.70	0.79	0.85	0.83

Notes: The table presents selected moments of the wage data in the SMM estimation for sectors 5 (i.e., construction), 6 (i.e., retail), 7 (i.e., hotel and restaurant), and 8 (i.e., transport). Δw denotes wage changes. The first block of rows (i.e., rows 1 to 9) describes the wage change moments in the data and in the model. The second block of rows (i.e., rows 10 to 13) describes the estimated parameters. The last block of rows (i.e., rows 14 to 17) describes the value of $\mathcal{K}$ across sectors and some statistics to evaluate the validity of the methodology. We truncate the wage change distribution at the 2nd and 98th percentiles in the data and in the model. CV(3) denotes the third order generalized coefficient of variation, i.e., $CV(3) = E[\Delta w^3]/E[\Delta w]^3$. The last column shows the average results across sectors weighted by the number of workers in each sector.
Source: SIPA, 1996–2015, and simulations.

Table A.6: Estimated Threshold Values and Break Test Evaluation, 9–12

	Sectors			
	9	10	11	12
Moments (data,model):				
Mean of 1-yr Δw	(0.20, 0.20)	(0.21, 0.21)	(0.21, 0.21)	(0.22, 0.09)
Std. of 1-yr Δw	(0.22, 0.22)	(0.23, 0.26)	(0.21, 0.21)	(0.23, 0.23)
CV(3) of 1-yr Δw	(3.53, 3.54)	(3.82, 4.11)	(2.88, 2.86)	(3.12, 3.23)
Std. of 1-mo Δw	(0.17, 0.17)	(0.24, 0.20)	(0.15, 0.15)	(0.15, 0.14)
Mean of 1-mo Δw in Jun/Dec	(0.32, 0.31)	(0.32, 0.31)	(0.29, 0.28)	(0.17, 0.18)
Std. of 1-mo Δw in Jun/Dec	(0.19, 0.20)	(0.23, 0.23)	(0.20, 0.20)	(0.20, 0.17)
Share of 1-yr $\Delta w = 0$	(0.02, 0.02)	(0.05, 0.05)	(0.04, 0.04)	(0.08, 0.10)
Share of 1-mo $\Delta w = 0$	(0.16, 0.16)	(0.21, 0.23)	(0.25, 0.25)	(0.52, 0.35)
Share of 1-mo $\Delta w > 0$	(0.46, 0.45)	(0.43, 0.41)	(0.42, 0.41)	(0.29, 0.35)
Parameters:				
$(T, \tilde{w}^-, \tilde{w}^+)$	(20, -0.21, 1.5)	(36, -0.26, 1.5)	(30, -0.21, 1.5)	(32, -0.19, 1.4)
σ_η	0.05	0.06	0.06	0.08
(m_ϕ, σ_ϕ)	(0.34, 0.05)	(0.37, 0.04)	(0.35, 0.04)	(0.25, 0.06)
(σ_γ, β)	(0.13, 0.57)	(0.16, 0.49)	(0.12, 0.45)	(0.12, 0.36)
Threshold and break test evaluation:				
Threshold value $\mathcal{K}$	0.49	0.52	0.47	0.48
$\Pr(w_t^R \neq w_{t-1}^R)$	(0.11, 0.12)	(0.09, 0.09)	(0.11, 0.12)	(0.09, 0.09)
Pr(no break in t | no break t)	0.92	0.95	0.93	0.95
Pr(break between $t \pm 2$ | break t)	0.77	0.79	0.82	0.84

Notes: The table presents selected moments of the wage data in the SMM estimation for sectors 9 (i.e., financial activities), 10 (i.e., real state activities), 11 (i.e., education), and 12 (i.e., social services). Δw denotes wage changes. The first block of rows (i.e., rows 1 to 9) describes the wage change moments in the data and in the model. The second block of rows (i.e., rows 10 to 13) describes the estimated parameters. The last block of rows (i.e., rows 14 to 17) describes the value of $\mathcal{K}$ across sectors and some statistics to evaluate the validity of the methodology. We truncate the wage change distribution at the 2nd and 98th percentiles in the data and in the model. CV(3) denotes the third order generalized coefficient of variation, i.e., $CV(3) = E[\Delta w^3]/E[\Delta w]^3$. The last column shows the average results across sectors weighted by the number of workers in each sector.
Source: SIPA, 1996–2015, and simulations.

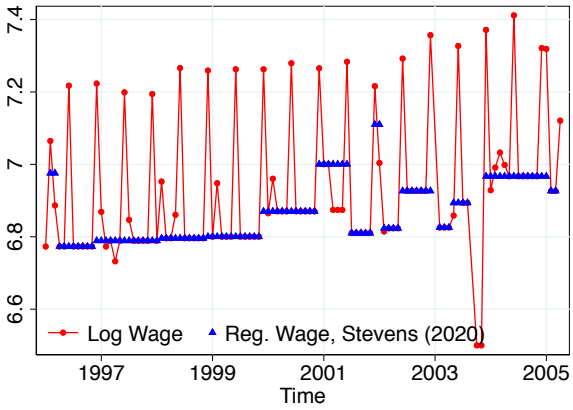
Table A.7: Estimated Threshold Values and Break Test Evaluation, Sectors 13–14

	Sectors	
	13	14
Moments (data,model):		
Mean of 1-yr Δw	(0.20, 0.19)	(0.21, 0.21)
Std. of 1-yr Δw	(0.20, 0.19)	(0.21, 0.21)
CV(3) of 1-yr Δw	(2.99, 2.82)	(3.05, 2.95)
Std. of 1-mo Δw	(0.15, 0.15)	(0.15, 0.16)
Mean of 1-mo Δw in Jun/Dec	(0.31, 0.30)	(0.28, 0.28)
Std. of 1-mo Δw in Jun/Dec	(0.20, 0.22)	(0.21, 0.21)
Share of 1-yr $\Delta w = 0$	(0.02, 0.02)	(0.04, 0.04)
Share of 1-mo $\Delta w = 0$	(0.27, 0.26)	(0.29, 0.28)
Share of 1-mo $\Delta w > 0$	(0.41, 0.41)	(0.40, 0.39)
Parameters:		
$(T, \tilde{w}^-, \tilde{w}^+)$	(28, -0.14, 1.5)	(31, -0.20, 1.5)
σ_η	0	0
(m_ϕ, σ_ϕ)	(0.37, 0.09)	(0.36, 0.06)
(σ_γ, β)	(0.13, 0.42)	(0.13, 0.42)
Threshold and break test evaluation:		
Threshold value $\mathcal{K}$	0.43	0.50
$\Pr(w_t^R \neq w_{t-1}^R)$	(0.17, 0.16)	(0.10, 0.11)
Pr(no break in t | no break t)	0.89	0.94
Pr(break between $t \pm 2$ | break t)	0.87	0.83

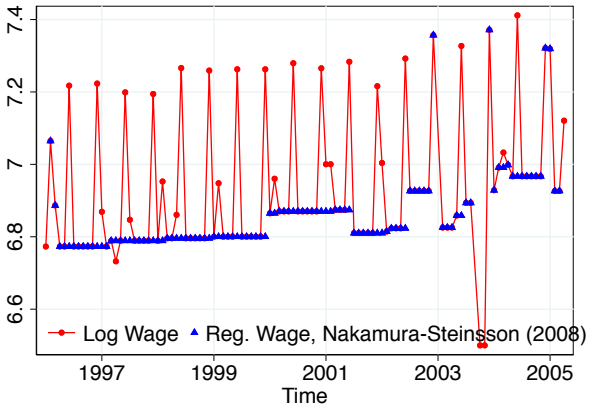
Notes: The table presents selected moments of the wage data in the SMM estimation for sectors 13 (i.e., health) and 14 (i.e., personales and comunity services). Δw denotes wage changes. The first block of rows (i.e., rows 1 to 9) describes the wage change moments in the data and in the model. The second block of rows (i.e., rows 10 to 13) describes the estimated parameters. The last block of rows (i.e., rows 14 to 17) describes the value of $\mathcal{K}$ across sectors and some statistics to evaluate the validity of the methodology. We truncate the wage change distribution at the 2nd and 98th percentiles in the data and in the model. CV(3) denotes the third order generalized coefficient of variation, i.e., $CV(3) = E[\Delta w^3]/E[\Delta w]^3$. The last column shows the average results across sectors weighted by the number of workers in each sector.
Source: SIPA, 1996–2015, and simulations.

Figure A.19: Wages and Regular Wages under Different Methods

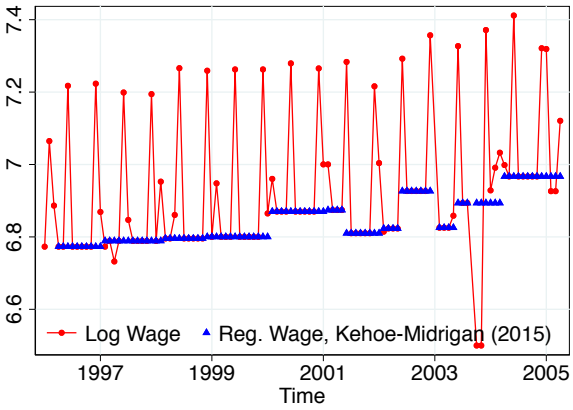
(a) Stevens (2020) method



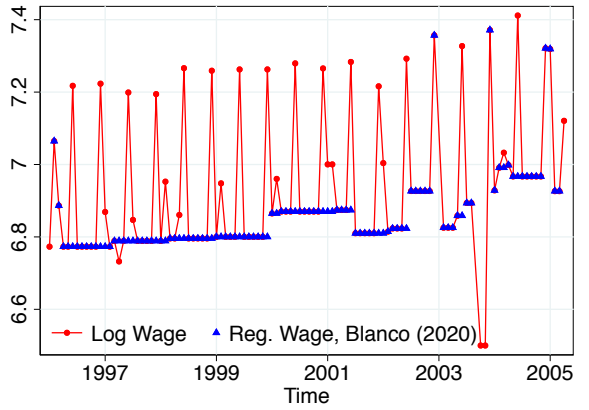
(b) Nakamura and Steinsson (2008) method



(c) Kehoe and Midrigan (2015) method



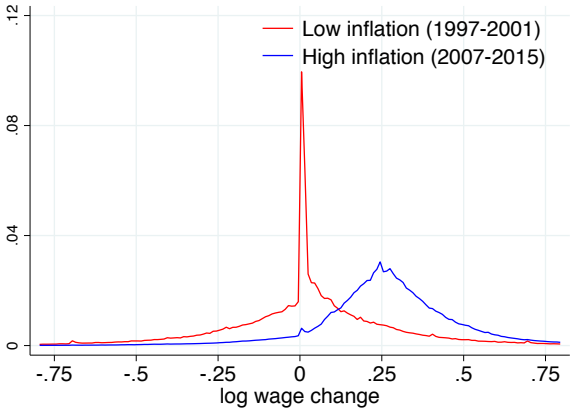
(d) Blanco (2020) method



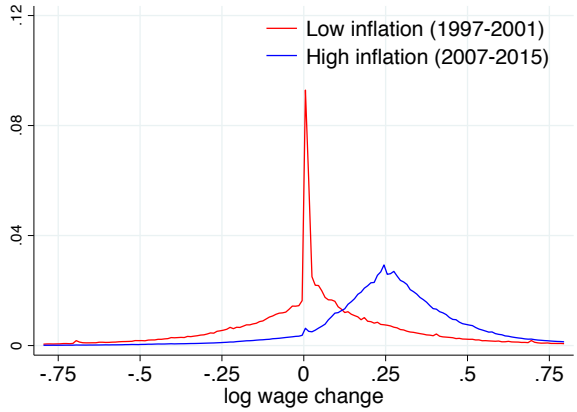
Notes: Panels (a) to (d) of Figure A.19 show the (log) wage (red line with dots) and the regular wage (blue triangle) for a worker in our sample constructed with four methods by Stevens (2020), Nakamura and Steinsson (2008), Kehoe and Midrigan (2015), and Blanco (2020), respectively.

Figure A.20: Distribution of 12-Month Regular Wage Changes across Inflation Regimes

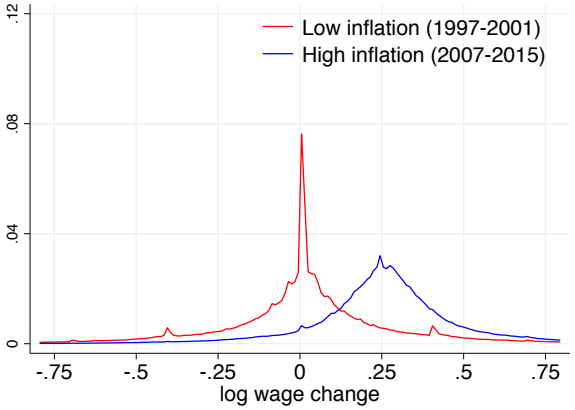
(a) Regular wage changes within jobs



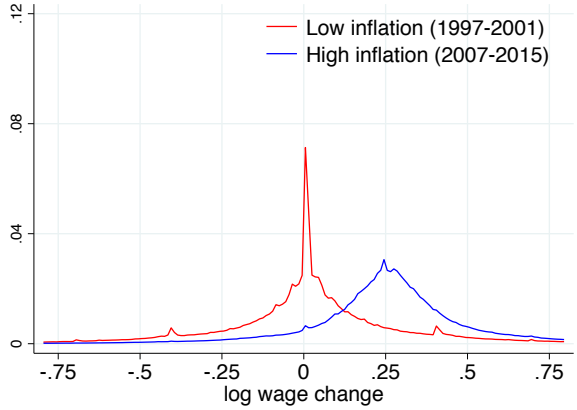
(b) Regular wage changes



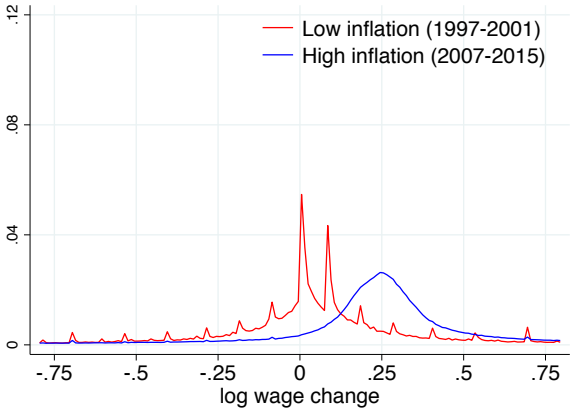
(c) Wage changes within jobs



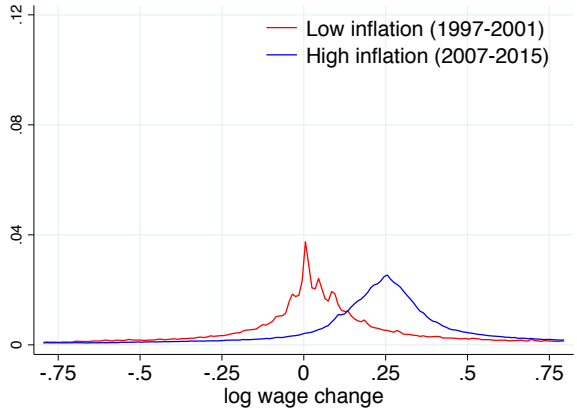
(d) Wage changes



(e) Annual regular wage growth



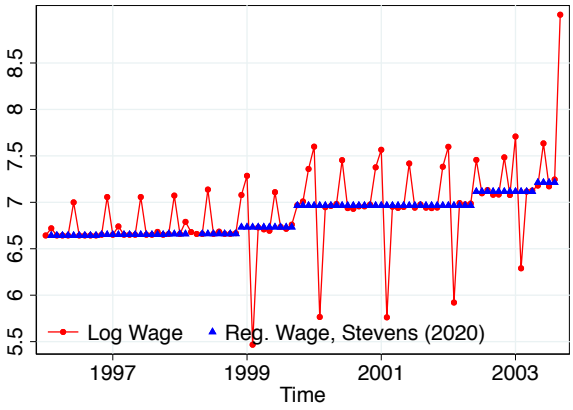
(f) Annual wage growth



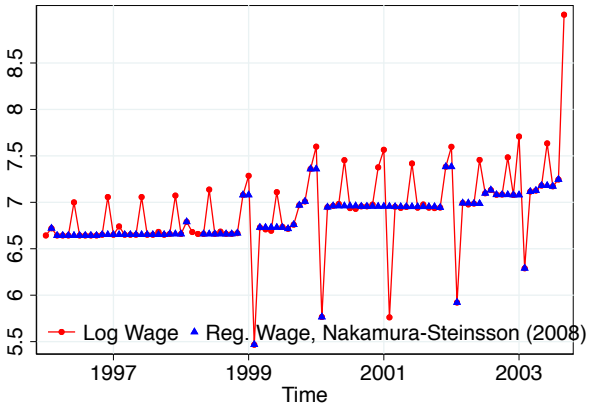
Notes: Panel (a) of Figure A.20 plots the distribution of 12-month regular wage changes within jobs in the low- and high-inflation regimes (i.e. 1997-2001 and 2007-2015, respectively). Panel (b) plots the distribution of 12-month regular wage changes within and across jobs in both regimes. Panels (c) and (d) repeat panel (a) and (b) for total wages. Panels (e) and (f) plot the growth rate of the sum of regular wages and total wages across workers within a year.

Figure A.21: Wages and Regular Wages under Different Methods

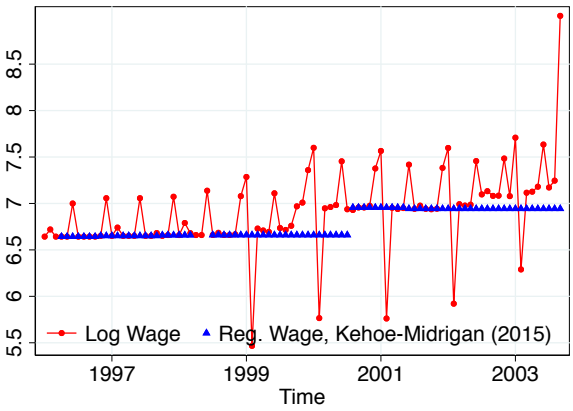
(a) Stevens (2020) method



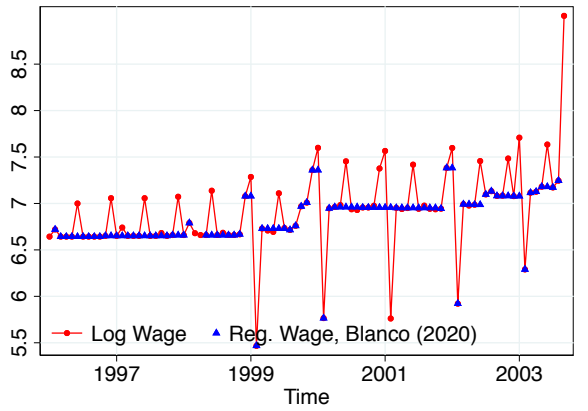
(b) Nakamura and Steinsson (2008) method



(c) Kehoe and Midrigan (2015) method

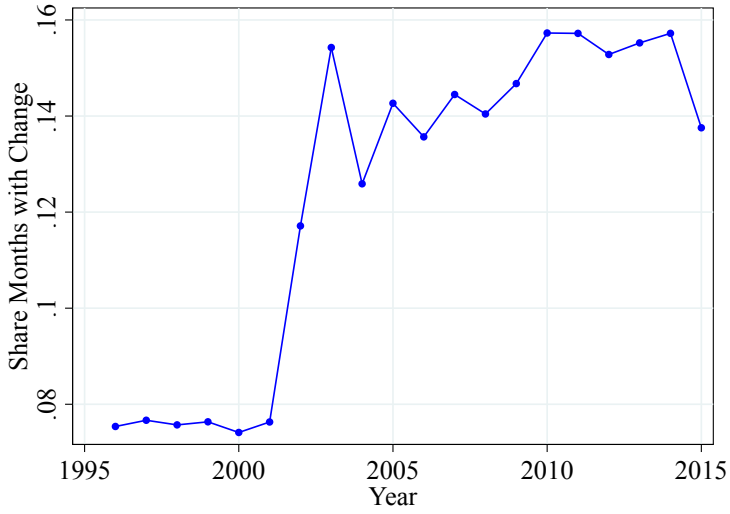


(d) Blanco (2020) method



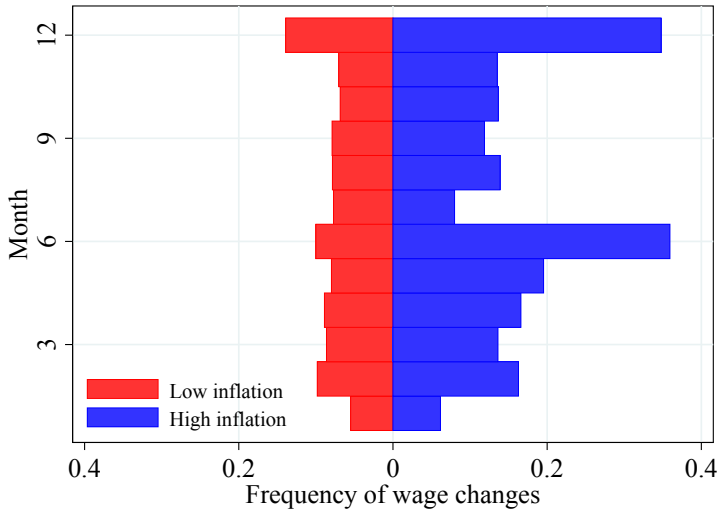
Notes: Panels (a) to (d) of Figure A.21 show the (log) wage (red line with dots) and the regular wage (blue triangle) for a worker in our sample constructed with four methods by Stevens (2020), Nakamura and Steinsson (2008), Kehoe and Midrigan (2015), and Blanco (2020), respectively.

Figure A.22: Wage Adjustment within Job Spells



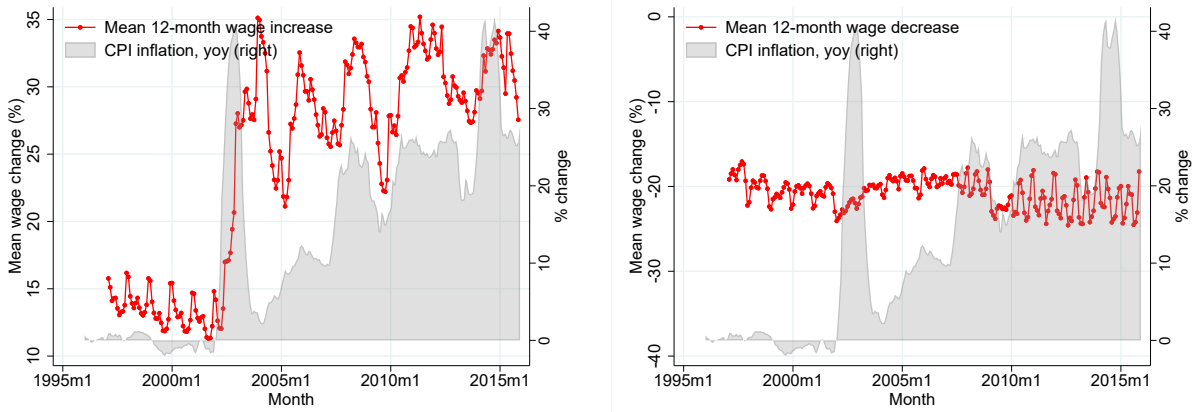
Notes: Figure A.22 plots the time series of the average across job spells of the share of months with regular wage changes within the year.

Figure A.23: Seasonal Patterns of Wage Changes



Notes: Figure A.23 plots the average frequency of regular wage changes by calendar month. The left panel shows the results for the subperiod of low inflation (i.e., between 1997 and 2001), and the right panel shows the results for the subperiod of high inflation (i.e., between 2007 and 2015).

Figure A.24: Average 12-Month Regular Wage Change

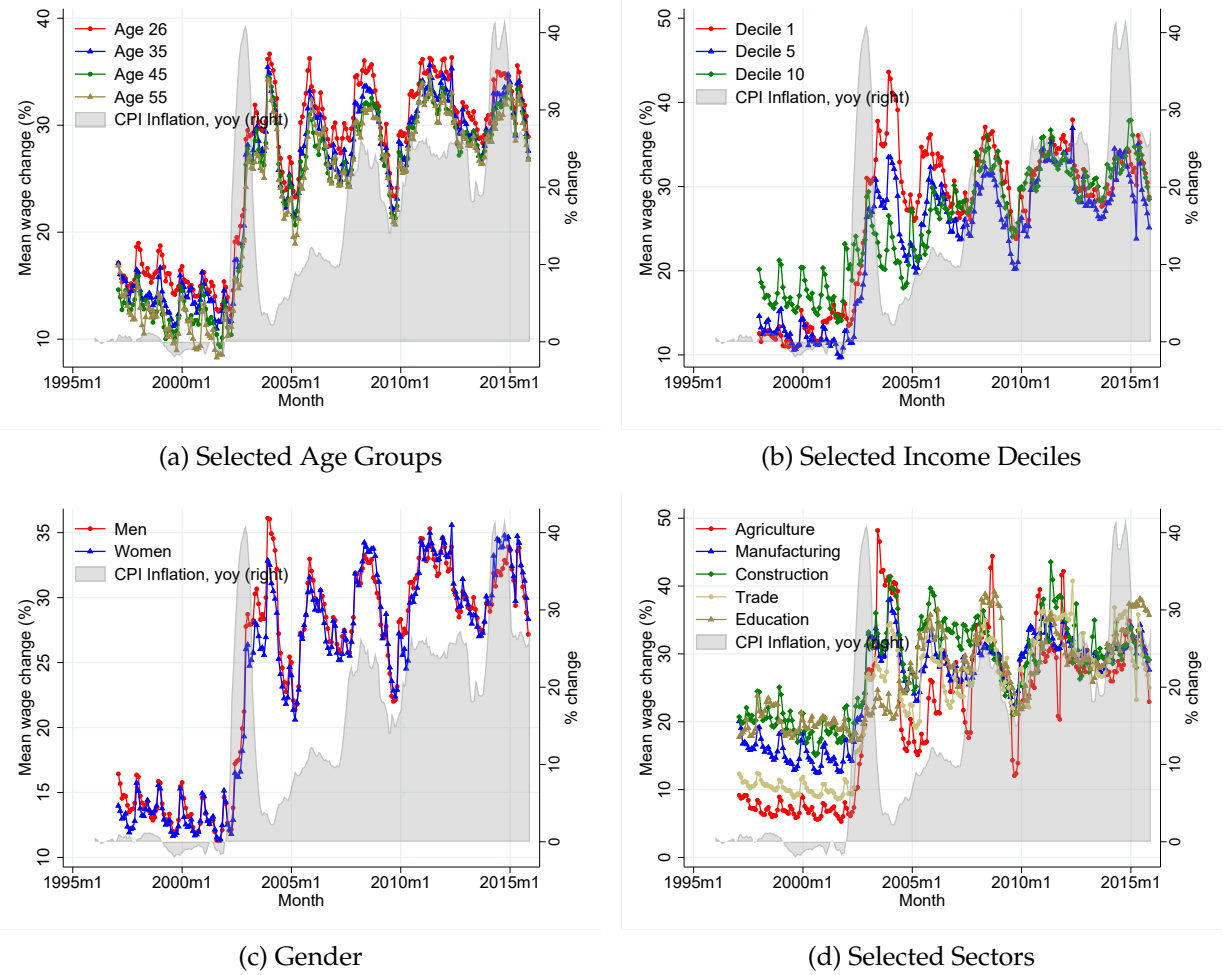


(a) Increase

(b) Decrease

Notes: Panels (a) and (b) of Figure A.24 plot the 12-month average change in regular wages conditional on positive and negative changes, respectively.

Figure A.25: Average of 12-Month Regular Wage Increases by Groups of Workers



(a) Selected Age Groups

(b) Selected Income Deciles

(c) Gender

(d) Selected Sectors

Notes: Figure A.25 plots the average size of annual wage increases for the following groups of workers: (a) Ages 26, 35, 45 and 55; (b) Income deciles: 1, 5 and 10; (c) Women and Men; (d) Sectors: Agriculture, Manufacturing, Construction, Trade, and Education. The shaded area shows the annual percentage change in the consumer price index.

Table A.8: Frequency and Size of 12-Month Wage Changes and Correlation with Inflation

Group	Average frequency				Average size (percent)				Correlation with inflation		
	Change		Cond. prob. of increase		Increase		Decrease		Frequency of wage change		
	Low Inflation	High Inflation	Low Inflation	High Inflation	Low Inflation	High Inflation	Low Inflation	High Inflation	All sample (1997-2015)	Low Inflation	High Inflation
All workers	0.64	0.95	0.69	0.95	13.4	30.2	20.2	21.4	0.67	0.16	0.66
By age:											
26	0.65	0.95	0.72	0.95	15.6	31.9	20.6	21.3	0.66	-0.14	0.60
35	0.63	0.95	0.69	0.95	14.0	30.2	20.4	22.2	0.67	0.29	0.64
45	0.63	0.95	0.67	0.95	12.5	29.4	20.4	20.5	0.68	0.12	0.66
55	0.59	0.94	0.69	0.95	11.7	29.0	21.0	20.3	0.68	-0.37	0.60
By income decile:											
Decile 1	0.64	0.96	0.73	0.94	12.9	31.4	21.9	19.8	0.58	0.29	0.42
Decile 2	0.69	0.96	0.75	0.93	9.5	30.9	22.0	23.4	0.61	-0.61	0.57
Decile 3	0.64	0.96	0.78	0.94	7.5	29.5	19.7	22.7	0.60	-0.56	0.50
Decile 4	0.65	0.97	0.73	0.96	9.8	28.9	18.7	21.3	0.61	-0.71	0.44
Decile 5	0.65	0.97	0.67	0.96	12.3	29.0	19.2	19.5	0.65	-0.53	0.64
Decile 6	0.65	0.96	0.65	0.96	13.6	29.3	20.0	19.3	0.66	-0.48	0.67
Decile 7	0.63	0.95	0.63	0.95	15.0	29.6	19.9	19.9	0.65	-0.09	0.67
Decile 8	0.61	0.94	0.61	0.95	15.6	29.8	20.1	19.8	0.65	0.08	0.63
Decile 9	0.60	0.93	0.62	0.94	16.6	29.9	21.3	20.1	0.68	0.40	0.66
Decile 10	0.58	0.92	0.67	0.93	17.1	31.3	21.6	23.5	0.72	0.80	0.69
By gender:											
Women	0.64	0.96	0.74	0.95	13.1	30.3	20.6	24.3	0.68	-0.12	0.64
Men	0.64	0.95	0.67	0.94	13.6	30.1	20.1	20.1	0.66	0.53	0.67
By sector:											
Agriculture	0.82	0.97	0.79	0.93	7.1	28.6	19.3	18.5	0.64	0.14	0.42
Manufacturing	0.60	0.93	0.62	0.94	15.4	30.0	21.3	19.6	0.70	-0.71	0.52
Construction	0.72	0.96	0.58	0.89	19.6	31.1	21.6	20.0	0.66	0.14	0.35
Trade	0.59	0.96	0.75	0.96	10.2	30.1	19.2	22.9	0.67	-0.02	0.60
Education	0.64	0.98	0.74	0.94	19.9	30.9	24.9	25.9	0.55	0.48	0.51

Notes: This table reports, for both the low- and high-inflation periods (1997-2001 and 2007-2015, respectively) and the aggregate and different groups of workers (i) the average frequency of 12-month regular wage changes, (ii) the conditional probability of an increase—i.e., the share of changes that are increases calculated as freq. of increase / (freq. of increase + freq. of decrease), (iii) the average size of annual regular wage increases and decreases (in absolute terms), and (iii) the correlation of the annual frequency of regular wage changes with annual inflation.