Nominal Devaluations, Inflation and Inequality*

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July 15, 2024

Abstract

We study the distribution of labor income during large devaluations. Across countries, inequality falls after large devaluations within the context of a surge in inflation and a fall and subsequent recovery of real labor income. To better understand inequality dynamics, we use a novel administrative dataset covering the 2002 Argentinean devaluation. We show that following a homogeneous fall in real labor income across workers, the bottom of the income distribution recovers faster than the top. Low labor mobility and lack of union coverage among high-income workers explain their slow recovery.

JEL: F31, F41, F44

Keywords: large devaluations, inflation, labor income risk, inequality.

*We thank Hassan Afrouzi, Ariel Burstein, Olivier Coibion, Javier Cravino, Fatih Guvenen, Loukas Karabarbounis, Andrei Levchenko, Chris Moser, Virgiliu Midrigan, Pablo Ottonello, Diego Perez, Felipe Saffie, Ayşegül Şahin, Matthew Shapiro, and Linda Tesar for helpful discussions, as well as seminar participants at the University of Michigan, SED, UC Davis, UC Santa Cruz, International Macro-Finance Conference at Chicago Booth, Columbia University, Cleveland FED, Universidad de San Andres, Universidad Torcuato Di Tella, NYU, Kansas City Fed, St. Louis Fed, and Chicago Fed. We thank Javier Tasso and Lucas Rosso Fones for their superb research assistance. We are particularly grateful to the Ministry of Production and Labor in Argentina for granting access to the data. We are also grateful to Eric Verhoogen and the Center for Development Economics and Policy for granting access to the data from Brazil, and Christian Moser for sharing useful codes. All analysis of confidential data was carried out on-site and in accordance with Argentinian confidentiality laws. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Federal Reserve Bank of Atlanta, the Federal Reserve Board, or the Federal Reserve System.

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1 Introduction

Sudden and large nominal exchange rate (NER) devaluations are important and frequent episodes in emerging economies. While it is well known that large devaluations cause significant increases in inflation, much less is known about their effects on the distribution of nominal labor income. In the short run, several frictions (e.g., nominal rigidities and search frictions) could mitigate the pass-through of inflation to nominal labor income. Our central hypothesis is that the impact of these frictions could be heterogeneous across workers, and thus affect labor income inequality in the short run. The purpose of this paper is to document the dynamics of income inequality and understand their drivers during large NER devaluations.

Following devaluations, prices respond faster than nominal labor income; thus, real income falls. This paper establishes a novel empirical regularity across countries: Labor income inequality falls significantly during the recovery of real income. Two years after a NER devaluation, the Gini coefficient falls by 3% relative to its pre-devaluation level. As a benchmark, the Gini coefficient in the U.S. has increased by 12% over a span of 40 years. To dissect the adjustment mechanisms in the labor market, we use labor income microdata covering the 2002 devaluation in Argentina. We discover that across the income distribution, heterogeneity in both labor mobility and bargaining power—captured by union coverage—are critical drivers of the drop in income inequality, while heterogeneous trade exposure plays a minor role. In a nutshell, high-income workers are less likely to jump between employers to seek a better wage and are less protected by union bargaining, which slows the recovery of their real income. A back-of-the-envelope calculation shows that these two mechanisms can account for 42% of the decline in inequality.

Our paper starts by establishing new facts about the labor market during large devaluations. With this objective, we study average real income conditional on being employed, aggregate employment, and the Gini coefficient of income across countries. We find that, in the year of the devaluation, inflation increases by around one-third of the devaluation rate and output drops by 3%. Since mean nominal wages remain constant and inflation increases during the devaluation, real wages fall by 12%. As predicted by the theory (see Tobin, 1972, Schmitt-Grohé and Uribe, 2016), the significant fall in real wages precipitates a strong recovery of aggregate employment and output. The novel finding of this paper is that income inequality—as measured by the Gini coefficient—declines during the recovery of real wages.

In contrast to large devaluations, we show that recessions with stable exchange rates are associated with a larger drop in employment and stable inflation, real wages, and inequality. Within episodes of large devaluations, we find that the dynamics of real wages, employment, and inequality documented above are more pronounced in the subsample that exhibits the largest increases in inflation. We verify that these facts are not driven by specific episodes, such as devaluations contemporaneous with sovereign defaults or banking crises.

While the cross-country evidence allows us to establish these aggregate facts, it does not allow us to understand the anatomy and adjustment mechanisms behind the drop in inequality. To analyze the fall in inequality and its drivers, we leverage an administrative employer-employee matched dataset comprising monthly, uncensored income data for the universe of formal workers in Argentina.

We first corroborate the cross-country results by analyzing the dynamics of output, inflation, employment, and the mean and the Gini coefficient of real labor income conditional on employment during the 2002 Argentinean devaluation. During the 2 years before the devaluation, we find almost no movement of the income distribution despite the decrease in output of 19%. In the year of the devaluation, there is a homogeneous drop of 26% in real labor income across the distribution due to rigid nominal wages and a pass-through of the NER to inflation of 28%. During the recovery of the labor market, the Gini coefficient declined by 20%. To illustrate this heterogeneous income growth, the 10th percentile of the income distribution recovered their pre-devaluation real income levels 21 months after the devaluation, but the 90th percentile recovered after 61 months. Given the low fluctuations in hours worked across the income distribution, the compression of the distribution of real labor income is driven by the compression of nominal wages. According to most theories, the nominal marginal revenue product of labor is the crucial driver of nominal wages. Since inflation completely drives the rise in the nominal marginal revenue product of labor in this episode, we then study how workers' incomes respond to the sudden and significant rise in inflation.

While the dynamics of different percentiles of the distribution are informative of cross-sectional statistics, they do not necessarily reflect the individual income dynamics of workers across the income distribution. Our rich microdata allow us to extend the analysis by ranking workers according to their pre-devaluation (2000-2001) earnings and analyzing their within-worker average income growth. Whereas in the year after the devaluation all workers experience similar income losses proportional to the surge in inflation, low-income workers see their real income recover more quickly in the following years. That is, after 2 years, workers in the 10th percentile of the pre-devaluation distribution had experienced an average cumulative income growth of 17% relative to the month preceding the devaluation, while workers in the 90th percentile experienced an average cumulative income growth of -17%. After 4 years, the gap in these growth rates further increased to 49%. To guide our analysis of the drivers of the fall in inequality, we decompose the recovery of income across the pre-devaluation income distribution into between-sector, between-firm, and within-firm components. We find that 39%, 45%, and 16% of the 4-year gap in cumulative income growth is accounted for by the sector-, firm-, and worker-components, respectively. The analysis shows that the nominal incomes of low-income workers are more responsive to the increase in inflation and that it is key to explain the drivers of firms' average labor income.

We then provide evidence for three potential drivers of the decline in inequality during large devaluations. Given the importance of the between-firm income component for heterogeneous recovery, we study the contribution of labor mobility across firms. We find that labor mobility is the primary adjustment channel that drives the heterogenous income dynamics, not only because job transitions are more prevalent among low-income workers but also because they experience higher income growth when changing jobs relative to high-income workers. We perform an accounting exercise by constructing several counterfactual income series to evaluate the quantitative role of labor mobility. We construct these series by assuming no income growth following separations, job-to-job transitions, or both. We show that workers in the 10th percentile of the income distribution experienced a 8.9% faster recovery in the data relative to the counterfactual series that exclude changes in income after job changes. The corresponding number for workers in the 90th percentile was -2.6%. Therefore, labor mobility can account for one-half of the heterogeneous recovery observed in the between-firm component of labor income and 23% of the overall heterogeneity in income growth.

A second relevant driver of the drop in inequality could be differences in workers' abilities to renegotiate higher wages. An important source of such differences is the presence of collective bargaining. To demonstrate this, we perform two empirical exercises. First, we digitize the wage scales in collective bargaining agreements (CBA hereafter) in sectors with strong unions and broad coverage (which employ 18% of workers in the sample) to study the income dynamics by unionization status. We find that the income growth of unionized workers with incomes close to the CBA-mandated floors is 30% higher than that of non-unionized workers. In those sectors, unions negotiated an increase in income between 30% and 60% above inflation. Second, we study unionization rates across the pre-devaluation income distribution. We find that across all sectors, unionized workers are mainly middle-income earners, and their income recovers 5.5% more than non-unionized workers. Combining these two facts, we find that collective bargaining can account for 19% of the overall heterogeneity in income growth.

Finally, given the large change in relative prices induced by the devaluation, we investigate the role of trade exposure in shaping income inequality by comparing labor income dynamics across and within sectors with different trade exposure. As predicted by the theory (see Schmitt-Grohé and Uribe, 2016), following the devaluation, income falls less in sectors with a high export share and high import penetration and more in sectors with a high share of imported intermediate inputs. Despite these findings, trade exposure cannot explain the decline in inequality. Why? Because the relative winners and losers generated by the trade channels are quite evenly distributed across the pre-devaluation income distribution.

Our analysis concludes by showing that our results are robust to alternative mechanisms and additional dimensions of the labor market. Here, we consider the roles of (i) the extensive and intensive margins of employment, (ii) changes in labor income risk, (iii) policy interventions (e.g., changes in the minimum wage), (iv) the informal labor market, (v) the cyclicality of labor income, and (vi) household-specific inflation rates. Crucially, in addition to verifying the external validity of aggregate facts across countries, we externally validate key micro-level results using administrative panel data from Brazil.

Although we study labor market dynamics following large NER devaluations, our mechanisms have broader relevance and help in understanding the aggregate and distributional consequences of a surge in inflation (e.g., following a monetary shock).[1] Previous theoretical literature has highlighted heterogeneous labor mobility and bargaining power as important drivers of income dynamics across the distribution (see Burdett and Mortensen, 1998, Cahuc, Postel-Vinay and Robin, 2006, Menzio and Shi, 2010). Regarding the broader empirical relevance, recent work (see Karahan, Ozkan and Song, 2019, Donovan, Lu and Schoellman, 2020, Faberman, Mueller, Sahin and Topa, Forthcoming, for evidence from the U.S. and 5 other countries) shows that separation and job-to-job transition rates, and job search effort are declining in workers' recent earnings in several countries, mirroring the patterns in Argentina. Regarding the role of unions, most workers in OECD countries (with the exception of the U.S.), have their wages determined by collective bargaining agreements (see ILO, 2015). Therefore, the mechanisms highlighted by this paper should have broader relevance and thus be important for understanding the effects of a rise in inflation.

Literature review. We highlight our contributions to two areas of the literature: (i) the macroeconomic consequences of large devaluations and (ii) real labor income dynamics after a surge in inflation.

Active literature studies the implications of large devaluations for macroeconomic fluctuations, price-setting, and trade dynamics. In particular, Eichengreen and Sachs (1985) and Schmitt-Grohé and Uribe (2016) focus on the role of nominal wage rigidities. They argue that a devaluation—and its upward pressure on prices—can overcome downward nominal wage rigidities and stimulate output and employment.[2] Burstein, Eichenbaum and Rebelo (2005) and Cravino and Levchenko (2017) study price-setting in the aggregate and across households, respectively. They find that 38% of nominal exchange rate depreciations pass through to CPI prices within 24 months, and even more to the prices of goods consumed by low-income households. Finally, Gopinath and Neiman (2014) and Blaum (2019) study the

[1]For example, Coibion, Gorodnichenko, Kueng and Silvia (2017) find that contractionary monetary shocks increase income inequality. Using data from Sweden, Amberg, Jansson, Klein and Rogantini Picco (Forthcoming) also document that expansionary monetary policy shocks have positive and large effects at the bottom of the labor income distribution.

[2]See Mendoza (2010), Ates and Saffie (2016), Benguria, Matsumoto and Saffie (2020) for an analysis of the business cycle consequences of large devaluations. Another strand of the literature analyzes the joint dynamics of the nominal exchange rate and the labor market in developed economies (see Campa and Goldberg, 2001, Goldberg and Tracy, 2001, Gourinchas, 1998, 1999, among others).

effect of large devaluations in aggregate productivity through fluctuations in input trade. In this paper, we extend the previous analysis by documenting heterogeneous pass-through to wages and its implications for inequality dynamics during large devaluations and dig deeper into these findings using administrative microdata from an emerging economy.

Previous work has documented facts regarding the distribution of wage changes in low- and stable-inflation environments, which are interpreted as evidence of downward nominal wage rigidities. These findings are reported in the U.S. and Europe by Kahn (1997), Dickens *et al.* (2007), Sigurdsson and Sigurdardottir (2011), Le Bihan, Montornès and Heckel (2012), Barattieri, Basu and Gottschalk (2014), and more recently by Grigsby, Hurst and Yildirmaz (2021). In this paper, we document the evolution of Argentina's real income distribution after an increase in inflation of 35%. We provide novel evidence detailing the different speeds at which real labor income adjusts for workers across the income distribution after a significant increase in inflation. We find that the recovery of real income is heterogeneous, can be predicted by workers' characteristics, and has large effects on inequality.

Layout. The paper is organized as follows. Section 2 describes the data. Section 3 presents the aggregate facts in the cross-country analysis of large devaluations. Section 4 revisits those aggregate facts in our main episode of analysis. Section 5 presents evidence on the mechanisms behind these facts. Section 6 demonstrates the robustness of our findings, and Section 7 concludes.

2 Data

This section describes the cross-country data and the novel administrative dataset from Argentina we leverage to study the dynamics of the income distribution after large devaluations. Interested readers should refer to Online Appendix Section A.1 for a detailed description of the data construction for the cross-country analysis and Online Appendix Section A.2 for further description of the administrative dataset and sample construction.

Data for cross-country analysis. We analyze six aggregate variables across countries: output, NER, inflation, average real labor income, employment, and a measure of inequality. For output, we use GDP at constant prices in local currency from the World Bank. The nominal exchange rate is measured as units of local currency per U.S. dollar. To measure inflation, we use the consumer price index. Inflation and NER data mainly come from the IMF International Financial Statistics Dataset. Average real labor income is measured conditional on being employed, and for the majority of countries is reported as the average wage in local currency deflated by the CPI (see Tables A.1 and A.2 for data sources in each country). Data on employment are obtained from the Penn World Tables. Finally, we measure inequality with the Gini coefficient, based on household survey data from national statistical agencies and World Bank country departments (see the end of Section 3 for a broader discussion of this measure).

Labor income data for the 2002 Argentinean devaluation. We use administrative employer-employee matched monthly panel data from Argentina. The dataset starts in July 1994 and ends in June 2019. Our data source is Argentina's national social security system ("Sistema Integrado Previsional Argentino," SIPA hereafter). By law, all employers in the formal sector must submit sworn statements providing relevant worker compensation information to SIPA every month.

SIPA records each worker's total monthly labor income in the formal sector, including all forms of payment that could trigger tax liabilities or social security contributions (e.g., base wage, bonuses, overtime compensation, etc.). The dataset also includes relevant demographic information on each worker and their job and some characteristics of the firm, such as 4-digit industry and state. Importantly, SIPA also provides firm and worker identifiers that are consistent across the entire period, which allow us to analyze income dynamics for individual workers and firms at a monthly frequency for up to 26 years.

We leverage three characteristics of these data: frequency, coverage, and quality. First, we observe workers and employers at monthly frequency, so we can differentiate between income fluctuations that result from variations in earnings and employment status. The higher frequency, in turn, allows us to precisely capture patterns of labor mobility. Second, our dataset covers the universe of formal firms and workers employed in all regions, private industries, types of contracts (internships, temporary workers, full-time employees, etc.), and the public sector.[3] This allows us to study the role of sectors and firms for workers' income dynamics across the entire income distribution. Third, our data source is employers' sworn statements. Hence, our data contain little measurement error and no top-coding, which are common problems with survey-based micro data.

When analyzing labor income dynamics in a large devaluation in Argentina, we present facts about the (log) real pretax total labor compensation—which is the main source of income for the large majority of the population (see Online Appendix A.2.2 for evidence on this)—of male workers aged between 25 and 65 in the private sector.[4] Unless noted otherwise,

[3]One of the benefits of analyzing the Argentinian labor market is that relative to other emerging market economies, the share of formal employment is high—e.g., Gasparini and Tornarolli (2009) report a formality rate in Mexico of 45%.Figure E.18-Panel B shows the time series of the share of formal employment in the private sector for male salaried workers aged between 25 and 65 in Argentina. Throughout the period of analysis, the average formality rate was 65%.

[4]Due to the intervention of inflation statistics in Argentina in 2007, we use consumer price indices provided by national statistics before 2007 and PriceStats from 2007 onward to construct real labor income (although most of our analysis focuses on the pre-2007 period). In our baseline analysis, we deflate nominal income using the aggregate CPI. In Section 6, we verify the robustness of our analysis by computing income-specific levels of prices, as in Cravino and Levchenko (2017).

whenever we report facts about real labor income, we refer to the (log) real income conditional on being employed. We restrict our sample to male workers aged between 25 and 65 years to avoid issues related to labor force participation and retirement. Finally, we omit income observations from job spells that involve workers employed in the public sector, since their wages might not be market-determined and instead subject to other nonmarket forces.

We apply some filters to the data on monthly real labor income in our analysis. We first eliminate outliers and winsorize top observations. We define outliers as workers who earn less than half of the monthly minimum wage. Because the minimum wage in Argentina has fluctuated over time, we use the 1996 value in real terms (i.e., \$200 per month) and adjust it by the average growth rate of real wages in the entire sample (i.e., 2% annual growth) to drop a stable small fraction of outliers in each period. We winsorize observations above the 99.999th percentile. Second, we also omit the first and last salary in each job spell due to time aggregation concerns, since we do not know the day a spell starts/ends or whether the last wage includes severance pay.[5] Although we do not consider these monthly salaries in our analysis of labor income, we include them when we analyze employment flows. After applying our sample selection and filters, the final dataset contains more than 700 million worker-month observations. Finally, we seasonally adjust all time series using the X-13ARIMA-SEATS seasonal adjustment program developed by the U.S. Census Bureau.

Since this is one of the first papers that use the SIPA dataset, we further discuss the quality of the data by providing a cross-validation of results using data from the national household survey in Argentina (see Online Appendix A.2.1) and a comparison with the income distribution in the U.S. (see Online Appendix A.2.3).

Additional data for the 2002 Argentinean devaluation. We complement the SIPA dataset with the information contained in collective bargaining agreements negotiated by trade unions at the sectoral level. We digitize these contracts for several of the most relevant unions (those sectors employ 18% of workers in the overall sample). We also use microdata from the Permanent Household Survey ("Encuesta Permanente de Hogares," EPH hereafter), which is the main household survey in Argentina and covers all workers.

Labor income data from Brazil. We use administrative employer-employee matched data from Brazil. Our data source is the *Relação Anual de Informações Sociais* (RAIS hereafter). To the best of our ability, we apply the same data filters and analysis as in the Argentinean dataset. We relegate the description of these data to Online Appendix G.

[5]We purge the monthly labor income of the 13th salary paid in June and December to avoid spurious seasonality. This extra salary is mandated by law and equals one-half of the highest wage paid over the semester. Because we only observe total income before 2008, we use the formula established by law to calculate each worker's 13th salary.

3 Facts Across Large NER Devaluations

Which empirical regularities characterize the dynamics of the labor income distribution during large NER devaluations? This section documents that during the 4 years after a devaluation, average real labor income drops by up to 15%, employment increases by 5.8%, and the Gini coefficient falls by 3.5% relative to their pre-devaluation levels. Since large NER devaluations are associated with significant recessions, we revisit these facts during recessions without devaluations. In those episodes, average real labor income experiences a smaller and less persistent decline, employment increases by 0.7%, and the Gini coefficient falls by up to 1%. As we document below, these facts are not driven by specific episodes or special types of devaluations or recessions, such as sovereign defaults or banking crises.

To define large NER devaluations, we follow the definition of currency crises of Laeven and Valencia (2012). They define currency crises as periods in which the annual nominal depreciation rate of a country's currency vis-à-vis the U.S. dollar is at least 30%, and is also at least 10% higher than the depreciation rate in the previous year. Our sample of large NER devaluations includes 19 episodes with complete data on both the Gini coefficient and labor income. Based on Calvo, Izquierdo and Talvi (2006), we classify recessions without devaluations as episodes with a cumulative output drop of at least 2% in consecutive years and without a large NER devaluation. Our final sample includes 40 recessions without devaluations.[6]

Macroeconomic context behind large NER devaluations. Figure 1 plots the evolution of the average annual NER devaluation rate, real GDP, and inflation in an 8-year window around large devaluations and recessions without devaluations. Large nominal devaluations are associated with a recession, faster recovery of output, and an increase in inflation.[7] The average initial GDP drop across episodes is 3.2%, which is slightly lower than the average output drop during recessions without devaluations (4.8%). Faster recovery in output also characterizes large devaluations: Four years after a devaluation, the output is 12 log points above its pre-devaluation level. In comparison, the output is only 4 log points higher after recessions without devaluations.

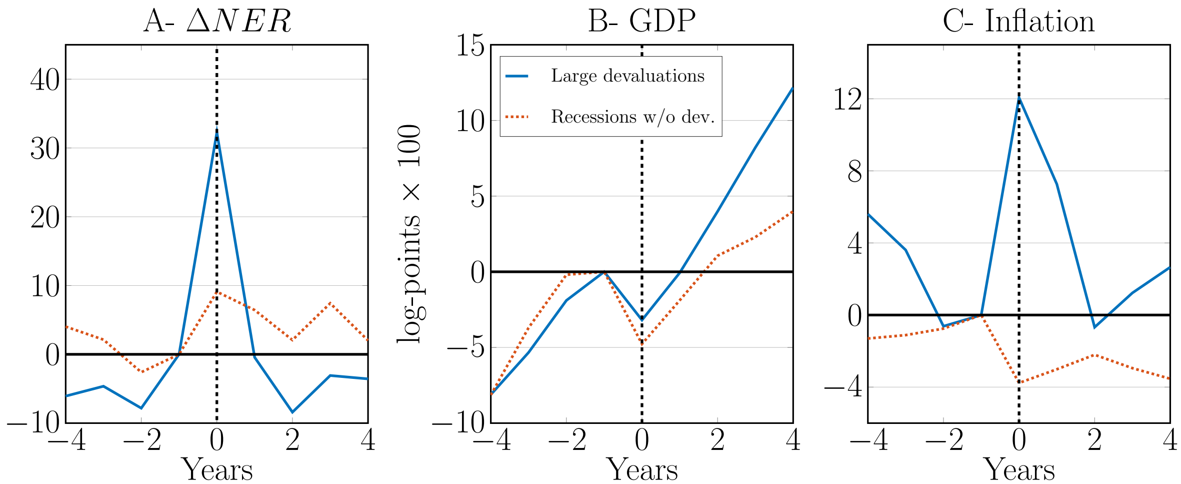
Heterogeneous dynamics in output also extend to inflation. During recessions without devaluations, inflation drops relative to its pre-recession level. On the other hand, there is a large pass-through into domestic inflation during large devaluations. Burstein *et al.* (2005) document an average elasticity of annual inflation to a large nominal devaluation of

[6] We follow Laeven and Valencia (2012) by computing the growth rate as $\frac{e_{t+1}-e_t}{e_t}$, where e_t is the NER; however, our figures below are based on log-deviations. When our filters identify either large devaluations in 2 or more consecutive years or recessions lasting more than 1 year, we center the window of the event around the last year. Section A.1 in the Online Appendix describes the data sources and the procedure we follow to obtain the sample of episodes. Table A.4 lists all episodes included in the analysis.

[7] In Online Appendix B.2, we document, using data from a survey of professional forecasters, that the timing and magnitudes of the devaluations analyzed here were largely unanticipated.

one-third across emerging economies. This number coincides with the pass-through in our sample: The average ratio of annual changes in inflation over annual changes in the NER is 37.5% (i.e., $12/32 = 0.375$).

Figure 1 – Macroeconomic Facts After Large NER Devaluations

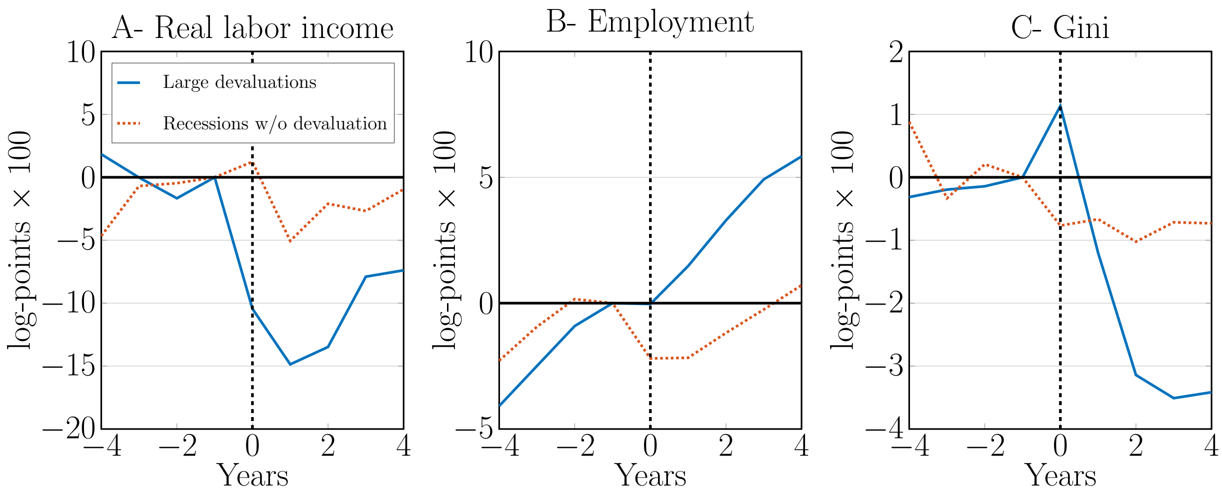


Notes: Panels A, B, and C plot the change in the NER, real GDP, and inflation at an annual frequency, respectively. Δ NER and inflation are computed as annual log differences of the nominal exchange rate and the CPI ($\times$ 100). We winsorize the normalized change in the NER and inflation at the 2.5% and 97.5% percentiles across all 59 episodes in our sample. Real GDP is measured in log-points $\times$ 100. All variables are normalized to zero in year -1. The solid blue line plots the average of each variable across episodes in an 8-year window around a large devaluation. The dotted red line plots the same variables for recessions without devaluations. The year zero corresponds to either the year of the devaluation or the year of the recession. When our filters identify either large devaluations or recessions without devaluations in 2 or more consecutive years, we center the window of the event around the last year. See Table A.4 for the description of the episodes.

Labor market facts during large NER devaluations. Figure 2 plots the evolution of the average labor income, employment, and Gini coefficient across episodes. Before each type of episode, the figure shows no pre-trends in average labor income or the Gini coefficient. Employment, however, exhibits an increasing trend in both types of episodes. During devaluations, *nominal* labor income remains almost constant; thus *real* labor income falls by the same magnitude as the increase in inflation. One year after the devaluation, real labor income drops by less than the increase in inflation and starts recovering from thereon. Whereas average real labor income falls significantly during large devaluations, we do not find this pattern in recessions without devaluations, since nominal and real labor income show much less variation during these episodes.

In episodes of large devaluations, employment deviates from the trend in the year of the devaluation but starts growing at a rate similar to the pre-devaluation rate in the following years. This dynamic differs from the average dynamics in recessions without devaluations, in which employment exhibits a persistent decline in the year of the recession. Moreover, employment barely recovers to its pre-recession level 4 years after the start of the recession. In contrast, employment is more than 5% higher than its pre-devaluation level 4 years after large devaluations.

Figure 2 – Labor Market Facts After Large NER Devaluations



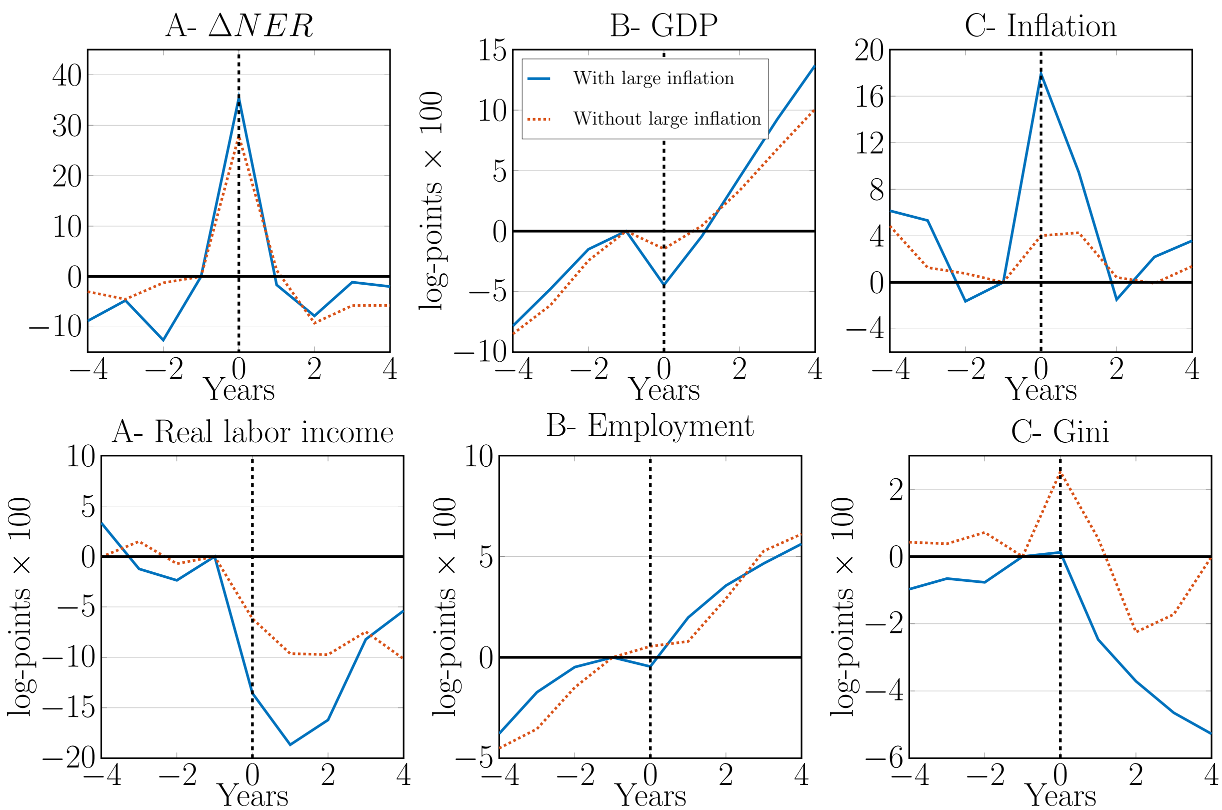
Notes: Panels A, B, and C plot the average real labor income, employment, and Gini coefficient, respectively. All series are expressed in log-points × 100 and normalized to zero in year −1. The solid blue line plots the average of each variable across episodes in an 8-year window around a large devaluation. The dotted red line plots the same variables for recessions without devaluations. The year zero corresponds to either the year of the devaluation or the year of the recession. When our filters identify either large devaluations or recessions without devaluations in 2 or more consecutive years, we center the window of the event around the last year. The episodes included in large devaluations and recessions without devaluations are the same as in Figure 1.

The Gini coefficient falls when real income recovers. Four years after the devaluation, the Gini coefficient is 3.5% lower than its pre-devaluation level. This fall in inequality is significant. For reference, in the U.S.—a country in which income inequality receives considerable attention in academic and political circles—the Gini coefficient has increased by 12% *over 40 years*.

The role of inflation. There are two direct effects of large nominal devaluations: a change in relative prices across sectors with different trade exposures and an increase in the aggregate price level and the nominal marginal revenue product of labor.[8] Regarding the former, below we quantify the effect of changes in relative prices precipitated by the

[8]To further highlight the role of inflation as the key driver of the nominal marginal revenue product of labor and the recovery in the aftermath of large devaluations, Figure B.11 in the Online Appendix compares the dynamics of physical TFP across episodes of large devaluations and recessions without devaluations (the data were obtained from the Penn World Table 10.0; the measure of physical TFP is adjusted for inflation). The key finding is that the dynamics of aggregate TFP across episodes are similar within the first two years, the period it takes inequality to fall after a large devaluation. Thus, aggregate TFP cannot be the main force driving the heterogeneous recovery.

Figure 3



Notes: The figure plots (in the following order) the change in real GDP, NER, inflation, average real labor income, Gini, and employment at an annual frequency. Δ NER and inflation are computed as annual log differences in the nominal exchange rate and the CPI ($\times$ 100). We winsorize the normalized change in NER and inflation at the 2.5% and 97.5% percentiles across all 59 episodes in our sample. Real GDP, average labor income, employment, and the Gini coefficient are measured in log-points $\times$ 100. All variables are normalized to zero in year -1. The solid blue line plots the average of each variable across episodes in an 8-year window around a large devaluation associated with an inflation episode. The dotted red line plots the same variables for devaluations without an inflation episode. The year zero corresponds to either the year of the devaluation.

devaluation in Argentina. To analyze the importance of the latter, we split our sample of large devaluations into those followed by large and small increases in inflation. We classify a country-year pair as a large inflation event if the annual inflation rate is larger than 15% and also 7% larger than in the previous year.[9] Results are reported in Figure 3.

We find that the changes in average real labor income and inequality documented above are more pronounced in the subsample of similarly-sized devaluations that are followed by large increases in inflation. In particular, average real wages fall by almost 15% one year after the devaluation when inflation is high compared with less than 10% in episodes with low inflation and the Gini coefficient reaches an overall decline of more than 5% four years

[9] We choose a threshold of 15%, which closely corresponds to the 85th percentile of the distribution of annual inflation and would usually be considered a high level of inflation.

after the devaluation.

Given the predominant role that inflation plays in our results, one might be puzzled by our focus on exchange rate devaluations. However, there are two related reasons for exploiting episodes of large NER devaluations as a laboratory to study the distributional effects of inflation on the labor market. First, as Online Appendix B.1 documents, large changes in the nominal exchange rate are typically associated with large increases in inflation. Second, large devaluations have specific characteristics that render them particularly well-suited for empirical analysis: They are unanticipated (see Online Appendix B.2) and induce a sudden and significant increase in inflation.[10]

Measures of income inequality. Given the lack of readily available quality administrative labor income data across multiple emerging economies, we rely on the Gini coefficient computed by the World Bank to establish an empirical regularity with respect to labor income inequality during devaluations. Several features of this measure are worth noting. First, its frequency is annual, and thus we can study its evolution within an 8-year window after large devaluations. Second, while in principle the Gini coefficient is constructed using consumption or income data—depending on the country—in 14 out of 19 episodes of large devaluations (and in 35 out of 40 episodes of recessions without devaluations), inequality is computed using income data. Third, in principle, the World Bank's objective is to measure the inequality of total income. In practice, the Gini coefficient mostly captures labor income inequality for two reasons: (i) the lack of capital income for the majority of households in emerging economies and (ii) the focus on labor income (or the lack of data on capital income) in household surveys. Finally, the Gini coefficient is computed using data on household income per capita and, importantly, also includes observations with zero income. These data have been used previously in the literature (see, e.g., Pinkovskiy and Sala-i Martin, 2016) and are one of the data sources used in the World Income Inequality Database (developed by the United Nations and used by, e.g., Young, 2013, Fajgelbaum and Khandelwal, 2016).

Robustness. One concern is that these aggregate facts might be driven by a few particular devaluations or special types of recessions. Given the sample size in our list of episodes, a detailed multivariate analysis that controls for differences across episodes would not be feasible. However, to demonstrate that this is not the case, we reproduce the main graphs for different subsets of episodes.

In Online Appendix B, we show that similar patterns are observed when we consider the following: (i) episodes that coincide (or fail to coincide) with banking crises, (ii) episodes

[10] Moreover, exchange rates are highly volatile in emerging economies (in our sample of 138 countries during the 1990-2015 period, the standard deviation of annual first differences in log exchange rates vis-à-vis the U.S. dollar was 34 and 7.15 for emerging and rich economies, respectively) and, given our findings, relevant on their own.

without sovereign defaults, (iii) episodes in which inequality measures are based on households' income—and not consumption, (iv) episodes without hyperinflation, (v) episodes with short recessions, (vi) episodes that occurred from 2000 onward, and (vii) devaluation episodes that occur during recessions. In addition, our baseline sample is restricted to episodes with available data on both average labor income and the Gini coefficient. In the Appendix, we report the results from a larger sample of episodes with available inequality data only. We also report similar results when analyzing the detrended time series. Although there are quantitative differences across sub-samples, we consistently find that declines in average real labor income and inequality follow large devaluations. Finally, in Online Appendix B.3, we apply the synthetic control method developed by Abadie and Gardeazabal (2003) and Abadie, Diamond and Hainmueller (2010), which allows us to control for pre-existing trends and regional or global factors, and find similar results.

Taking stock. The facts behind Figure 2 are novel and surprising, and the goal of the rest of the paper is to examine the economic mechanisms behind them. They are surprising because they show that labor income becomes less unequally distributed during nominal devaluations. We do not study the consequences or the policy implications of lower inequality. Instead, our contribution is to document, for the first time, the dynamics of the *distribution* of labor income after devaluations and provide an empirical evaluation of the mechanisms that drive them.

4 Inequality Dynamics: The Case of Argentina

This section uses microdata on monthly labor income to revisit the previous section's empirical regularities in the 2002 Argentinean devaluation. We find similar qualitative patterns: (i) output and employment exhibited a significant drop and recovery, (ii) inflation increased by one-third of the change in the NER, (iii) mean labor income dropped by the same amount as the increase in inflation in the first year, and (iv) the Gini coefficient declined when mean labor income recovered. We end this section with a more detailed discussion of inequality dynamics based on cross-sectional moments. Across all of the inequality measures in the cross-section, inequality falls during the recovery of real income after the devaluation mainly because the bottom of the income distribution recovers faster than the top.

Macroeconomic context. To contextualize our measurement exercise, we first describe the macroeconomic environment during the period of analysis (see Daseking, Ghosh, Lane and Thomas, 2005). Following a history of high and volatile inflation, in April 1991 Argentina implemented a currency board regime that pegged the local currency to the U.S. dollar. This policy brought inflation under control, thus providing nominal stability accompanied by rapid growth. However, in 1998, the economy went into recession in the aftermath of the Russian crisis, which reduced capital flows to emerging markets and increased sovereign spreads. The economy was also affected by the 1999 devaluation in Brazil, Argentina's main trading partner; the global appreciation of the U.S. dollar; and the large decline in commodity prices, all of which reduced export revenues and the government's tax capacity.

In a context of negative growth, increasing spreads, and lower tax revenues, the government's fiscal deficit deteriorated and public debt rose. The government implemented an austerity plan to improve its fiscal position by reducing public spending and increasing taxes, which further contributed to the recession. In response to this deterioration, there were large capital flights and a run on the local banking system, which culminated in the default on Argentina's external debt, a deposit freeze, and the end of the exchange-rate peg.

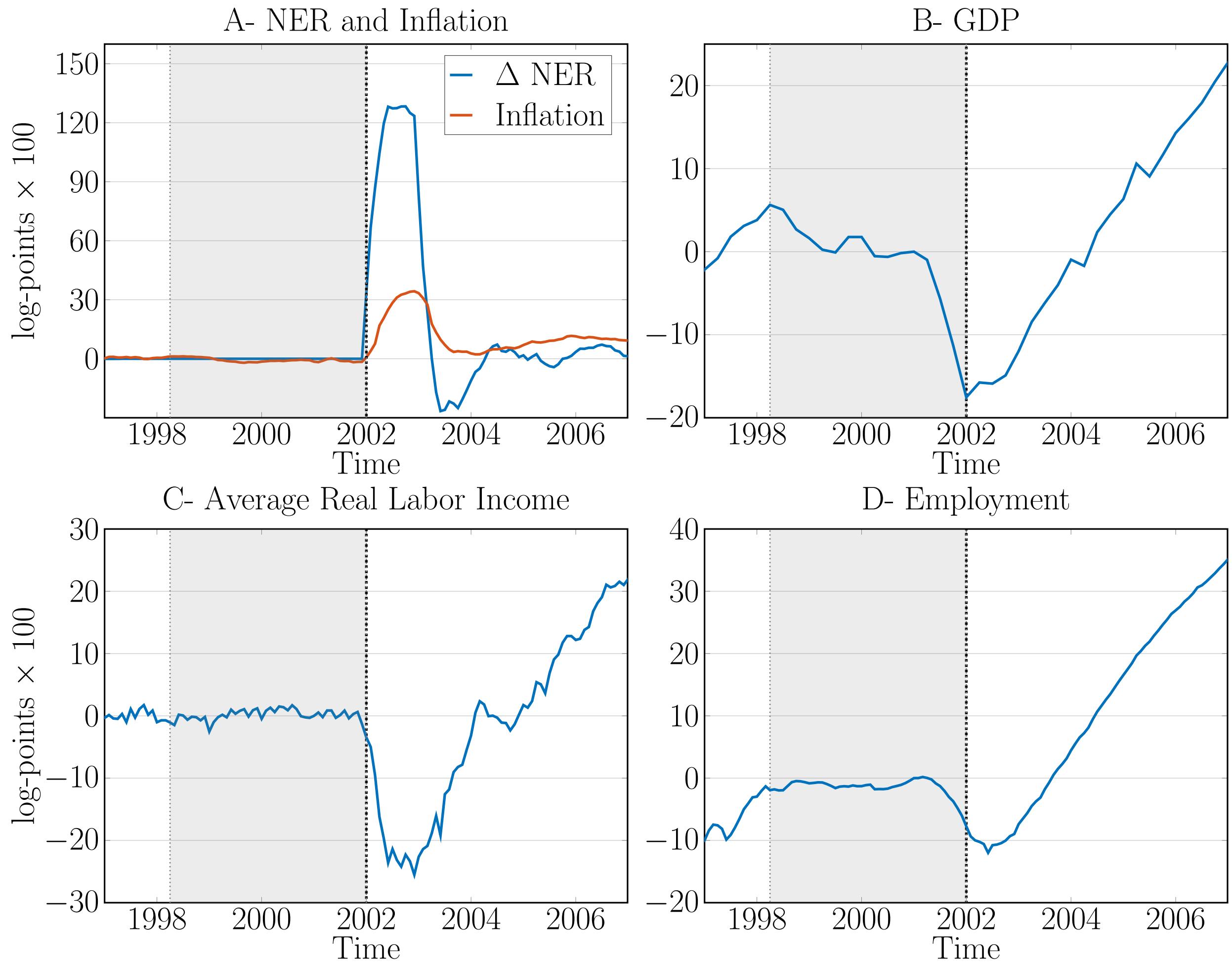
After our brief discussion of the macroeconomic context, we now revisit the cross-country facts in the 2002 Argentinean devaluation. This episode presents dynamics similar to our cross-country analysis. Figure 4-Panel A shows year-over-year inflation and nominal exchange rate growth, and Figure 4-Panel B shows the (log) real quarterly output. Figure 4-Panels C and D show average real labor income and employment at monthly frequency. We mark the recession period in gray and the month of the devaluation with a dotted black vertical line. In the last three panels, variables are normalized with respect to their values in the first quarter or month of 2001.

The 2002 devaluation episode was associated with a significant increase in aggregate prices and the end of the 1998-2002 recession, as in our cross-country analysis. The ratio of cumulative logarithmic changes (relative to 1 month prior to the devaluation) in the price level to cumulative changes in the NER amounted to 0.28 (consistent with the average pass-through measured by Burstein *et al.*, 2005). It is worth noting that the size of the devaluation took market participants by surprise.[11] Thus, this episode allows us to analyze the labor market response to a policy change that generated a large and unexpected increase in inflation. Finally, concerning the output level, the 1998-2002 recession featured a cumulative output drop of -21%.

We postulate theoretical predictions before analyzing the labor market, assuming that real wages reflected the marginal product of labor before the start of the recession. While output is an important force for labor demand according to firm-level cost minimization, profit maximization implies that the main determinant of nominal wages is the nominal marginal revenue product of labor. In turn, this variable is determined by the price level and the marginal product of labor; Figure C.2 in the Online Appendix plots output per worker, which is a simple proxy for the latter.

[11] In Appendix B.2, we present data on exchange rate expectations from a survey of professional forecasters provided by Consensus Economics. In December 2001, professional forecasters were expecting a devaluation of 7% within the following 12 months—so a devaluation rate of more than 100% clearly had a sizable unexpected component.

Figure 4 – Labor Market Facts after the 2002 Argentinean Devaluation



Notes: The figure plots four macroeconomic and labor market time series in Argentina for the period between January 1997 and December 2006. Panel A plots the NER (blue) and inflation (red), and Panel B plots the real GDP. Panel C shows average real labor income and Panel D total employment from SIPA. All variables are expressed in log-points × 100. GDP is computed at quarterly frequency, seasonally adjusted, and normalized to zero in the first quarter of 2001. Inflation, NER, average real labor income, and employment are computed at a monthly frequency. Average real labor income and employment are normalized to zero in the first month of 2001. Recession periods are in gray, and monthly devaluations larger than 30% are marked with dotted black lines.

A drop of 7% of the marginal product between 1998 and 2001 implies that in principle, real labor income should have fallen by 7%. Given the cumulative deflation rate close to 2%, nominal labor income should have fallen by 9%. Whereas prices and the marginal product of labor moved in the same direction before the devaluation, these dynamics reverted following the large devaluation: Inflation spiked to 35% and the marginal product continuously decreased by 10%. According to the theory, nominal wages should have increased by 16%. In the years after the devaluation, the marginal product of labor returned to its pre-devaluation level, which put further upward pressure on nominal wages.

Labor market facts. During the 5 years before the 2002 devaluation, the average real labor income remained almost constant—even as cumulative output dropped by 21% and the marginal product of labor decreased by 7%. In the first 6 months after the 2002 devaluation, log average labor income dropped by 26%. After this significant drop, it took 2 years for average income to revert to its pre-devaluation level. Employment stagnated after the beginning of the recession in 1998 and declined significantly in 2001. In the aftermath of the devaluation and the drop in real labor income, employment reverted the downward trend and experienced a period of persistent and rapid growth.

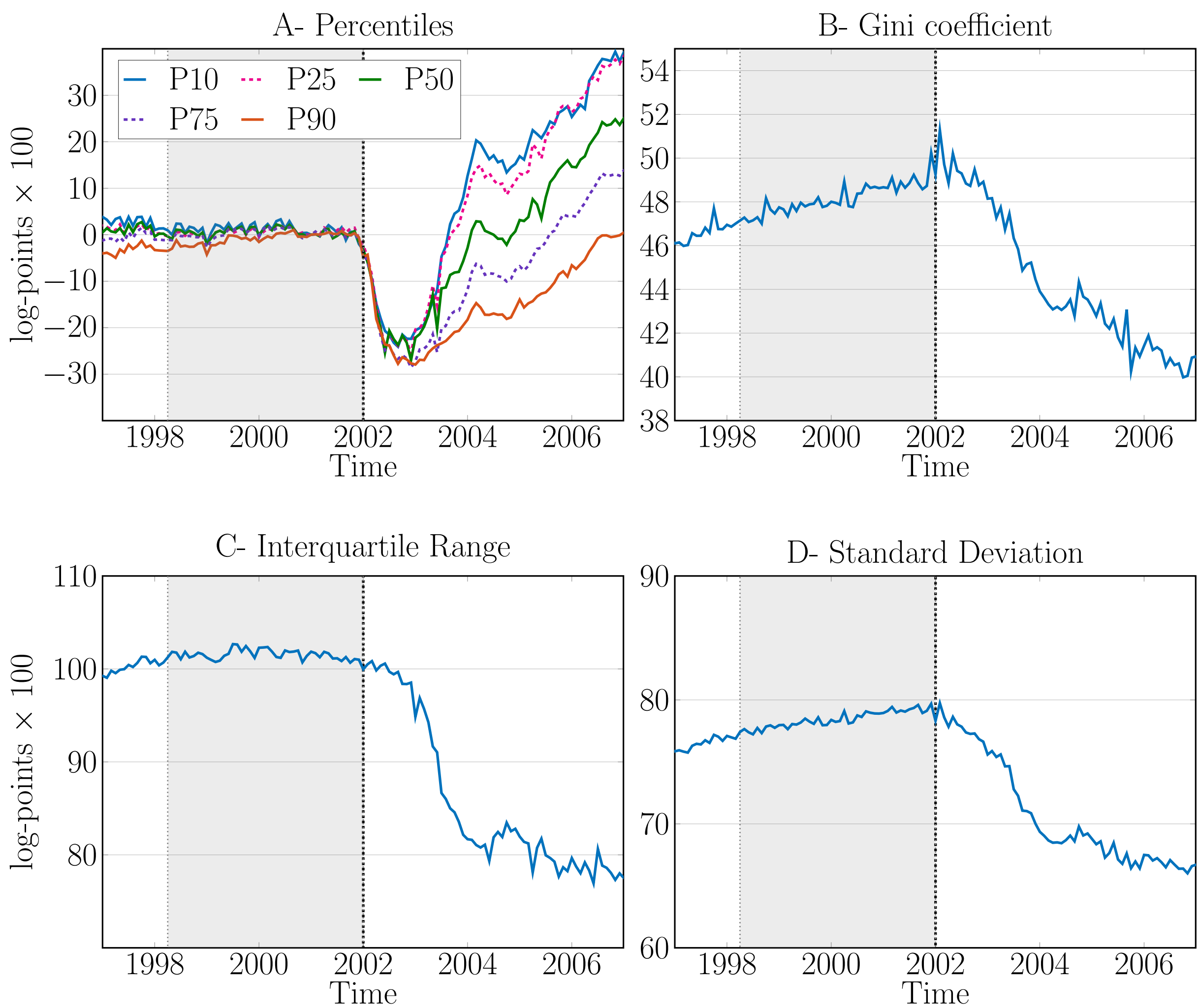
In what follows, we analyze real labor income inequality conditional on being employed (in Section 6, we analyze the role of the extensive margin of employment). Inequality, measured by the Gini coefficient of the monthly income in Figure 5, increased during the recession, peaked during the months of the devaluation, and declined thereafter, following the dynamics described in our cross-country analysis. The drop in the Gini coefficient accelerated in 2003, as real income started to recover. Although the Gini coefficient is a useful measure to establish our empirical fact across countries, we next leverage the microdata in Argentina to analyze other moments of the labor income distribution.

Figure 5 plots additional moments of the income distribution—normalized percentiles, the interquartile range, and the standard deviation—for the 5 years before and after the devaluation. The first important observation is that, as we can see in the figure, there were no significant fluctuation across percentiles of the income distribution before the 2002 devaluation, despite the severity of the recession. This lack of large fluctuations is also reflected in the evolution of the interquartile range and the standard deviation. Second, there was a *homogeneous* drop of 26% across the distribution of real income during the first 2 quarters after the devaluation. This drop resulted from the rapid increase in inflation and a lack of nominal adjustment of wages.

Despite this homogeneous drop, Figure 5 shows the significant *heterogeneity* in the speed of the recovery of real income across different parts of the distribution. Although percentiles below the median start recovering after the third quarter, percentiles above the median continued to fall for 2 additional quarters. Alternatively, note that the 10th percentile of the income distribution recovered to its pre-devaluation level in 21 months, while it took 61 months for the 90th percentile to recover. This faster recovery of the bottom of the income distribution implies that the distribution became less unequal after the devaluation.

The compression in the distribution during the recovery is reflected in the evolution of the interquartile range and the standard deviation. The interquartile range dropped from nearly 100% to 80% and the standard deviation from 79% to 68%. This recovery can be more easily seen in Figure 6, which compares the real income distributions in 2001 and 2006. Four years after the devaluation, there was a substantial upward shift in the bottom of the distribution and a compression of real wages from the top.

Figure 5 – Moments of the Distribution of Labor Income

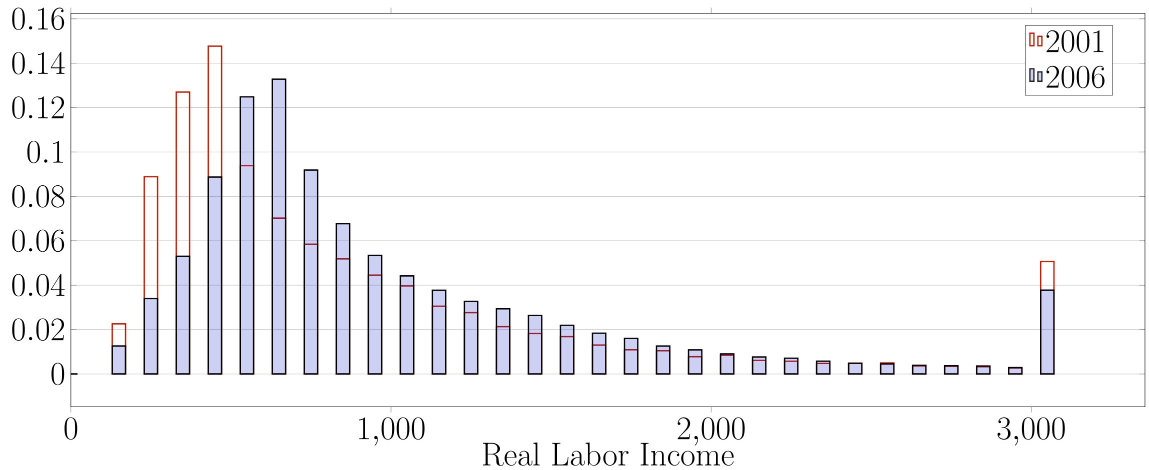


Notes: The figure plots moments of the distribution of monthly real income from January 1997 to December 2006. Panel A plots the percentiles of the log income distribution (× 100) normalized by their average during 2001. We use Px to denote the x-th percentile of the distribution. Panels B, C, and D plot the Gini coefficient, the interquartile range ($P75 - P25$), and the standard deviation for the same period. Recession periods are in gray, and monthly devaluations larger than 30% are marked with dotted black lines.

5 Why does Inequality Fall during Large Devaluations?

This section explores the mechanisms behind the fall in inequality during large devaluations. With this goal in mind, we proceed in three steps. First, we study workers' income dynamics conditional on their pre-devaluation income. We find that low-income workers recover from the drop in real income faster than high-income workers. Second, we decompose the variance of conditional income growth into between-sector, between-firm, and between-worker components. We find that the between-firm component is the main contributor to the heterogeneous recovery. Third, we explore three mechanisms that generate the observed differences in sensitivity to the nominal exchange rate. Based on the relevance of the between-firm component,

Figure 6 – Income Distribution in 2001 and 2006



Note: The figure plots the income distribution in May 2001 and May 2006. Distributions are winsorized using the 95th percentile of distribution as the upper bound.

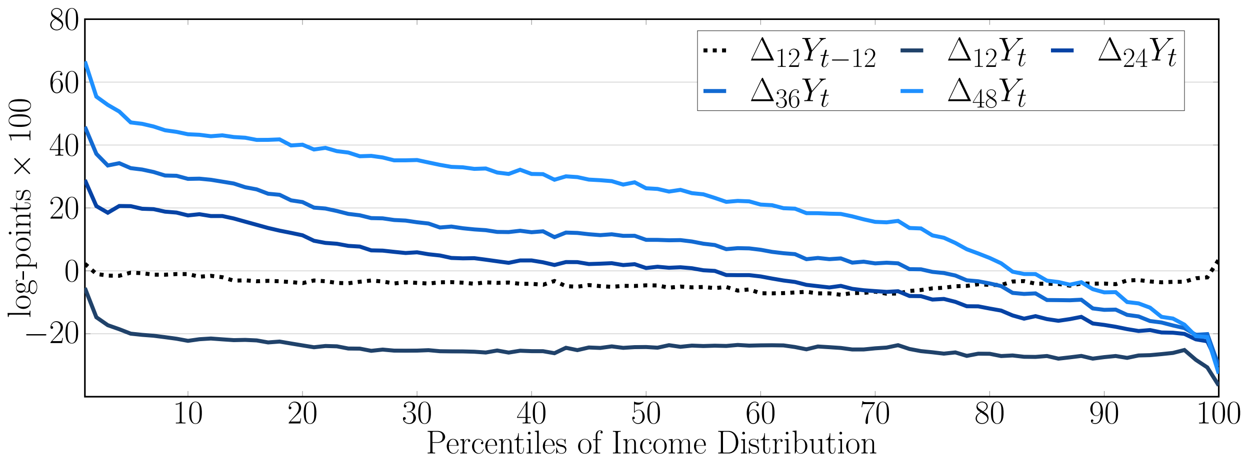
we examine the role of labor mobility across firms in compressing the income distribution. Given the slower recovery of the between-worker components at the top, we explore the role of different income floors set by unions. Given the large change in relative prices induced by the devaluation, we analyze how much of the inequality decline can be explained by the heterogeneous exposure to international trade.

5.1 Workers' Income Growth Conditional on Income Level

Although the analysis in Sections 3 and 4 is informative of cross-sectional statistics, it does not reflect the income dynamics of individual workers across the income distribution during and after the devaluation. This is because the identities of the workers within each percentile can change drastically over time. We address this issue by studying workers' income growth conditional on their pre-devaluation level of income.

To do this, we rank workers according to their permanent real monthly income during the pre-devaluation period and group them in percentiles according to this ranking. However, the presence of an age profile in income renders this ranking more favorable toward older workers, thus confounding income and age differences. We address this issue following Guvenen, Ozkan and Song (2014). We first run a pooled regression with the complete sample of log labor income on a set of age and year dummies. Then, we rank workers according to their average log monthly income net of the life-cycle profile during the 2 years before the devaluation. We drop workers with less than 6 months of employment during the period 2000-2001, since we cannot precisely capture their average income over the period. Figure 7 shows the average year-over-year growth of real monthly income (net of the life-cycle profile) from December 2001 onward on the y-axis and the percentiles of the permanent income (net of the life-cycle profile) on the x-axis.[12] Note that the analysis is conducted using monthly income data conditional on being employed. Thus, the ranking of workers and the measures of income growth are not affected by periods of non-employment.

Figure 7 – Average Income Growth Conditional on Average Income in 2000-2001



Notes: The figure describes average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period.

The first result is that during the year before the devaluation, the average year-over-year income growth ($\Delta_{12}Y_{t-12}$) is close to zero for all percentiles.[13] This homogeneous average growth disappears after the devaluation, and the pattern that emerges across the income distribution is of a "parallel drop and pivot." That is, in the year after the devaluation, there is a parallel drop in real monthly income ($\Delta_{12}Y_t$) of 24% across percentiles, followed by a pivoting of the cumulative average income growth centered around the highest-income workers. The gap is quantitatively significant in the short run. After two years ($\Delta_{24}Y_t$), the average income growth of workers in the 10th percentile of the pre-devaluation distribution had experienced average cumulative income growth of 18% relative to the month preceding the devaluation, while the average cumulative growth of those in the 90th percentile was -17%. Thus, the gap in these two growth rates was 35% and further increased to 49% 4 years after the devaluation.

[12]Formally, we define the permanent component of income net of the life-cycle profile for worker i as

$$\bar{Y}_t^i \equiv \sum_{m=0}^{23} e^{\tilde{y}_{t-m}^i} \times \mathbb{1}\{N_{t-m}^i = 1\} / \left[\sum_{m=0}^{23} e^{d_{a-m}} \times \mathbb{1}\{N_{t-m}^i = 1\} \right],$$

where t corresponds to the month prior to the devaluation, $\tilde{y}_t^i$ is the log real labor income, d_a are the coefficients of the age dummies in the pooled regression, and N_{t-m}^i is an indicator variable equal to one if the worker was employed in period $t - m$ and zero otherwise. We scale the age dummies so that the fixed effect of a 25-year-old worker matches the average labor income of a 25-year-old worker in the regression sample.

[13]From here on, we use the notation $\Delta_z Y_t \equiv Y_{t+z} - Y_t$.

We extract three conclusions from this analysis. First, income dynamics monotonically depend on the worker's position in the pre-devaluation income distribution. Second, the asymmetric recovery and the decline in inequality are the result of the larger *within-worker* average growth rates for workers at the bottom of the distribution. Third, as we show in Figure C.1 in the Appendix, after the 2002 devaluation there was a decrease in the labor share from 40% to 31% due to the rapid increase in the inflation rate and the lack of a similarly rapid adjustment of nominal labor income—implicitly, a redistribution from workers to firms. This section shows that the redistribution from firms to workers during the recovery of real labor income was faster at the bottom of the income distribution.

Robustness. We perform similar analyses using different subsamples of the data to address a few sources of concerns. In each case, we find that the main finding on the heterogeneous recovery of real income after the 2002 devaluation still holds. We present our results in Online Appendix Section D.1.

First, we explore the possibility that a subgroup of workers drives the main aggregate result. To address this, we perform additional splits of the data. Given the large change in relative prices across sectors brought about by the devaluation, the observed pattern could be the result of a compositional effect. Although we will explore this further below, we reproduce the main finding by splitting the sample according to the 1-digit sector of employment of each worker in December 2001. Figure D.1 shows that the qualitative pattern is present in each of the broad sectors. Similar compositional effects might arise due to differences in the growth rates of income by age. Figure D.2 reproduces the main figure by groups of workers according to their age in December 2001 (25-29, 30-34,. . .,60-65) and shows similar patterns in each subgroup of workers. We reproduce the figure using data on women (see Figure D.3) and find similar results. We also verify that our finding is not determined by how we construct the measure of permanent income. Thus, following Guvenen *et al.* (2014), we recompute the measure of permanent income as the average monthly income during the 5 years prior to the devaluations (as opposed to 2 years, as in the baseline analysis). Figure D.4 shows the results, which are quite similar to those found in the baseline analysis. Finally, we check that the results are not driven by potentially different dynamics of income during the month of December by computing income growth using the average monthly income within the last quarter of the year (see Figure D.5).

One potential concern regarding this analysis is that the observed "pivoting" might be the result of the mean reversion of labor income. While this concern is qualitatively valid, it is not quantitatively relevant, since labor income exhibits a high degree of persistence. We verify this by conducting a placebo exercise in which we replicate Figure 7 starting in 1997, when aggregate labor income was stagnant, to isolate the effect of mean reversion (see Figure D.6 in the Online Appendix). The patterns illustrated in the two figures are clearly different. In the analysis starting in 1997, average income growth is muted, and there is no "pivoting" effect across the income distribution. In addition, following Guvenen *et al.* (2014), we directly control for different pre-devaluation income growth rates (in addition to controlling for age and level of income), and find that controlling for past income growth has almost no effect on Figure 7 (see Figure D.7). From this analysis, we conclude that income dynamics after the devaluation are not an artifact of mean reversion and depend on the worker's position in the pre-devaluation income distribution.

5.2 The Role of Sectors, Firms, and Workers

Is the decrease in inequality following large devaluations explained by between- or within-group dynamics? This is an important question, since devaluations are associated with large changes in relative prices across sectors and firms, and thus could affect particular groups of workers differently. In Online Appendix Section D.2.1, we perform a variance decomposition analysis to decompose the overall cross-sectional variance of log real income into between and within components across sectors and firms (see, for example, Song, Price, Guvenen, Bloom and Von Wachter, 2018). There, we find that each of the between-sector, -firm, and -worker components almost equally account for 33% of the decline in labor income inequality.

Although the variance decomposition is a useful starting point in the literature, it does not provide a characterization of the relevance of the different components (sector, firm, and worker) for the recovery of workers located *in different parts of the income distribution*. Therefore, we go beyond the standard variance decomposition and, through a series of counterfactual exercises, document how the sectoral and firm components of income differentially affected workers in different percentiles of the distribution.

In the first exercise, we gauge the relevance of between-sector heterogeneity across the labor income distribution by asking: What would the dynamics of labor income be if, in each period, workers had earned the average income in the sector? That is, for each worker we compute $\Delta\bar{Y}_{s(it)}$, where $\bar{Y}_{s(it)}$ is the average income in 4-digit sector s employing worker i in period t net of the overall average income in period t. Figure 8-Panel A plots the results by averaging this counterfactual income growth across workers in each percentile of the pre-devaluation distribution (the ranking of workers is the same as the one used in the baseline Figure 7). The two main findings are (i) heterogeneous sectoral labor income growth did not lead to widely heterogeneous recoveries across workers below the 60th percentile, and (ii) part of the decrease in inequality was due to the slower recovery of average sectoral labor income in sectors that employed workers at the top of the distribution.

To measure the contribution of the between-firm component across the income distribution, we replace the worker's income growth shown before with the worker's growth in $\bar{Y}_{j(it)} - \bar{Y}_{s(it)}$, which is the average income paid by firm j employing worker i in period t net of the average income paid in sector s of the firm. Figure 8-Panel B shows that this component is responsible for the largest fraction of the "pivoting" observed in the baseline

Figure 7. Workers below the 60th percentile of the pre-devaluation income distribution experience positive income growth from the between-firm component, while workers above this percentile experience negative income growth. Thus, the decrease in inequality accounted for by the between-firm component is due to monotonically lower average income growth in firms employing higher-income workers.

The remaining piece of the decomposition is given by changes in $Y_{it} - \bar{Y}_{j(it)}$, which is a worker's i labor income in period t net of the average income paid in the firm employing him. Figure 8-Panel C plots the average growth of this component across the distribution. Most of the heterogeneity in the within-firm and between-worker component comes from faster income growth for workers below the 10th percentile of the pre-devaluation distribution and slower growth for workers at the top of the distribution.

Finally, we quantify the relative importance of each component in accounting for the heterogeneous recovery across the distribution. For this, we compute the difference in the average cumulative growth 4 years after the devaluation between workers at the 10th and 60th percentiles. The differences in the sector-, firm-, and worker-components are 6%, 18%, and 0.4%, respectively. Across the entire distribution, the difference between the 10th and 90th percentiles is 20%, 23%, and 8% for the sector-, firm-, and worker-components, respectively. The main takeaway is that the firm component plays the predominant role, particularly at the bottom of the income distribution; however, in order to explain the labor income dynamics of individual workers at the top of the distribution, one must focus also on the between-sector and within-firm components.[14]

5.3 Mechanisms

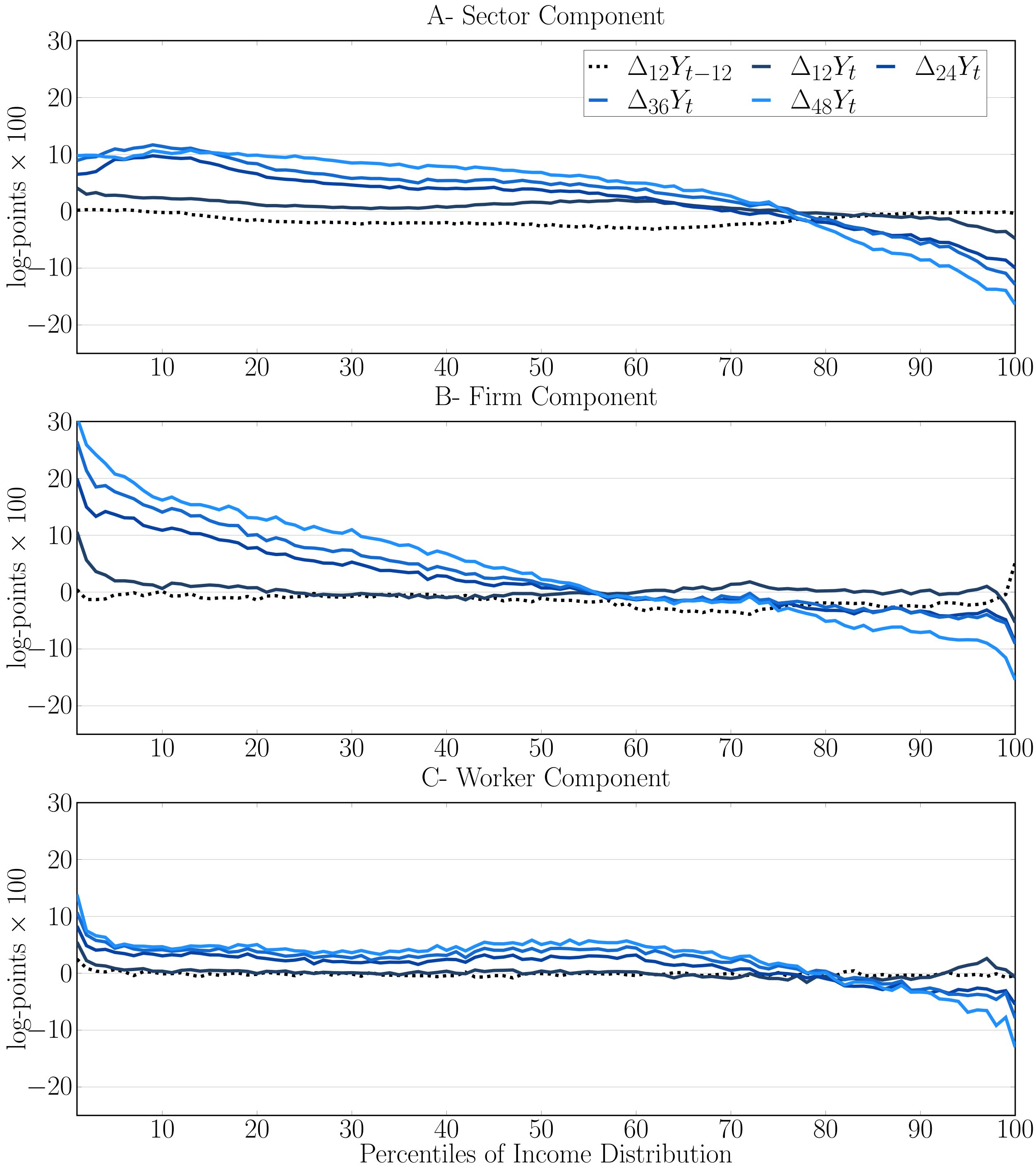
In this section, we quantify the role of three mechanisms driving the decline in inequality.

5.3.1 Mechanism I: Labor Mobility

The importance of firm heterogeneity for the pivoting effect prompts the following question: What is the role of mobility across jobs for the decline in inequality during devaluations? This question is motivated by the previous theoretical and empirical literatures. Theoretically, models with search frictions identified labor mobility as a mechanism that produces heterogeneous income growth across workers in response to aggregate shocks. Empirically,

[14]In Figure D.9, we perform the same analysis on the subsample of workers who, in December 2001, were employed in firms that had on average (during the 2000-2001 period) at least 10 employees. We show that the "pivoting" effect found in the firm component of income is equally important when excluding smaller firms. Also, the counterfactuals reported in Figure 8 are constructed using sector- and firm-level average incomes in the entire sample of workers. Figure D.10 in the Online Appendix shows similar results when constructing sector- and firm-level average incomes using only data on workers who were employed in December 2001 (i.e., the baseline sample behind Figure 7).

Figure 8 – Decomposition of Average Income Growth Conditional on Average Income in 2000-2001



Notes: The figure plots average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. Panel A replaces a worker's labor income with the average labor income in the sector of employment net of the overall average labor income for a given year. Panel B replaces a worker's labor income with the average labor income in the firm of employment net of the sectoral average labor income. Panel C replaces a worker's labor income with the worker's labor income net of the firm's average labor income.

several papers have documented differences in mobility patterns across groups of workers.[15]

We answer our question in two steps. First, we document the incidence of different types of transitions and the conditional average income growth by type of transition across the income distribution. Second, we compute a set of counterfactual income dynamics that quantify the role played by labor mobility.

Workers at the bottom (resp. top) of the pre-devaluation income distribution experienced separation shocks at a higher (resp. lower) rate, but on average their income increased (resp. decreased) with each transition, especially during the recovery of real income. Figure 9-Panel A plots the cumulative probability of experiencing a separation over the first 4 years after the devaluation as a function of a worker's pre-devaluation income (the same ranking of workers as in Figure 7). This probability is monotonically decreasing in the position of the distribution, with the exception of workers above the 90th percentile. Relatedly, Figure 9-Panel B plots the average income growth across all job transitions that involve an unemployment spell within percentiles of the distribution. In the first year after the devaluation, workers below the 50th percentile experienced an average income growth of -7.7%, while workers above the 50th percentile experienced an average growth of -15.4%.[16] Four years after the devaluation, workers below the 50th percentile experienced an average growth of 6.4% during job changes that involved an unemployment spell, while high-income workers faced losses of -10.8% on average.

Low-income workers were also more likely to make job-to-job transitions and to experience larger income growth on average when making such transitions.[17] Figure 9-Panels C and D plot the same objects for the case of job-to-job transitions. Qualitatively, the patterns are the same as those observed for separations. The only difference is that, starting from the second year after the devaluation, workers in all percentiles experienced a positive income growth after a job-to-job transition on average. Importantly, overall the average income growth is still decreasing in the position in the income distribution.

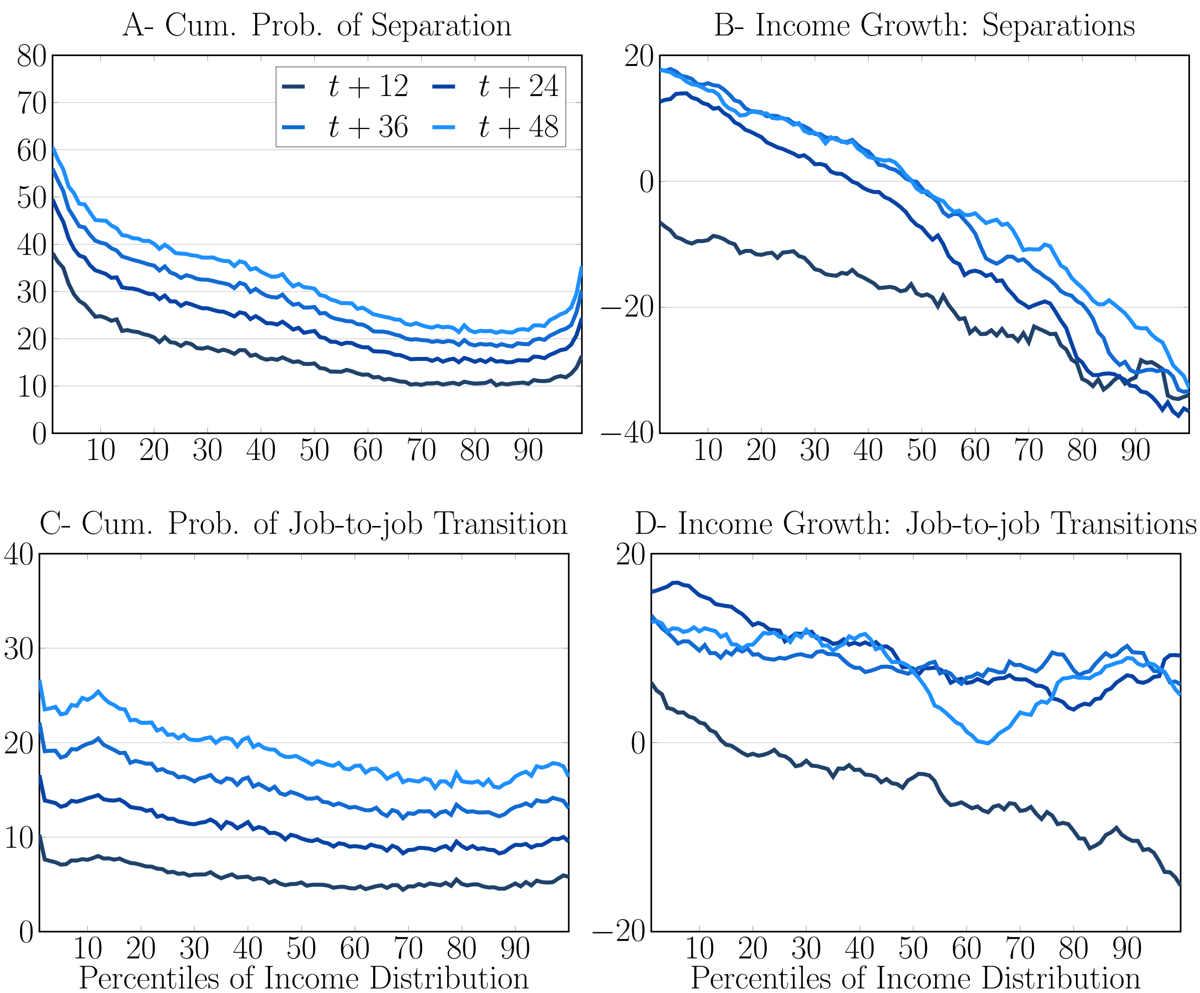
Now that we have established that labor mobility is heterogeneous across the income distribution, we next document that it is an important driver of the heterogeneous recovery of income. For this, we construct several counterfactual series of income. First, we compute counterfactual income dynamics without changes due to job-to-job transitions. For each worker, we compute changes in income for each pair of subsequent observations over time. Then, we identify the changes in income that are due to job-to-job transitions and replace

[15]For example, Karahan *et al.* (2019) show that in the US (i) the number of employers during the working life (resp. the fraction of job stayers) is decreasing (resp. increasing) in workers' lifetime earnings, and (ii) separation and job-to-job transition rates are declining in workers' recent earnings. Donovan *et al.* (2020) present similar evidence for 5 other countries. See Section G for similar evidence in Brazil.

[16]The labor income drop after a separation is consistent with Davis and Wachter (2011).

[17]We define a job-to-job transition as an event in which a worker switches firms, with at most a month of non-formal employment in between.

Figure 9 – Income Mobility across the Income Distribution



Notes: Panel A plots the cumulative probability of experiencing a job separation between December 2001 and each December in the following 4 years. Panel B plots the average difference between the (log) income in the new job found after a separation and the (log) income in the previous job for each year after the devaluation. Panel C plots the cumulative probability of experiencing a job-to-job transition between December 2001 and each December in the following 4 years. Panel D plots the average difference between the (log) income in the new job found after a job-to-job transition and the (log) income in the previous job for each year after the devaluation. All figures are conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. We truncate the distribution of income changes by the 1% and 99% percentiles to construct Panels B and D.

them with a zero.[18] Finally, we reconstruct for each worker the time series of the level

[18] Formally, let $Y^i_{t(j)}$ be the j-th chronological observation of worker i in period $t(j)$ in the dataset. Then, we can write

$$Y^i_{t(j)} = Y^i_{t(1)} + \sum_{l=2}^{j} \Delta Y^i_{t(l)},$$

where $\Delta Y^i_{t(l)} \equiv Y^i_{t(l)} - Y^i_{t(l-1)}$. Then, we construct a counterfactual series for $Y^i_{t(j)}$ by setting $\Delta Y^i_{t(l)} = 0$, of labor income with these counterfactual income changes. These counterfactual income dynamics reflect the actual income growth for incumbent and separating workers and omit income growth experienced during job-to-job transitions.

Figure 10-Panel A compares the baseline results with the counterfactual income dynamics (for ease of exposition, Figure 10-Panel B plots the difference between both lines). We can see that job-to-job transitions did not generate any heterogeneous income growth before or immediately after the devaluation. However, during the recovery phase, we see that job-to-job transitions positively contributed to higher income growth, especially for workers below the 50th percentile. Quantitatively, job-to-job transitions generated a significant fraction of the pivoting observed in Panel B of Figure 8 (which also shows similar changes before and immediately after the devaluation, followed by positive income growth for workers below the 50th percentile).

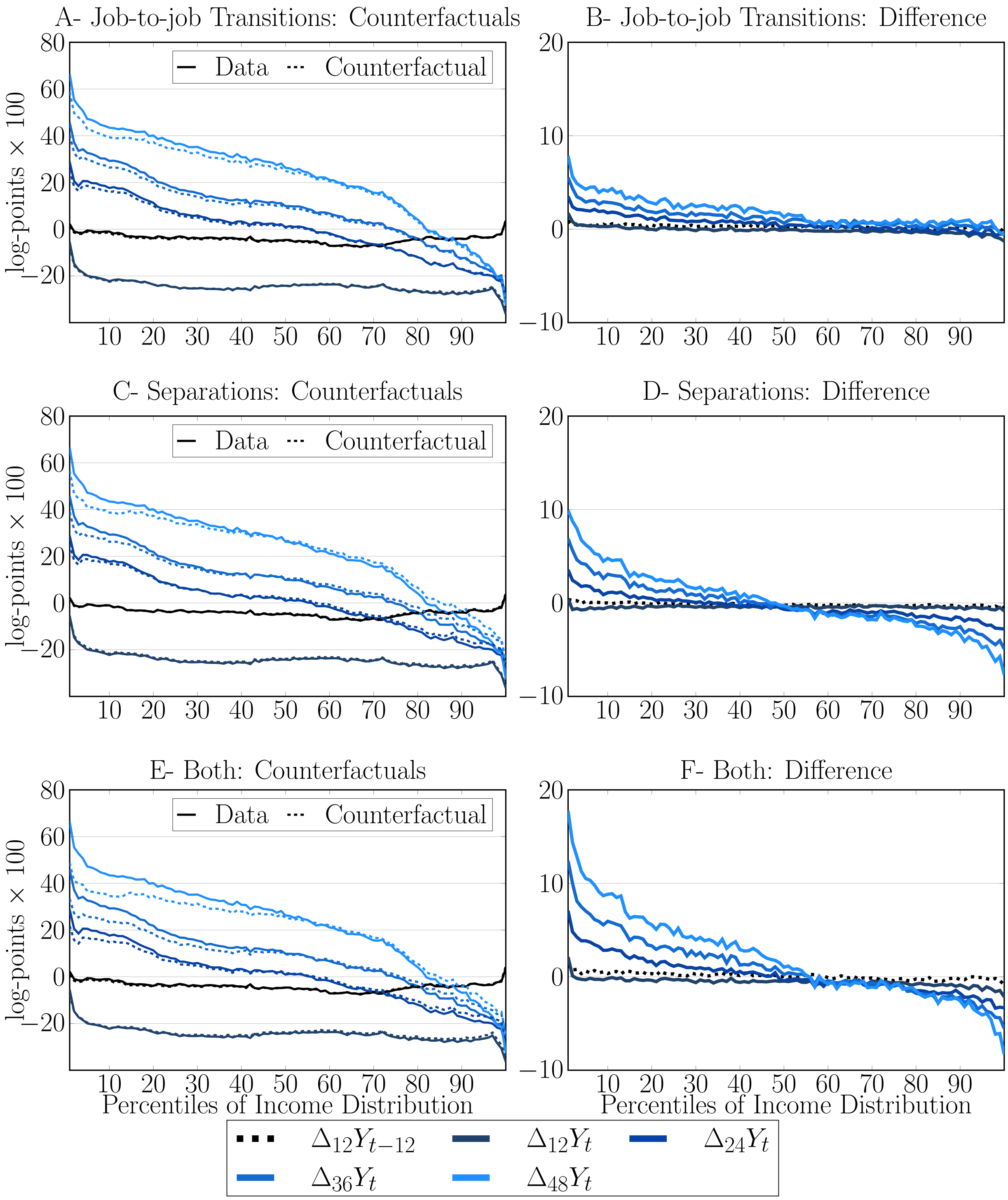
Next, we perform a similar exercise with the aim of quantifying the role of mobility due to separations. In this case, we identify the changes in income that are due to separations and replace them with a zero. With these counterfactual growth rates, we reconstruct the time series of labor income for each worker. Figure 10-Panel B shows the results. In this case, the pivoting that can be attributed to income growth generated by separations is even stronger.

Combining these two results, labor mobility can account for 48% of the heterogeneous recovery of the firm-component. Panels E and F combine the effects of both types of labor mobility. The average cumulative income growth for workers at the 10th percentile was 8.9%. In contrast, workers at the 90th percentile experienced an average cumulative income growth of -2.6%. As a comparison, the average cumulative income growth for workers at the 10th (resp. 90th) percentile in Panel B of Figure 8 was 16.2% (resp. -7.4%).

Online Appendix F describes the Burdett and Mortensen (1998) and Menzio and Shi (2010) models. We show that these search and matching models can micro-found the labor mobility patterns observed in our data. More specifically, the models predict that the probability of switching jobs is decreasing in the current wage. Second, conditional on experiencing a job transition, the wage difference between the new and the previous job is also a decreasing function of the wage received in the previous job. This is because both models feature a job ladder. As workers climb the ladder they find it harder to switch to jobs offering even higher pay. As a result, the prevalence and gains from labor mobility are more significant for low-income workers. Thus, a stronger demand for labor precipitated by higher inflation (more generally, higher TFPR) and lower real wages affects more workers at the bottom of the income distribution, who have higher chances to move up the job ladder. These differences are further amplified when search effort is endogenous (as in Faberman, Mueller, Şahin and Topa, 2022) since the presence of a job ladder makes the benefits of

whenever worker i makes a job-to-job transition between $t(l-1)$ and $t(l)$ (i.e., whenever employers differ in those two periods and $t(l) - t(l-1) \leq 1$).

Figure 10 – Counterfactual Income Growth across the Distribution



Notes: Panel A plots both the actual average income growth and the counterfactual income growth that omits income changes experienced during job-to-job transitions. Panel B plots the difference between the actual and the counterfactual dynamics to ease comparison. Panel C plots both the actual average income growth and the counterfactual income growth that omits income changes experienced after separations. Panel D plots the difference between the actual and counterfactual dynamics to ease comparison. Panels E and F present similar results for the combined effects of job-to-job transitions and separations. All figures are conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period.

search more significant for low-income workers.

5.3.2 Mechanism II: Heterogeneous Income Floors Set by Unions

A relevant driver of the drop in inequality could be differences in workers' abilities to renegotiate higher wages. An important source of such differences in many developed and developing countries is the presence of collective bargaining. We show how unionization status shapes heterogeneous individual recoveries across the income distribution in three steps. First, we briefly describe the role of unions in Argentina. Second, we present evidence on the role of unions for income growth within sectors.[19] Finally, we reproduce our main fact by unionization status and find significant differences across workers covered and not covered by a CBA.

In Argentina, a single union has monopoly power to represent workers and negotiate a CBA at a sectoral level. A CBA determines the minimum labor income for all workers employed in that sector and in a subset of occupations, regardless of their individual membership status (thus, we interchangeably refer to workers covered by a CBA as unionized). That is, if a certain occupation is covered by a CBAs in a given sector, then all workers employed in that sector and performing that occupation are affected by the same income floors. By law, negotiated wages must be above the national minimum wage. For the largest firms in a sector, unions also negotiate firm-specific CBAs, which have to offer better terms to workers than the sectoral CBA. Online Appendix D.3 provides an extensive description of the union system in Argentina, demonstrates that it is similar to union systems in many other countries, and describes the timing of collective bargaining in our period of analysis.

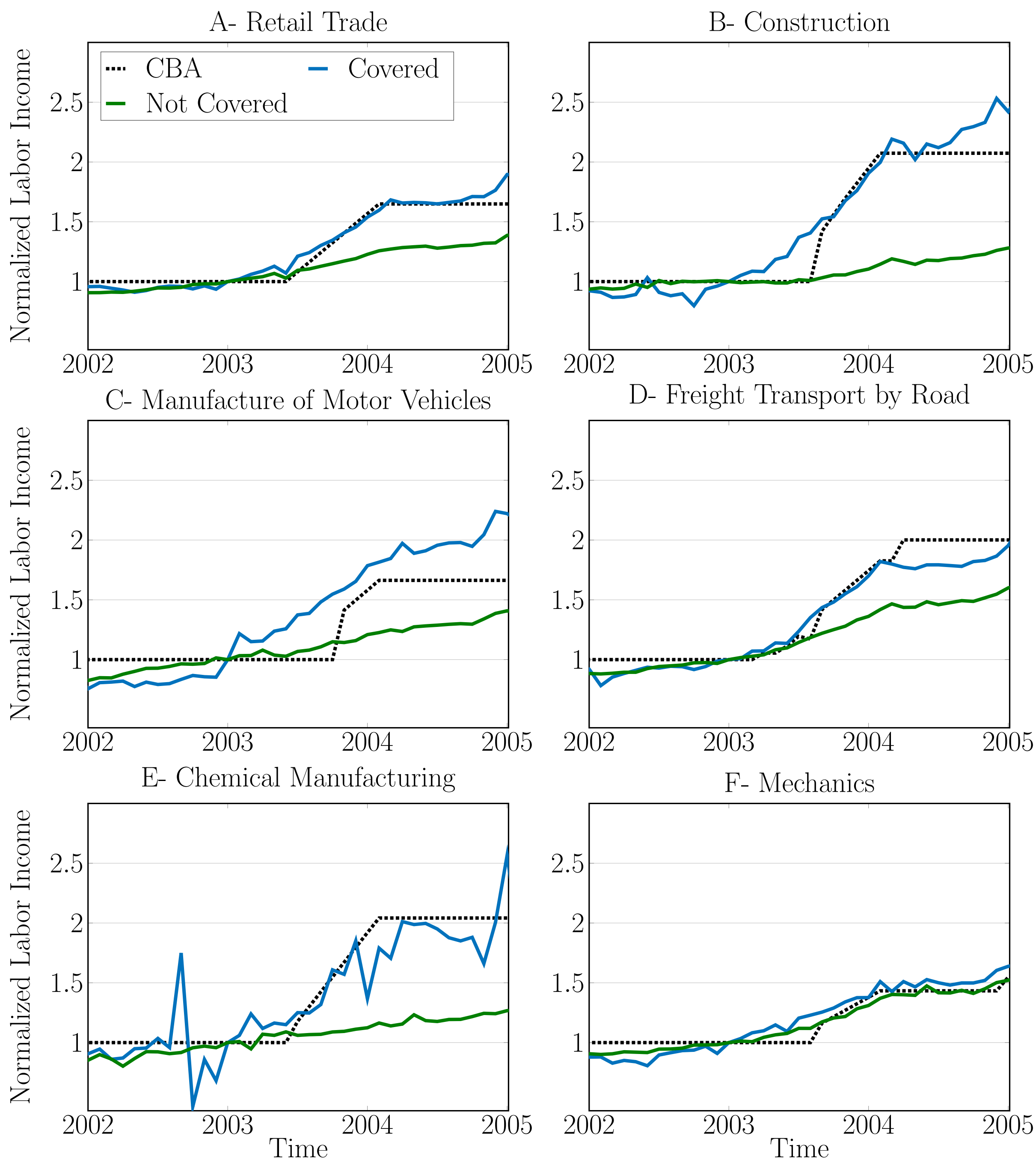
Following the 2002 devaluation, workers whose incomes were covered by a CBA saw their labor income recover faster than non-unionized workers. Figure 11 plots income by unionization status over time for some sectors with strong unions. The figure plots the income of the lowest-paid occupation in the CBA and the average income of workers covered and non-covered by the CBA. Covered workers are those who are unionized according to the SIPA dataset, and whose labor income is within 0-10% above the income of the lowest-paid occupation established by the CBA in October 2002. We choose October 2002 because between 1995 and that date unions did not renegotiate their CBAs. By law, an expired CBA still remains legally binding until a new one is negotiated.[20]

For all the sectors in which bargained income changes were above inflation, the average nominal income growth of covered workers was 30% higher than non-covered workers. The

[19] As we showed above, the primary source of heterogeneous recovery of labor income is within sectors.

[20] These groups are constructed using the unionization status variable in the SIPA data. The unionization variable becomes available in March 2003 and presents a high degree of persistence in the sample. For this reason, we are confident that the majority of these workers maintained their unionization status between October 2002 and March 2003. Since unions negotiate a minimum monthly labor income for specific occupations, we added the second condition to identify workers near the prevailing minimum income in October 2002.

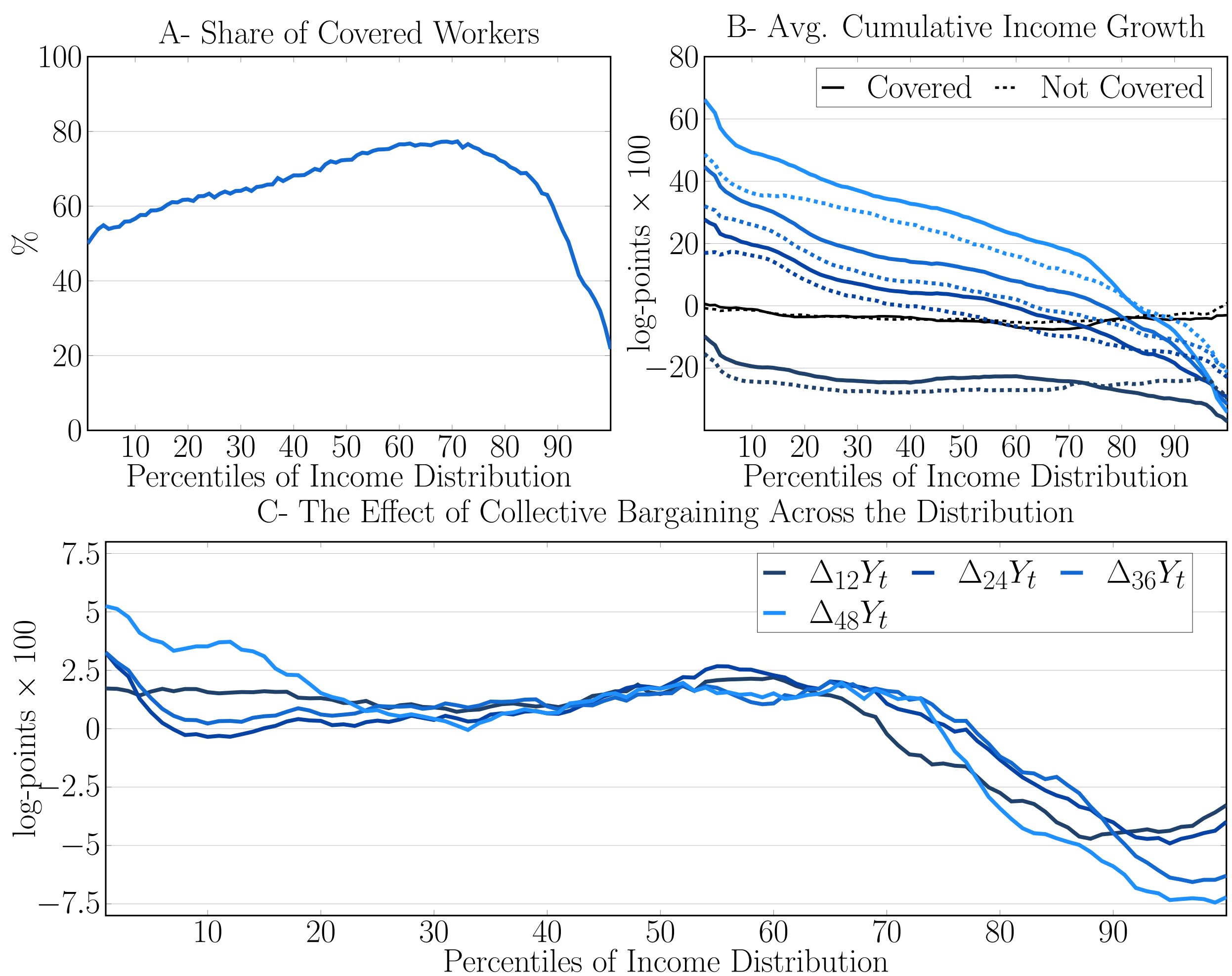
Figure 11 – Normalized Labor Income by Union Coverage and Labor Income in CBAs



Notes: Panels A to F plot the nominal income of the lowest-paid occupation in each CBA and the average nominal income of workers covered and non-covered by the CBA across six sectors (i.e., retail trade, construction, manufacture of motor vehicles, freight transport by road, chemical manufacturing and mechanics). A worker belongs to the group "Covered" if she is covered by a CBA at any point in 2003 according to the SIPA dataset and her labor income is within 0-10% above the income of the lowest occupation established by the CBA in October 2002. A worker belongs to the group "Not Covered" if she is not covered by a CBA during 2003 in the SIPA dataset. Average nominal income is normalized to one in January 2003.

labor income growth rate of unionized workers closely follows the average growth specified by the CBA. This pattern holds for all sectors, except mechanics. In that sector, the CBA's income growth is almost equal to the cumulative inflation between 2002 and 2005, which is much smaller than in the rest of the unions. Therefore, income growth does not vary much by unionization status. We conclude that there is significant heterogeneity of income growth by unionization status in sectors with unions that hold sufficient power to negotiate wage increases in excess of inflation.

Figure 12 – Collective Bargaining and Heterogeneous Income Growth



Notes: Panel A plots the share of unionized workers by percentiles of income, as in Figure 7. Panel B plots average cumulative income growth by percentiles and unionization status. Panel C plots the difference in the average cumulative income growth between unionized and non-unionized workers by percentiles weighted by the share of unionized workers in that percentile. Panel C is normalized by subtracting the mean across percentiles for each series.

Until now, we illustrated the role of unions in a subset of sectors. Next, we present the contribution of unionization status to the main fact of this paper. Figure 12 reports the share of unionized workers and average labor income growth by unionization status as a function of pre-devaluation income. To construct Figure 12, we split workers according to their unionization status only, regardless of their income relative to bargained income floors.[21]

The share of unionized workers is increasing for the worker between the 1st and 70th percentiles and decreasing from the 70th to 100th percentiles. The share of unionized workers is above 60% between the 20th and 90th percentiles. Thus, union bargaining is relevant primarily for workers in the bottom to top of the income distribution, and less so for workers at the very top of the income distribution.

Average cumulative income growth was higher for unionized workers than non-unionized workers. The average difference in income growth across unionization status is close to zero between December 2001 and December 2002. If we focus on workers below the 70th percentile, the differences in income growth for unionized workers relative to non-unionized workers increased over time. The average difference 1 year after the devaluation was 4%, and the difference became 8.7% four years after the devaluation. On the other hand, unionized workers at the top of the pre-devaluation income distribution experienced a slower recovery relative to non-unionized workers (see Card, 1996, for similar evidence of a smaller/negative union premium at the top of the distribution in the U.S.).

We quantify the role of unionization by computing the counterfactual income loss if a random worker in a given percentile became non-unionized. This loss is obtained by multiplying the difference between the average cumulative growth of unionized and non-unionized workers by the share of unionized workers within each bin. Figure 12-Panel C plots this weighted difference across the income distribution, which illustrates by how much average cumulative income growth in each bin would decrease if all workers were non-unionized. The difference in income growth between workers at the 10th and 90th percentiles was 9.4%, almost constant between the 10th and 60th percentiles, and largely heterogeneous between the 60th percentile and the top of the distribution.

5.3.3 Mechanism III: The Role of Trade Exposure

Since medium-run pass-through to domestic prices is incomplete, nominal devaluations induce large fluctuations in the real exchange rate. Such fluctuations have large effects on relative prices and revenues, which can affect the labor market outcomes of workers employed in sectors exposed to international trade. Here, we analyze whether trade exposure could be a driver of the observed fall in inequality.

A devaluation can affect workers according to the degree of trade exposure of their sector

[21] The digitalization of all sectors' CBAs and the merge with SIPA data is outside the scope of this paper. Each sector has its own sector-specific contract format that changes over time. Therefore, we were not able to standardize CBAs across all sectors. Nevertheless, we reproduce Figure 11 in the Online Appendix with different definitions of coverage to show how these definitions affect the measurement of income dynamics by unionization status (see Figure D.14). In addition, to construct the unionization share across the distribution, we classify a worker as unionized if she is covered by a CBA during the 2003-2006 period to avoid measurement error in the early years when the variable was introduced.

of employment. According to theory (see, e.g., Campa and Goldberg, 2001), a devaluation should positively affect workers employed in sectors with a large export share, since a devaluation increases the relative price of their output. A devaluation should negatively affect sectors that import a large fraction of their intermediate inputs, since it increases production costs. Finally, sectors that face strong competition from abroad should be positively affected by a devaluation, since it increases the relative price of foreign competitors. Thus, after a devaluation, we should observe a more significant income growth for the average worker employed in a sector with a high export share, low share of imported intermediate inputs, and/or high import penetration. If, in addition, this average worker is located toward the bottom of the pre-devaluation income distribution, then a devaluation could lower inequality through these trade-based mechanisms.

We present evidence on the role of these trade channels in two steps. We first estimate the response of sectoral average income growth to changes in the nominal exchange rate, allowing for heterogeneous responses as a function of a sector's trade exposure. Second, we compare the predicted growth in sectoral income across the pre-devaluation income distribution. To do so, we compute three trade-related variables for each sector defined at the three-digit level using data from the 1997 Input-Output matrix in Argentina: (i) the share of imported intermediate inputs (Import Share_{s1997}), (ii) the export share of output (Export Share_{s1997}), and (iii) the degree of import penetration (Import $\text{Penetration}_{s1997}$).[22]

Following the literature that estimates pass-through to prices (see, e.g., Gopinath, Itskhoki and Rigobon, 2010), we estimate how sectoral income changes correlate with changes in the nominal exchange rate by regressing

$$\begin{aligned}\Delta outcome_{st} = &\sum_{j=0}^{12} \phi_j \Delta NER_{t-j} \times \text{Import Share}_{s1997} + \sum_{j=0}^{12} \gamma_j \Delta NER_{t-j} \times \text{Export Share}_{s1997} \\ &+ \sum_{j=0}^{12} \delta_j \Delta NER_{t-j} \times \text{Import Penetration}_{s1997} + \alpha_s + \beta_t + \varepsilon_{st}, \qquad (1)\end{aligned}$$

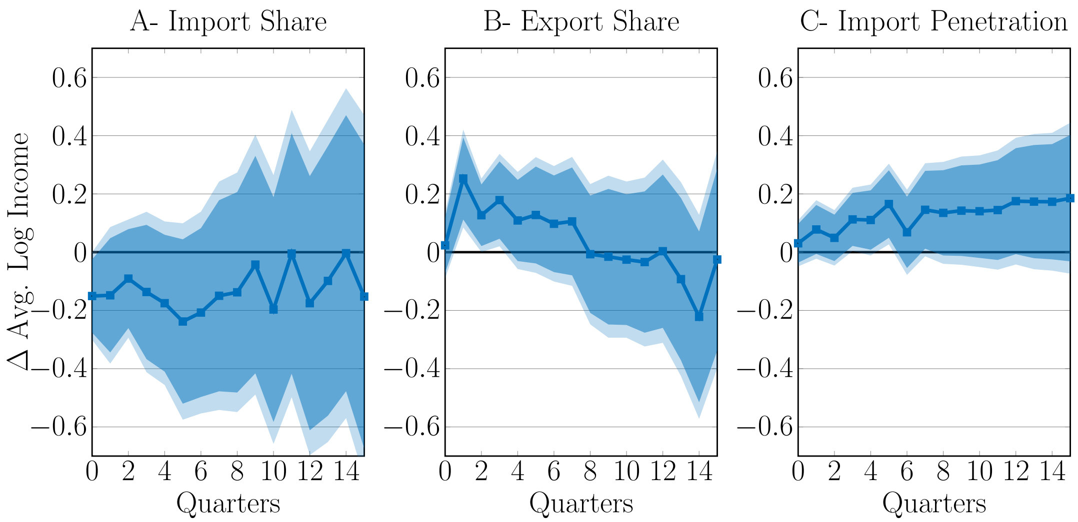
where $\Delta outcome_{st}$ is the change in the outcome variable in sector s at time t and ΔNER_t is the change in the nominal exchange rate. The vectors θ_s and β_t are sector and time fixed effects, respectively, which capture any permanent differences in growth rates across sectors and control for any aggregate factors that affect outcome variables. The statistics of interest are the partial sums $\sum_{j=0}^{n} \phi_j$, $\sum_{j=0}^{n} \gamma_j$, and $\sum_{j=0}^{n} \delta_j$, which capture the dynamic impact of the NER. Under the assumption that sectoral labor income comoves positively with sectoral revenue, theory predicts positive γ_j and δ_j and negative ϕ_j. We estimate (1) using quarterly

[22] We compute the intermediate import share of a sector as the share of intermediate inputs purchased from abroad and the export share as the share of output it sells to foreign markets. We compute the import penetration in each sector as the ratio between imports over domestic absorption (total imports/(output−trade balance)). To construct these measures, we use the National Input-Output Matrix in 1997, which is predetermined at the time of the 2002 devaluation (see Frías, Kaplan and Verhoogen, 2009, for a similar approach).

data around the 2002 devaluation from the first quarter in 1997 to the last quarter in 2006.

Figure 13 shows the results when the outcome variable is the log average income in each sector. Solid lines represent the cumulative sum of point estimates, while the shaded areas show 90% and 95% confidence intervals. To interpret the coefficients, remember that average labor income decreases with the devaluation of the NER. As predicted by the theory, in the first few quarters income falls by less in sectors with a high export share and high import penetration, and by more in sectors with a high share of imported intermediate inputs. Given a devaluation of approximately 120%, the predicted effects in the first two quarters are large: Going from the 10th to the 90th percentile of the import share, export share, and import penetration distributions induces a change in average sectoral income of -4.6%, 11.3%, and 5.3%, respectively.[23] Also, the effects are persistent over time, although less precisely estimated at longer horizons.

Figure 13 – Response of Sectoral Labor Income to the Nominal Exchange Rate



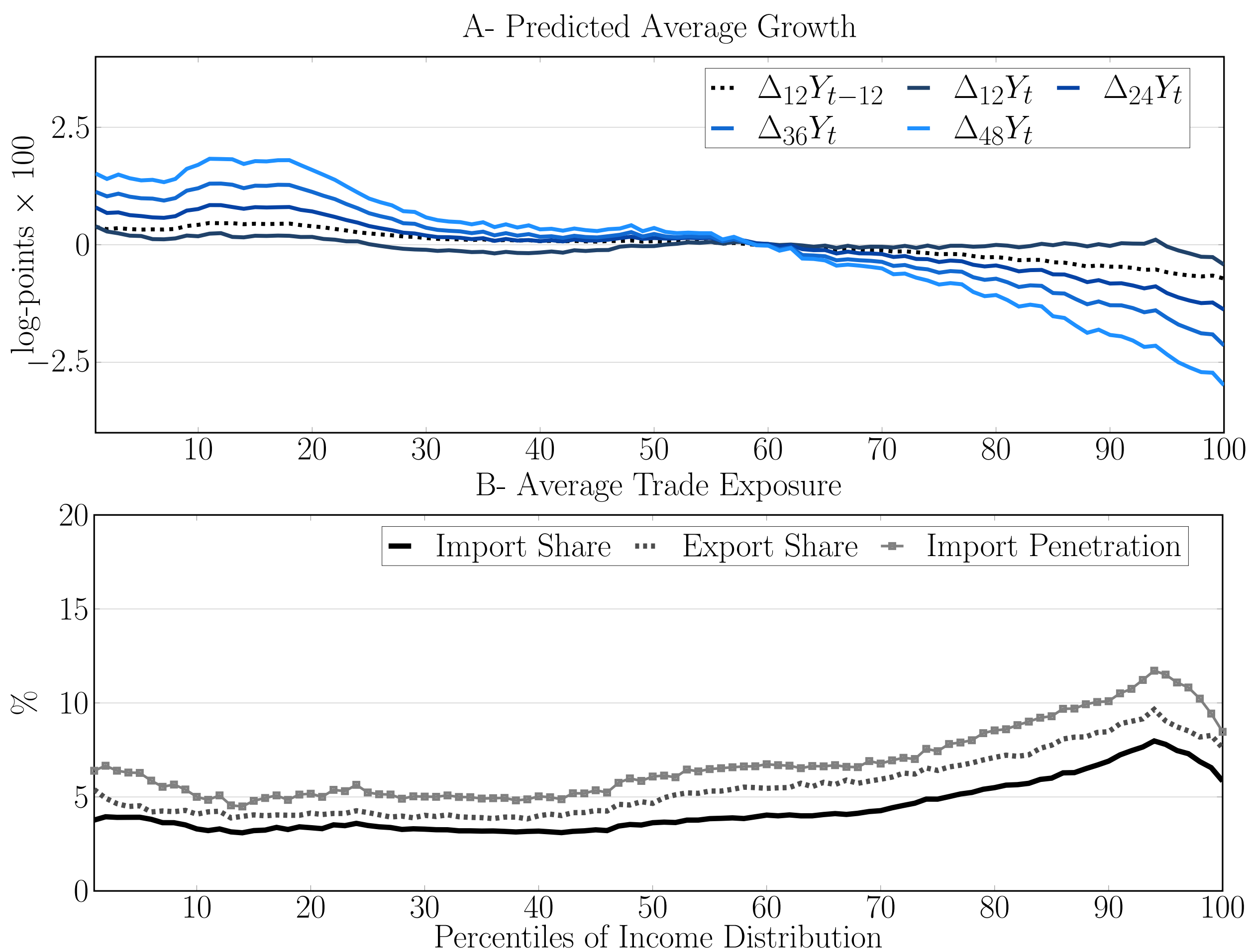
Notes: This figure reports estimates of equation (1). The dependent variable is the quarterly growth rate of log average sectoral income. Independent variables include the interaction of the quarterly change in the NER with the export share, the share of imported intermediate inputs, and import penetration by sector and time and sector fixed effects. Solid lines depict the cumulative sums $\sum_{j=0}^{n} \phi_j$, $\sum_{j=0}^{n} \gamma_j$, and $\sum_{j=0}^{n} \delta_j$ for $n \in [0, 12]$. Shaded areas depict the 90% and 95% confidence intervals based on robust standard errors. The estimation method is OLS and the equation is estimated using data over the 1997-2006 period.

Next, we analyze whether such heterogeneity in sectoral income growth can explain, at least in part, the observed decline in inequality after the devaluation. The lines in Figure

[23] Figure D.15 in Online Appendix D.4 shows the realized 3-year labor income growth rates by sector and the predictions from the OLS estimates of equation (1). As the figure shows, the three interaction terms in equation (1) provide a good fit of the data: They can account for 69% of the overall variation with an elasticity of 0.32. More importantly, this figure highlights the fact that these three measures of trade exposure can generate enough variation across sectors in the response of average income growth to changes in the NER, with most sectors experiencing heterogeneous growth rates between -15% and 10%.

14-Panel A show the weighted average of the predicted sectoral income growth from equation (1) by percentiles of the pre-devaluation income distribution. The weights are given by the within-bin sectoral composition in December 2001. Although the overall pattern is similar to the one in Figure 8-Panel A, the differences in income growth across the distribution are small. The gap in average cumulative growth 4 years after the devaluation between workers at the 10th and 90th percentiles is 3.3%—which only accounts for 16% of the corresponding gap in Figure 8-Panel A.

Figure 14 – Trade Exposure and Heterogeneous Sectoral Income Growth



Notes: Panel A plots the predicted average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The lines show the weighted average of the predicted sectoral income growth from the estimates of equation (1). The weights are given by the within-bin sectoral composition in December 2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. Panel B shows the average import share, export share, and import penetration of the sector of employment of workers in each percentile of the distribution of average monthly real income during 2000-2001.

Why does this between-sector trade mechanism fail to account for the decline in inequality? The answer is straightforward: Despite the substantial heterogeneity in average income growth across sectors (see Figure D.15 in the Online Appendix), the relative winners and losers generated by the trade channels and the devaluation are quite evenly distributed across the pre-devaluation income distribution. Figure 14-Panel B shows this by plotting the average export share, import share, and import penetration of the sector of employment of workers in each income percentile in December 2001 (which serve as the basis to construct Figure 14-Panel A). First, the small variation in sectoral income growth across the distribution is explained by the similarly small variation in the sectoral composition across the distribution (at least in terms of these trade-based sectoral characteristics).[24] Second, some of these channels offset each other—e.g., a well-known fact in the international trade literature is that sectors with high shares of importing firms are also sectors with high shares of exporters (see, e.g., Bernard, Jensen, Redding and Schott, 2007, Blaum, 2019). This means that the losses experienced by high-income workers, who tend to be employed in sectors with a high import share, are partially offset by the fact that they also tend to be employed in sectors with a higher export share and import penetration. Argentina is no exception to this pattern, as shown in the figure.

Trade could affect inequality not only through the *between*-sector mechanisms analyzed above, but also through *within*-sector mechanisms. According to the latter, inequality could be affected if the devaluation differentially affects workers employed within a given sector. For example, suppose that high-skill/high-income workers are complementary to imported inputs (e.g., imported capital). Then, a devaluation increases the cost of these inputs—which reduces the real marginal product of labor, especially for high-skill/high-income workers. As a result, high-income workers experience lower income growth after the devaluation, which reduces inequality. We close this analysis by quantifying how much of this decline can be explained by within-sector trade mechanisms. To study this, we estimate equation (1) using the sectoral Gini coefficient as the outcome variable. Figure D.16 in the Online Appendix reports the results. We find no significant coefficients from any of the trade exposure measures.

The fact that we find a small contribution from between-sector trade mechanisms and no evidence on within-sector trade mechanisms leads us to conclude that heterogeneous trade exposure cannot be the main driver of the decline in inequality after the devaluation. In Online Appendix D.4, we report similar findings by reproducing the analysis at a more aggregate level and by allowing for the effects of indirect trade exposure through the input-output matrix (see Dhyne, Kikkawa, Mogstad and Tintelnot, 2021).

[24] For a comparison of the heterogeneous trade exposure across the income distribution in Argentina, see **?** who provide similar facts in Ecuador. The exposure measures exhibit two similarities across countries. First, measures of export and import exposures are positively correlated across the income distribution. Second, the heterogeneity of these measures across the income distribution is similar in both countries. For example, for the export exposure measure, there is a 4 pp gap between the most and least exposed workers in Ecuador, whereas the gap is 6 pp in Argentina (see Figure 14-Panel B, which also includes indirect trade exposures).

5.4 Quantification of the Role of the Mechanisms

We conclude this section by providing a back-of-the-envelope quantification of the heterogeneous recovery across the distribution using the difference in average cumulative growth 4 years after the devaluation between workers in the 10th and 90th percentiles. The overall difference is 49%. Labor mobility and unionization mechanisms generate gaps in income growth of 11.5% and 9.4%, respectively. Thus these mechanisms account for 42% $((11.5 + 9.4)/49 \times 100)$ of the heterogeneity in the recovery. In addition, the trade-exposure mechanism leads to a heterogeneous recovery of 3.3%. Therefore, our mechanisms jointly explain 49% $((11.5 + 9.4 + 3.3)/49 \times 100)$ of the heterogeneous income growth across the distribution.

This section concludes with an important observation. Our counterfactual analysis, while valuable, provides a lower bound for the contributions of labor mobility and unionization to the heterogeneous recovery. As emphasized by Postel-Vinay and Robin (2002), within a model with on-the-job-search, workers can secure higher wages from their current employers upon receiving external offers, even without transitioning to a new employer. As a result, our measurement approach, which focuses exclusively on variations in income when transitioning between jobs, establishes a minimum for the contribution of labor mobility. This methodology overlooks income fluctuations within specific jobs that may arise from on-the-job-search. Furthermore, according to Engbom and Moser (2018) and Vogel (2023)—within the framework of the Burdett and Mortensen (1998) model—changes in income floors (in their case, determined by the minimum wage) not only influence workers with incomes close to the floor but also generate cascading effects. These income changes are extended to other workers, with their size decreasing in the distance from the income floor. Furthermore, firms employing non-unionized workers might respond by also increasing their wages, especially among workers similar to their unionized counterparts. Consequently, our empirical analysis of the role of unionization also represents a conservative measurement, as it overlooks equilibrium effects on the distribution of labor income among similar workers operating in different sectors and occupations.

6 Additional Mechanisms and Robustness

6.1 Additional Mechanisms

This section extends the analysis of inequality by considering the extensive and intensive margins of employment and studying the role of changes in labor income risk to explain the drop in inequality. We summarize the results here; the complete analysis can be found in Online Appendix Sections E.1 and E.2.

The extensive and intensive margins of employment. We now extend the analysis of income inequality with the extensive and intensive margins of employment during the 2002 Argentinean devaluation.

Regarding the extensive margin, first, we analyze the dynamics of aggregate employment and employment flows between formal and non-formal employment (i.e., flows into and out of our dataset) in the aggregate and across the income distribution. Following the devaluation, the labor market experienced a strong recovery, explained by an on-impact significant drop in the aggregate separation rate and a smooth recovery in the entry rate. These patterns were more pronounced at the bottom of the income distribution. Thus, after the devaluation, low-income workers are much less likely to lose and more likely to find a job in the formal sector.[25]

After understanding these labor market dynamics, we study the role of the extensive margin in shaping income inequality. We analyze several measures of inequality based on SIPA and the household survey, which include the employment margin, and extend the coverage to the entire population of workers. We obtain three conclusions from this analysis. First, measures of inequality that incorporate the employment margin drop by *more* than measures that do not include it. The intuition behind this result is the following: There was a strong employment recovery, so the prevalence of zero-income workers decreased. Second, our previous measures of inequality among workers with positive income (i.e., excluding the extensive margin) decreased despite of—and not *because of*—the strong recovery in the labor market. The reason is simple: Following the devaluation, the entry rate into employment of low-income workers increased and their exit rate decreased. Thus, selection arising from those two margins should have increased inequality among employed workers; instead, we find the opposite. Third, the key takeaways we obtain from the SIPA dataset remain valid—and, if anything, become more pronounced—once we broaden the population with informal and all workers.

Additionally, we extend the study of individual income dynamics in Figure 7 by incorporating the extensive margin of employment (e.g., we include observations with monthly zero income and also change the baseline income measure to total annual income). We find that the difference in income growth between the 10th and 90th percentiles almost doubles relative to our baseline analysis.

In conclusion, taking the extensive margin into account magnifies the decline in labor income inequality and masks the importance of the mechanisms we analyze in Sections 4 and 5.

Regarding the intensive margin, throughout the paper, we report facts about monthly

[25] In Online Appendix E.4, we examine the dynamics of informal employment and find that the informality rate decreases after the devaluation, which is in line with improving conditions in the formal labor market. Since the decline in the informality rate is associated with transitions from the informal to the formal sector, this finding further suggests that labor mobility played an additional role in compressing the overall income distribution.

real labor income and not hourly wages due to data limitations. Nevertheless, we perform four exercises to show that our main results are driven by changes in hourly wages and not by fluctuations in hours worked. In the first exercise, we compute average weekly hours and the distribution of average weekly hours by quintiles of the income distribution in the household survey, which contains information on hours of work. Average hours worked dropped by at most 2% after the 2002 devaluation; therefore, this magnitude cannot explain the drop in real labor income of almost 30%. We also find almost no difference in the evolution of hours worked across quintiles of the income distribution. Moreover, the small drop in hours is homogeneous across the income distribution. Thus, differences across income groups cannot account for the large decrease in inequality. The second exercise analyzes workers' real hourly wages using the same data. Again, we find that the dynamics of the hourly wage distribution closely follow the dynamics of the monthly income distribution.

In the third exercise, we divide workers according to their full- and part-time status using information on workers' type of labor contract in the SIPA dataset.[26] We find quite similar dynamics of the mean real labor income across groups of full- and part-time workers. We also find similar dynamics of the interquartile range and the standard deviation of the labor income distribution across groups. Finally, the last exercise reproduces our main Figure 7 using data on full-time jobs only and shows a pattern similar to the baseline analysis.

Changes in labor income risk. One potential mechanism that could explain the drop in inequality is a decline in labor income risk following the devaluation. To illustrate the logic of this question, suppose that the income process follows a standard AR(1) process. Then a decrease in the standard deviation of the innovation would translate into a compression of the stationary distribution, which could explain a lower level of inequality. However, we found no evidence of this mechanism: Inequality decreased *despite* a significant increase in the standard deviation of income growth.

6.2 Robustness

This section analyzes the role of policy changes and additional dimensions of the labor market to better understand the heterogeneous labor market dynamics during devaluations. We provide a summary of the results here; the complete analysis can be found in Online Appendix Sections E.3-E.6.

Social and labor market policies. Between 2003 and 2009, social spending as a share of GDP increased by 7.6 percentage points in Argentina. In response to the economic crisis, the

[26] The full-time group includes workers with and without a termination date specified in their contracts. The part-time group also includes seasonal workers, trainees, and temporary workers. In order to be overly cautious, we also include in this group all workers in the agriculture, mining, fishing, and construction sectors due to the intermittent working periods common in these sectors.

government increased spending on conditional cash transfer programs, pensions, education, and primary healthcare (see Lustig and Pessino, 2014, and the working paper version, for a detailed description of each of these programs). Lustig and Pessino (2014) and Gasparini and Cruces (2008) use data from the EPH and apply an incidence analysis to quantify the impact of social spending on inequality. The main conclusion is that between 2003 and 2006—our period of analysis—the change in the disposable income Gini (i.e., after including government transfers) is fully due to the decline in the market income Gini (i.e., before including government transfers). It is only *after* 2006, when commodity prices and the government's tax income increased, that the redistribution component accounts for 40% of the decline in the disposable income Gini.

Another policy change worth discussing relates to the minimum wage. The nominal monthly minimum wage in Argentina was fixed at $200 from August 1993 to July 2003.[27] After the 2002 devaluation, the real minimum wage fell continuously until its first adjustment in July 2003. Since then, it has experienced a series of increases, and by the end of 2005 its real value was equivalent to the 10th percentile of the real income distribution.

We provide evidence showing that changes in the real minimum wage could not have been the main driver behind the post-devaluation drop in inequality. First, we show that the timing of this potential explanation is misaligned. Six months after the devaluation, divergent dynamics of the bottom and top percentiles of the income distribution emerged. This occurred while the real minimum wage kept *decreasing* due to a lack of adjustment and became even less binding. Thus, the drop in inequality preceded the increase in the real minimum wage. In addition, it is worth pointing out that after the large increase in the real minimum wage in September 2004—above 20 log points—we do not see any further significant changes in inequality. Second, the heterogeneous recovery we observe in Figure 7 is almost a linear function of the position of a worker in the pre-devaluation income distribution. It is highly unlikely that changes in the minimum wage spilled over, up to the 80th or 90th percentile, in such a short period of time.

Inequality within the informal labor market. In Online Appendix Section E.4, we provide a broader picture of the Argentinian labor market during devaluations by extending the analysis to the informal labor market. We find that labor income also decreased in the informal market after devaluations. In fact, the drop is larger and even more persistent than in the formal sector. However, we do not see a clear compression of the cross-sectional distribution of informal income. This is consistent with the fact that unions—which are present only in the formal sector—facilitate a faster recovery of real incomes.

[27]Given the lack of adjustment for such a long period of time, it is not surprising that the monthly minimum wage became binding for a small fraction of the population. In 2001, it was equivalent to the monthly nominal income of a worker in the 2nd percentile of the income distribution.

The cyclicality of labor income. Can the decline in inequality be explained by the heterogeneous cyclicality of labor income across the income distribution? We find this implausible. In Online Appendix E.5, we document a low procyclicality of aggregate labor income once we control for nominal exchange fluctuations. Furthermore, the weak procyclicality of income exhibits small variation across the percentiles of the income distribution.

Worker-specific inflation. When interested in welfare or consumption inequality, the appropriate deflator to calculate a worker's real income should be based on each worker's consumption basket instead of the aggregate CPI. From the seminal work of Cravino and Levchenko (2017), it is well-known that poor households spend relatively more on tradeable product categories and consume lower-priced varieties within categories, which could affect the interpretation of our results. In Online Appendix Section E.6, we reproduce our baseline Figure 7 by constructing measures of income-specific deflators across product categories. Two years after the devaluation, the difference in growth rates between the 10th and 90th percentiles of the pre-devaluation distribution is 32% with income-specific deflators, instead of 35% in our baseline analysis. Thus, while it is the case that households with lower incomes experienced a higher inflation rate after the devaluation, these differences are too small to overturn our main result.[28]

External validity. Besides verifying the external validity of aggregate facts across countries in Section 3, we provide evidence on the external validity of the main micro-level results using administrative data around devaluation episodes in Brazil. In Online Appendix G, we reproduce the majority of our main analysis regarding (i) the post-devaluation heterogeneous income growth across the income distribution, (ii) the decomposition of income dynamics into sector-, firm-, and worker-components, and (iii) the role of heterogeneous labor mobility across the distribution. In a nutshell, the key results and insights obtained in Brazil are quite similar to those found in Argentina, which provides reassurance that our results are broadly relevant for labor income dynamics after devaluations.

[28]Since this quantification ignores price variation within categories, we provide a back-of-the-envelope calculation that includes variations across and within product categories by extrapolating the results in Cravino and Levchenko (2017). In our analysis based on price variation across categories, income-specific inflation for the first income decile was 2.75 log points higher than for the highest decile. Following a similar increase in inflation during the Tequila crisis, Cravino and Levchenko (2017) report a difference in income-specific inflation rates between the 1st and 10th decile of 4 log-points (i.e., $\log(1.87/1.79) \approx 0.04$) when using across variation at 1-digit categories and 10 log-points (i.e., $\log(1.95/1.76) \approx 0.10$) at 9-digit categories. After incorporating differences in inflation rates within categories, they find that the inflation rate experienced by low-income workers was 21 log-points (i.e., $\log(2.08/1.68) \approx 0.21$) higher than that experienced by richer households, still below the 35 log-point difference in income growth rates we find in our baseline analysis.

7 Discussion: Linking Empirical Evidence and Theory

Our empirical study shows that inequality decreases after large devaluations. Leveraging microdata from an emerging economy, we show that across the income distribution, heterogeneity in both labor mobility and bargaining power—captured by union coverage—are critical drivers of the drop in income inequality.

While our findings on inequality might be of interest on their own, our results also provide empirical guidance for some prominent theories. Following the seminal paper of Bils and Klenow (2004), there has been far greater theoretical work on price dynamics relative to wage dynamics, despite the importance of wage rigidities in macroeconomic fluctuations (see Christiano, Eichenbaum and Evans, 2005). Similarly, while the international literature has extensively estimated pass-through from the NER to the prices of goods, little is known about pass-through to labor income and broad labor market consequences. We conjecture that this differential development occurred in response to the availability of high-quality pricing data and the relative dearth of high-quality wage data. This paper provides an empirical footing for new theoretical work on the macroeconomic consequences of wage rigidities.

Our novel empirical facts characterize the dynamics of inequality in the aftermath of large NER devaluations. We foresee a path for future research. A recent literature (see, for example, Drenik, 2016, Cugat, 2019, Guo, Ottonello and Perez, 2020, Auclert, Rognlie, Souchier and Straub, 2021, and references therein) introduced heterogeneous households to the New Keynesian small open economy model. Our contribution is to provide empirical facts to guide this framework in one critical dimension: the distribution of labor income. Guided by these facts, Blanco, Drenik, Moser and Zaratiegui (2023) provides a model that studies the effects of nominal shocks on the labor market and Blanco and Drenik (2023) extends this theory to study their dynamics during large devaluations.

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Supplemental Material

Nominal Devaluations, Inflation, and Inequality

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Contents

A Data

A.1 Cross-country Data Description

Description and sources. Our aggregate analysis combines annual data on output, exchange rates, prices, inequality, wages, and employment for several countries. To measure output, we use constant GDP in local currency from the World Bank. To classify countries as emerging or rich, we use GDP per capita in PPP from the World Bank.[29] Prices and nominal exchange rates are obtained from the IMF International Financial Statistics Dataset, with the exception of Argentina, for which we use Billion Prices Project data for domestic prices. We use the consumer price index as our measure of the price level. The exchange rate is measured as units of local currency per U.S. dollar. We measure inequality using the Gini coefficient of household income per capita, which we obtained from PovcalNet (World Bank) via a direct query from STATA. It is important to note that Povcal does include observations from individuals with zero income in the estimation of the Gini coefficient. This is important, because if zeros were excluded, a decrease in aggregate employment could lead to a spurious decrease in inequality if, for example, low-income individuals lose their jobs more than high-income individuals. We complement this dataset with data from national statistical agencies to obtain time series of the Gini coefficient for Brazil and South Korea. To build our database on real labor income, we combine wage data from multiple sources (see a detailed description for each episode below). We draw on the Penn World Tables to obtain data on employment. Tables A.1 and A.2 describe the different sources for the six variables we consider. Finally, we use data from Laeven and Valencia (2012) (updated in Laeven and Valencia, 2018) to identify banking crisis and sovereign default episodes.

Sample selection. We study two types of episodes: large devaluations and recessions without devaluations. To identify the former, we follow Laeven and Valencia (2012), in which a large devaluation is defined as a nominal devaluation of more than 30% per year, which is at least 10% higher than the depreciation rate of the previous year. Recession episodes are defined as (consecutive) years with (i) negative output growth and (ii) a cumulative output drop of at least 2%.[30] Then, recessions without devaluations are episodes in which there is no large devaluation from the year before the beginning of the recession to the year after the end of the recession. When our filters identify either large devaluations in 2 or more consecutive years or recessions lasting more than 1 year, we center the window of the event around the last year.

To build our sample, we proceed as follows. First, we identify both kinds of episodes separately, focusing only on emerging and rich economies in the 1990-2015 period. The total initial sample size includes 91 devaluations and 230 recessions; of the latter, 46 overlap with a devaluation (i.e., there is a large devaluation either in the recession year or 1 year before or after the recession period). We further discard 141 recessions and 66 devaluations due to a lack of Gini or wage data. From the resulting 43 recessions and 25 devaluations, we discard a few additional episodes for various reasons, summarized in Table A.3. We do not consider episodes in Belarus, as it is mainly a centralized economy. The mechanisms we explore in this paper depend partly on the presence of markets; thus these episodes are not a good illustration of our market-based mechanisms. Because our paper focuses on devaluations, we do not consider episodes in Cyprus, the Slovak Republic, and Slovenia, which occurred just as these economies were transitioning into the Eurozone. We also do not include them in the group of recessions without devaluations since they move into a completely

[29] We follow Schmitt-Grohé and Uribe (2017) to classify countries as emerging or rich. They consider an economy to be emerging if the geometric mean of its GDP per capita in PPP U.S. dollars of 2005 is between 3,000 and 25,000, and rich if it is larger than 25,000.

[30] The threshold resembles Calvo *et al.* (2006), who establish a threshold of 4%. Our lower threshold allows us to increase the sample size, which is necessary given the scarcity of Gini data.

different monetary regime. Lastly, we exclude episodes in Ukraine and Venezuela during periods of civil war, strife, or military coups.

Our final sample includes 40 recessions and 19 devaluations, which are listed in Table A.4. We also consider different subsamples of episodes for robustness analysis in Section B, which describes the motivation and composition of each of them.

Variable construction. The devaluation and inflation rates are computed as annual log differences of the nominal exchange rate vis-à-vis the U.S. dollar and the domestic CPI (multiplied by 100), respectively. Real GDP, average labor income, employment and the Gini coefficient are expressed in log points (multiplied by 100). We normalize all variables to have a value of zero in the year before the episode. Gini data are sometimes not available at the annual frequency because a few countries release them on a biannual frequency. To avoid gaps in our panel, we linearly interpolate Gini data.

Because some episodes in the sample feature very high inflation and devaluation rates, we winsorize the normalized variables across our 59 episodes at the top and bottom 2.5% of their distribution. Winsorizing these variables improves the readability of the plots and has no impact on the interpretation of our results.

Table A.1 – Devaluation Episodes: Data Sources

Country	Year	GDP	CPI	NER	Gini	Employment	Labor Income
Argentina	2002	WDI[a]	BPP[b]	IFS[c]	Povcal[d]	Penn World Tables[e]	SEDLAC[f]
Argentina	2014	WDI [a]	BPP[b]	IFS[c]	Povcal[d]	Penn World Tables[e]	SEDLAC[f]
Brazil	1990	WDI[a]	IFS[c]	IFS[c]	IPEA[g]	Penn World Tables[e]	SEDLAC[f]
Brazil	1993	WDI[a]	IFS[c]	IFS[c]	IPEA[g]	Penn World Tables[e]	SEDLAC[f]
Brazil	1999	WDI[a]	IFS[c]	IFS[c]	IPEA[g]	Penn World Tables[e]	ILOSTAT[h]
Brazil	2015	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[h]
Colombia	2015	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[h]
Costa Rica	1991	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[h]
Dominican Republic	2003	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[h]
Georgia	1999	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[h]
Iceland	2008	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	Statistics Iceland[i]
Indonesia	1998	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[h]
Mexico	1995	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[j]
Moldova	1999	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[h]
Paraguay	2002	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[h]
South Korea	1998	WDI[a]	IFS[c]	IFS[c]	Statistics Korea[k]	Penn World Tables[e]	OECD[j]
Ukraine	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[h]
Uruguay	2002	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[h]
Thailand[l]	1998	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	-
Russia[m]	1999	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	-
Russia[m]	2015	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	-

[a]World Bank (2021)
[b]Cavallo (2015)
[c]International Monetary Fund (IMF) (2021)
[d]Castañeda, Lakner, Prydz, Lopez, Wu and Zhao (2019)
[e]Feenstra, Inklaar and Timmer (2015)
[f]Socio-Economic Database for Latin America and the Caribbean (CEDLAS and The World Bank) (2021b)
[g]Instituto de Pesquisa Econômica Aplicada (Brazil) (2016)
[h]International Labor Organization (ILO) (2021)
[i]Statistics Iceland (2015)
[j]OECD (2021a)
[k]Statistics Korea (2018)
[l]Not included in baseline analysis due to missing labor income data.

Table A.2 – Recession Episodes: Data Sources

Country	Year	GDP	CPI	NER	Gini	Employment	Labor Income
Argentina	1995	WDI[a]	BPP[b]	IFS[c]	Povcal[d]	Penn World Tables[e]	SEDLAC[f]
Argentina	2009	WDI[a]	BPP[b]	IFS[c]	Povcal[d]	Penn World Tables[e]	SEDLAC[f]
Armenia	2009	WDI[a]	IFS	IFS	Povcal	Penn World Tables[e]	ILOSTAT[g]
Austria	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Austria	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Bulgaria	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[g]
Colombia	1999	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT [g]
Cyprus	2014	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[g]
Czech Republic	2014	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[g]
Denmark	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
El Salvador	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	CEPAL[i]
Estonia	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	Statistics Estonia[j]
Finland	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Finland	2014	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
France	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Georgia	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT
Germany	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Greece	2013	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[g]
Honduras	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[g]
Hungary	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[g]
Ireland	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Italy	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Italy	2014	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Latvia	2010	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[g]
Lithuania	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Luxembourg	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Mexico	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Moldova	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[g]
Montenegro	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[g]
Portugal	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Portugal	2013	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Romania	2010	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	NIS[k]
Russia	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[g]
Slovenia	2013	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Spain	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Spain	2013	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Sweden	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
Switzerland	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	OECD[h]
United Kingdom	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	ILOSTAT[g]
Croatia[l]	2014	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	-
Turkey[l]	2009	WDI[a]	IFS[c]	IFS[c]	Povcal[d]	Penn World Tables[e]	-

[a] World Bank (2021)
[b] Cavallo (2015)
[c] IMF (2021)
[d] Castañeda *et al.* (2019)
[e] Feenstra *et al.* (2015)
[f] Socio-Economic Database for Latin America and the Caribbean (CEDLAS and The World Bank) (2021b)
[g] ILO (2021)
[h] OECD (2021a)
[i] United Nations Economic Commission for Latin America and the Caribbean (2021a)
[j] Statistics Estonia (2021)
[k] Institut national de statistica (Romania) (2009),Institut national de statistica (Romania) (2020)
[l] Not included in baseline analysis due to missing labor income data.

Table A.3 – Episodes Excluded from the Analysis

Episode	Reason for Exclusion
Belarus - 2009	Centralized Economy
Belarus - 2011	Centralized Economy
Belarus - 2015	Centralized Economy
Cyprus - 2009	Transition to Euro
Slovenia - 2009	Transition to Euro
Slovak Republic - 2009	Transition to Euro
Ukraine - 2015	Civil War
Venezuela -2002	Coup
Venezuela - 2011	Civil Strife

Table A.4 – Devaluation and Recession Episodes

Devaluations	Recessions
Argentina-2002, Argentina-2014, Brazil-1990, Brazil-1993, Brazil-1999, Brazil-2015, Colombia-2015, Costa Rica-1991, Dominican Republic-2003, Georgia-1999, Iceland-2008, Indonesia-1998, Mexico-1995, Moldova-1999, Moldova-2015, Paraguay-2002, South Korea-1998, Ukraine-2009, Uruguay-2002	Argentina-1995, Argentina-2009, Armenia-2009, Austria-2009, Belgium-2009, Bulgaria-2009, Colombia-1999, Cyprus-2014, Czech Republic-2009, Denmark-2009, El Salvador-2009, Estonia-2009, Finland-2009, Finland-2014, France-2009, Georgia-2009, Germany-2009, Greece-2013, Honduras-2009, Hungary-2009, Ireland-2009, Italy-2009, Italy-2014, Latvia-2010, Lithuania-2009, Luxembourg-2009, Mexico-2009, Moldova-2009, Montenegro-2009, Netherlands-2009, Portugal-2009, Portugal-2013, Romania-2010, Russia-2009, Slovenia-2013, Spain-2009, Spain-2013, Sweden-2009, Switzerland-2009, United Kingdom-2009

A.2 SIPA Data Description

Tax-reporting software. By law, all employers in the formal sector, both private and public, must submit sworn statements that provide the information included in workers' paychecks to SIPA every month. This information is used for tax purposes and to calculate employees' contributions to the social security system. For more information, we direct readers to working paper version of this article (Blanco, Drenik and Zaratiegui, 2024) and the manual for declaring sworn statements (Administracion Federal de Ingresos Publicos (AFIP), 2024).

We focus on three forms that employers must complete. The SICOSS general information form requires: worker identification number ("CUIL"), legal first and last name ("Apellido y Nombre"), type of contract ("Modalidad de Contratacion"), and CBA coverage ("Trabajador en convenio colectivo de trabajo"). The labor income components form asks for basic labor income ("Sueldo"), additional compensation ("addicionales"), bonuses ("premios"), extra hours ("Importe horas extras"), 13th salary ("SAC"), paid vacations ("Vacaciones"), and bonus for unfavorable area ("Plus zona desfavorable"). Additional compensation includes extra income from tenure or night shifts, among others. Finally, a third page calculated tax liabilities and social security contributions.

SIPA variable description. Table A.5 describes the variables in the SIPA dataset. Workers' variables include the social security number (*Código Unico de Identificación Laboral*, CUIL), gender, date of birth, type of contract, and CBA coverage. The type of contract can be used to identify full-time vs. part-time workers or distinguish between fixed length and permanent contracts.

Firm-specific variables include the tax ID, legal residency, and industry. The firm's residency is the state in which the firm is legally registered. The firm's industry is available at the 4-digit ISIC Rev. 3 level.

The SIPA dataset also includes variables on total labor income and its components for each worker. The total labor income variable is the total nominal income received by the worker before taxes in current pesos. Total labor income is available for the entire sample (i.e., from 1994 to 2019), while data on the components of labor income are only available after 2008.

Sample construction. Table A.6 describes the sample size used in the analysis. The total number of worker-month observations is just above 2 billion. The original dataset includes around 8 million workers and half a million firms per year.

In the original dataset, around 8% of workers are younger than 25 or older than 65 years, of which 41% are female. Therefore, 51% of the original sample is male and between 25 and 65 years of age.

We drop duplicate observations at the worker-date level for the following reasons. First, for each worker, we keep only the highest-paying job in each month. Second, labor legislation mandates that workers employed by temp agencies be registered in SIPA by both the client firm and the temp agency. Therefore, we drop the former, as it does not contain relevant information on labor income. These duplicate observations account for 2% of the original sample.

By further limiting our data to the private sector, we keep 39% of the initial sample. The last two filters consist of dropping observations with labor income below half of the monthly adjusted real minimum wage and labor income during the first and last month of a job spell. These filters further drop 4% of the sample. After implementing all of these sample restrictions, we keep 34.6% of the original sample.

13th wage. We purge the total monthly income of the 13th salary paid in June and December. This extra salary, known as *aguinaldo*, is mandated by law and equals one-half of the highest wage paid over a semester. Unfortunately, we only observe total income before 2008, which means that we have to calculate each worker's aguinaldo using the formula established by the law. We use the following equation to impute

Table A.5 – Variables in SIPA

Variable	Years in data	Short description
Worker's variables		
Worker identification number	1994-2019	Social Security Number (CUIL)
Gender	1994-2019	
Date of birth	1994-2019	
Type of contract	2000-2019	E.g., full-time, part-time, temp worker
CBA coverage	2003-2019	Binary variable (yes/no)
Firm's variables		
Firm identification number	1994-2019	Tax identification number
State	1994-2019	State in which the firm is registered
Industry	1994-2019	4-digit CIIU
Labor income components		
Total labor income	1994-2019	Nominal in pesos (per month)
Base salary	2008-2019	
Additional	2008-2019	Additional by tenure, night shifts, etc.
Extra hours	2008-2019	Additional by presentism, commissions, etc.
SAC	2008-2019	13th wage
Vacations	2008-2019	
Bonus for unfavorable area	2008-2019	

Notes: The table describes the variables in SIPA, along with the years of coverage in the sample.

Table A.6 – Data Description: Cleaning Statistics

Description	SIPA	
Start date	1994-m7	
End date	2019-m7	
Total number of date-worker observations	2,040,703,872	
Average annual number of workers	7,748,043	
Average annual number of firms	554,356	
Cleaning	Number of Removed Observations	
	Total	%
Age <25 or >65	171,245,799	8.39%
Female	836,877,943	41.01%
Temp. workers duplicate observations	1,069,314	0.05%
Workers date duplicate observations (second job)	46,084,756	2.26%
Public sector worker	198,904,673	9.75 %
Wage below half of the minimum wage	13,523,524	0.66%
First or last observation in an employment spell	66,086,398	3.24%
Remaining observations	706,911,424	34.64%

Notes: The table reports the size of the original sample, the size of different groups of workers, and the size of the dropped subsets of the sample after applying the sample restriction and filters discussed in Section 2. Percentages are over the original number of observations (i.e., 2 billion observations). Annual averages are calculated from 1995 to 2018.

the aguinaldo:

$$\text{Aguinaldo} = \frac{\sum_{i \in 1:6} I_i}{12} \times \max_{i \in 1:6} y_i, \tag{A.1}$$

where I_i is an indicator variable for whether the worker was employed in month i and y_i is total income (including bonuses, etc.) in that month. For example, according to the formula, a worker employed in the same firm for the entire semester receives half of the maximum monthly labor income she earned during the semester.

Sectoral CBA. The Argentinian union system exhibits a high degree of centralization, by which a single union is given monopoly power by law to represent workers within a specific industry, a branch of activity, or type of occupation, irrespective of whether the worker is a union member. Unions tend to negotiate the wages of blue-collar workers and the lower ranks of white-collar workers. Furthermore, the union has the power to negotiate collective agreements at different levels of representation, starting from firm-level agreements and extending to industry-wide agreements in which the agreement covers all workers represented by the union. For examples of such collective agreements and the resulting pay scales, we direct readers to the comprehensive online look-up tool developed by the Argentininian Ministry of Human Capital (Ministerio de Capital Humano, 2024) and the working paper version of this article (Blanco *et al.*, 2024).

A.2.1 Comparison with Argentina's Household Survey

This section compares the main findings in Section 4 using SIPA data with similar empirical exercises using Permanent Household Survey data.

Data description. The primary household survey in Argentina is the Permanent Household Survey (EPH). It covers 31 large urban areas with estimated representativeness of more than 60% of the total population. In any given year, the overall sample size is around 100,000 households and the average response rate is on the order of 90% (which is similar to the U.S. March Current Population Survey). The questionnaire contains extensive information on labor market participation (e.g., hours worked, labor income, tenure, industry of occupation) and demographics (e.g., level of education, age). The survey was conducted twice a year from 1995 and 2002 and quarterly from 2003 onward.

The EPH distinguishes between informal and formal employees, which allows us to make almost direct comparisons with the SIPA dataset. This distinction is made using a standard definition of informality proposed by the International Labour Organization. A lack of compliance with labor legislation determines the formal/informal classification. More specifically, we classify any worker as formal (resp. informal) if the employer does pay (resp. does not pay) mandatory social security contributions.

Sample. To compare SIPA and EPH, we follow the same sample selection process. That is, we focus on male workers aged 25-65 who are employed in the formal private sector and earn at least half of the 1996 minimum wage. EPH's frequency is biannual (i.e., May and October) between 1996 and 2002 and quarterly from 2003 to the present.

General comparison between SIPA and EPH. The main caveats of the comparison between EPH and SIPA are: (i) the household survey is less (resp. more) representative of high (resp. low) income earners, since it is top-coded; (ii) statistics are noisier due to a much smaller sample size and the presence of measurement error; (iii) the household survey describes after-tax income, while SIPA includes data on pre-tax income; and (iv) there is a rotating sample of households, so we cannot follow households for more than 1 year.

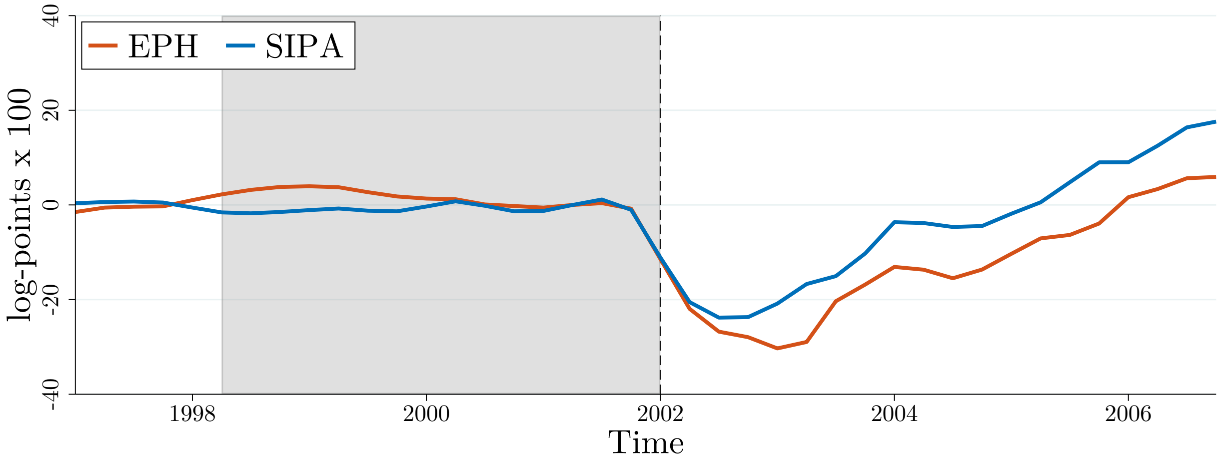
Main facts with EPH. We organize our discussion around the four facts presented in Section 4.

- **Average real income:** Real labor income in the SIPA dataset closely follows real labor income in the EPH in the period 1997-2007. Figure A.1 plots the time series of mean log real income in both datasets. The levels are different because the SIPA dataset reports before-tax income, and EPH respondents usually report their after-tax income. For this reason, we normalize the average income in the second quarter of 2001 to zero in both datasets.

- **Distribution of real income:** The main fact reported in Section 4 is the significant *heterogeneity* in the within-worker speed of recovery of real income across different parts of the distribution. We cannot reproduce this fact in the EPH, since the EPH dataset is a short rotating panel. Nevertheless, we can reproduce cross-sectional facts. Figure A.2 shows the evolution of the normalized percentiles in the SIPA and EPH data. The compression of the labor income distribution holds across datasets with a main difference: As expected, percentiles in the EPH are much noisier due to the sample size and measurement error.

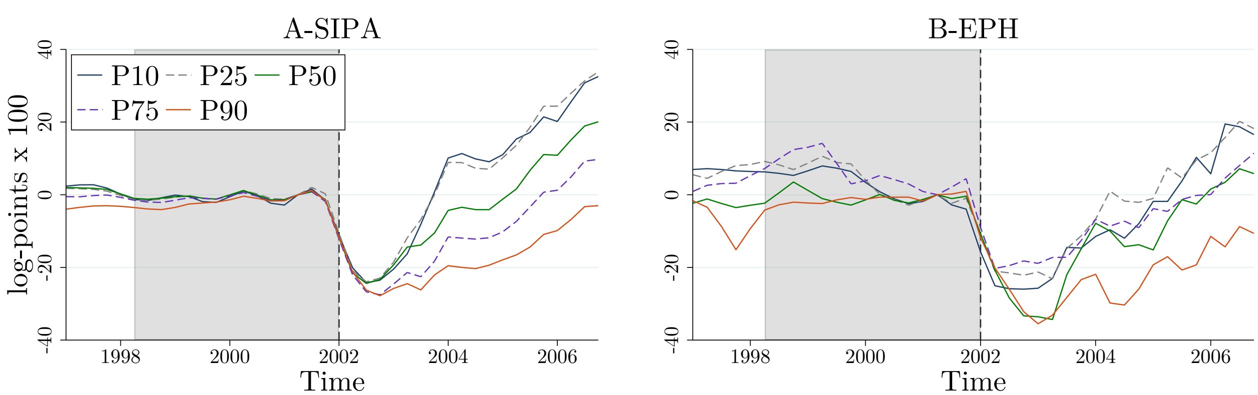
  Figure A.3 reports the histogram of the income distribution in 2001 and 2006 using the EPH and SIPA datasets. As expected, the income distribution in the SIPA data has a longer tail, showing the lack of top-coding in the administrative dataset. Despite this, the distributions of income in the

Figure A.1 – Average Log Real Income in Argentina: SIPA and EPH



Notes: The figure plots the mean (log) real labor income in EPH and SIPA from the first quarter of 1997 to the last quarter of 2006 for male workers aged 25-65 and employed in the private sector. We normalize average labor income in the second quarter of 2001 to zero in the EPH and SIPA. EPH population estimates are obtained using the survey's expansion factors.

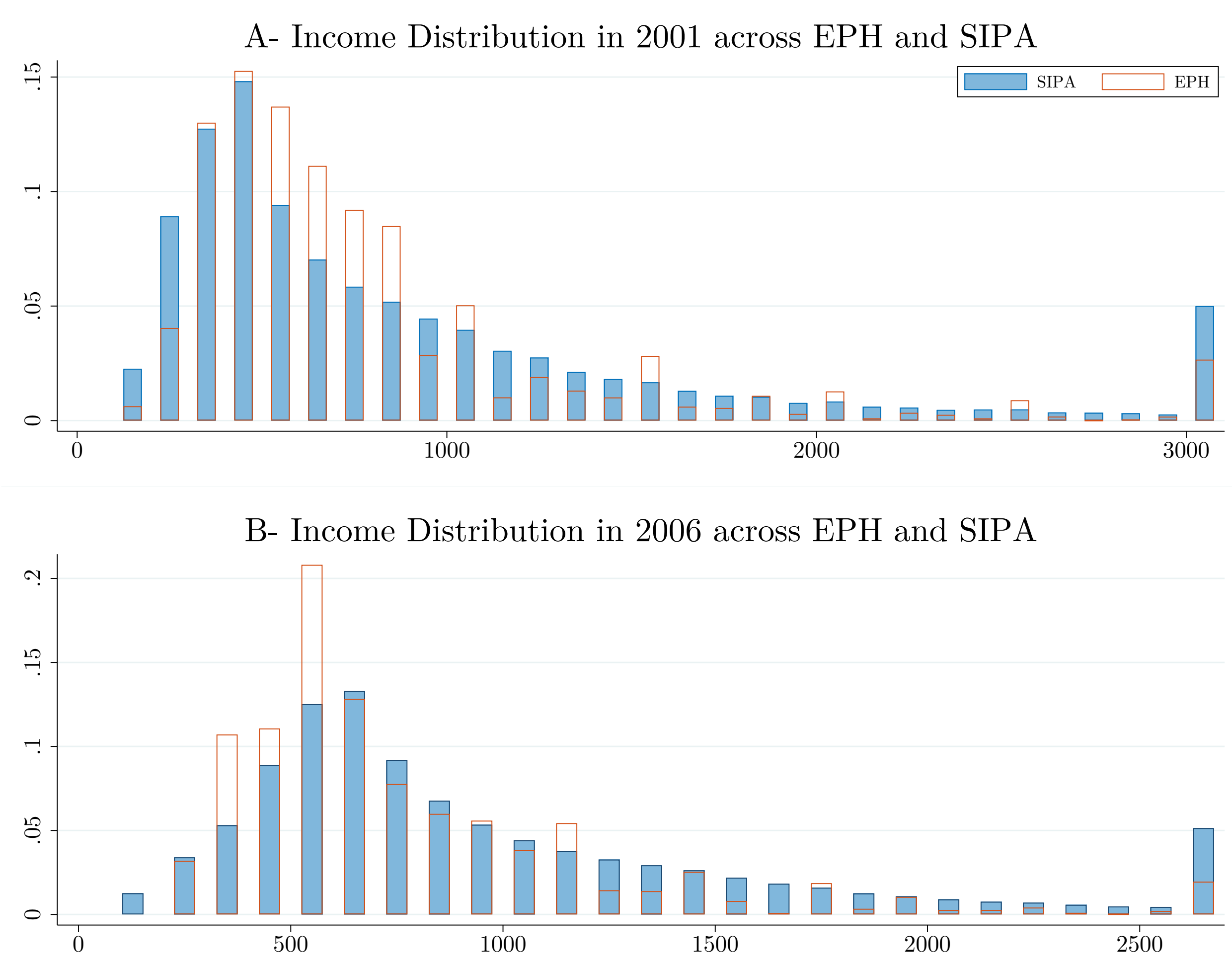
Figure A.2 – Percentiles of labor income: EPH and SIPA



Notes: The figure plots moments of the monthly real income distribution from the first quarter of 1997 to the last quarter of 2006. Panel A (B) plots the percentiles of the log real income distribution (× 100) normalized by the value in the second quarter of 2001 from SIPA (EPH). EPH population estimates use the survey's expansion factors.

formal sector are quite similar across datasets and the rightward shift of the bottom mass is visible in both datasets.

Figure A.3 – Income Distribution in 2001 and 2006 across EPH and SIPA



Notes: The figure plots the income distribution in SIPA and EPH during the second quarter of 2001 and 2006. Distributions are winsorized using the 95th percentile of the SIPA distribution as the upper bound. Distributions correspond to male workers aged 25-65 and employed in the private sector. EPH population estimates use the survey's expansion factors.

A.2.2 The Relevance of Labor Income in Argentina

This section documents the contribution of labor income to total market income for employed individuals in Argentina. Previous literature has shown that labor income is a major component of total income in Latin America. For example, Gasparini, Cruces, Tornarolli and Mejía (2011) report that across the entire population, labor income represents 80% of both total household and individual income on average, and pensions and transfers account for three-quarters of nonlabor income. Furthermore, capital and profit income represents only 2.7% of total individual income on average. This is not surprising for two reasons. First, even in the U.S., household surveys tend to underestimate wealth at the top of the wealth distribution (see Pfeffer, Schoeni, Kennickell and Andreski, 2016). Second, many top-income households hold their wealth offshore in low-tax jurisdictions: According to Londoño-Vélez and Tortarolo (2022), 36.5% of the country's gross domestic product (GDP) had been stored offshore during our period of analysis.

Despite these caveats, we reproduce these facts using data from the EPH from 2003 to 2018 in Argentina, which asks individuals about both their labor and nonlabor income in the month of reference. To render the sample comparable to the baseline analysis, we focus on all employees aged 25-65. For each employee, we compute total monthly labor income as the sum of salaries and wages, the 13th salary, severance payments, overtime, and other additional earnings across all occupations. We compute total monthly market income as the sum of labor income, rents from properties, dividends/earnings from businesses in which the individual did not work, and interest and rents from bank accounts and other investments. Given our sample restrictions in terms of employment status and age range, we exclude pension income from the analysis.

Table A.7 reports the share of monthly labor income of total market income in the population of reference and by decile of the distribution of labor income in the main occupation, which is the main variable of analysis in SIPA. Income deciles are computed within each survey wave of the EPH. The table reports this share for two groups of workers: (i) employees in the formal private sector (the baseline sample of analysis) and (ii) all employees (which includes both workers in the informal sector and the public sector). The main result is that employees overwhelmingly rely on their labor income, since the average share of labor income is 0.997 and shows small variation across the income distribution.

Unfortunately, there are no detailed household balance sheet data in Argentina to further explore capital income dynamics. However, Sanroman and Santos (2021) document, using data from surveys of household finances in Uruguay and Chile (neighboring countries with a similar socioeconomic background), that financial assets only account for 4% and 9% of total assets for the average household, respectively. This number increases to only 6.5% for households in the top quintile of the income distribution. In comparison, the corresponding share in the U.S. is 40%. Thus, given the low holdings of financial assets among households in these Latin American countries, our findings should not be surprising.

Finally, in the context of our episode of analysis, it is worth highlighting a mechanism that might go in the opposite direction of the labor income channel. As documented in Drenik, Pereira and Perez (2018), households in emerging economies tend to have a fraction of their assets denominated in foreign currency, and Argentina is no exception. More importantly, holdings of these assets are increasing in the income of the household. Thus, the devaluation might have revaluation effects that disproportionately benefit high-income households.

Table A.7 – Share of Labor Income of Total Market Income

	Formal Private Sector Employees	All Employees
All	0.997	0.997
Decile		
1st	0.993	0.996
2nd	0.997	0.997
3rd	0.997	0.998
4th	0.998	0.998
5th	0.998	0.998
6th	0.998	0.997
7th	0.998	0.997
8th	0.998	0.997
9th	0.997	0.996
10th	0.995	0.995

Notes: This table reports the share of labor income of total market income in the population of reference and by decile of the distribution of labor income in the main occupation. The sample includes all employees aged 25-65 (in the public and private sectors and the formal and informal sectors) from 2003 to 2018. Income deciles are computed within each EPH survey wave. EPH population estimates were obtained using the survey's expansion factors. Labor income captures total income from the main and any secondary occupation (i.e., salaries and wages, the 13th salary, severance payments, overtime, and other additional earnings across all occupations). Total market income captures labor income, rents from properties, dividends/earnings from businesses in which the individual did not work, interest and rents from bank accounts, and other investments. The second column only includes employees in the formal private sector, which captures the population in the main analysis, and the third column includes all employees.

A.2.3 Moments of the Labor Income Distribution: Comparison with the U.S.

This section describes income distribution statistics across the sample period and compares them with the same statistics computed for the U.S. by Guvenen *et al.* (2014). For this exercise and this exercise only, we apply the same filters to our data as the ones used by Guvenen *et al.* (2014), and report statistics at annual frequency. We construct annual income for male workers by aggregating the monthly income of workers who satisfy the following criteria: (i) between 25 and 60 years of age, and (ii) annual income larger than a threshold value set following Guvenen *et al.* (2014) and lower than the 99.999th percentile. To replicate their methodology, we target a minimum wage such that it generates the same log difference between the minimum and median annual income. Therefore, by construction, we generate the same statistics for the relative minimum annual income.

Table A.8 compares annual labor income statistics in Argentina and the U.S. By construction, the only statistic that is almost identical across datasets is the "Min minus Perc. 50." The standard deviation and percentiles of annual log income between the U.S. and Argentina are close to each other. There is a quantitative difference in the growth rate of annual income, since the P10 and P90 are 10% lower in the U.S.

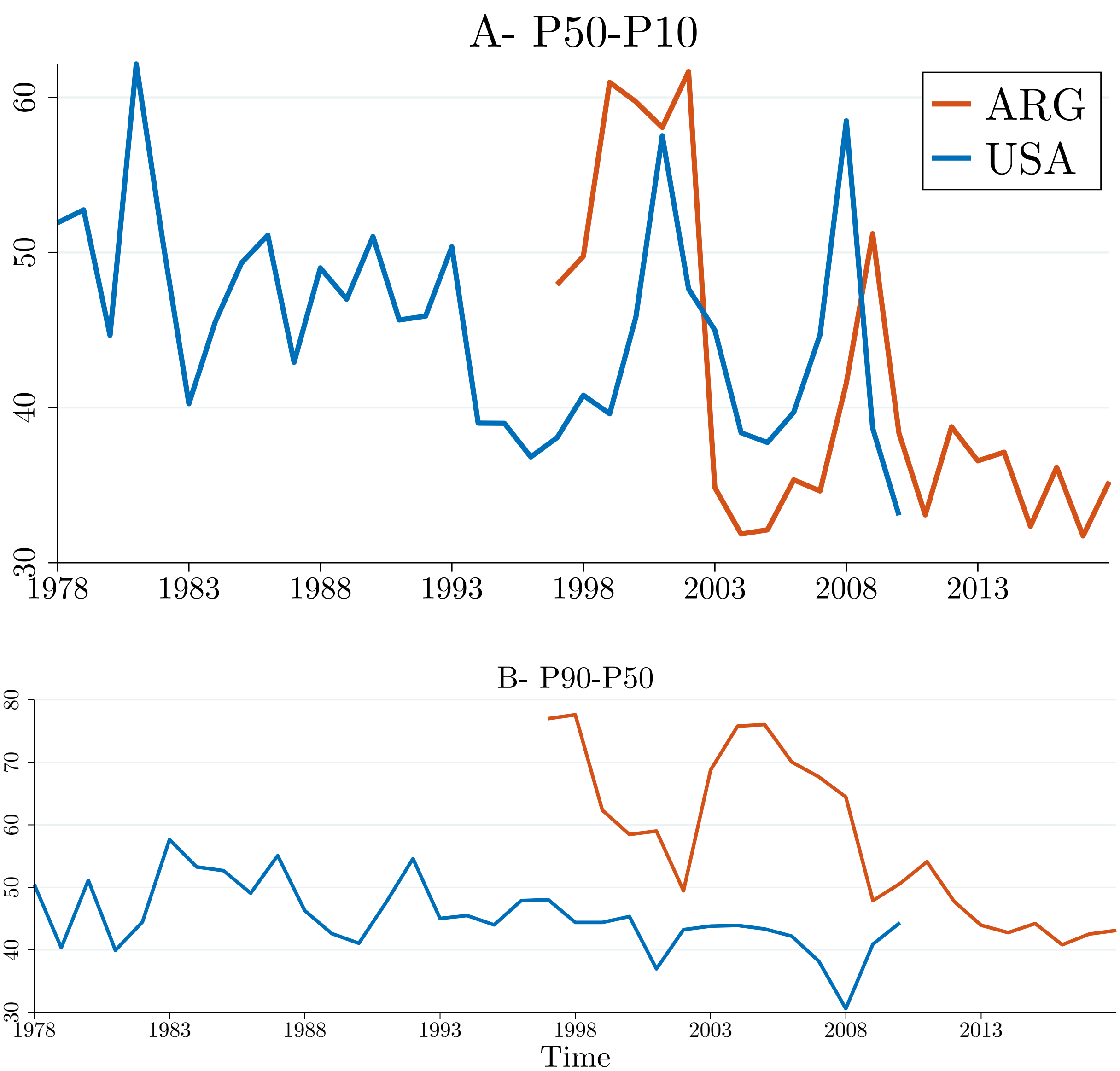
The main fact in Guvenen *et al.* (2014) is that the skewness of annual income growth is procyclical, while the standard deviation of annual income growth does not present significant fluctuations. We replicate these facts for Argentina. Figures A.4 and A.5 plot the comparison of the same statistics used by Guvenen *et al.* (2014) to verify these business cycle properties across countries. While the Argentinian labor market is more volatile, as shown by P50-10 and P90-50 (Figure A.4), the reaction to crisis episodes is remarkably similar. This is particularly evident in Figure A.5, in which the skewness of annual income growth follows a similar cyclical pattern.

Table A.8 – Cross-sectional labor income statistics: Argentina and the US

Moments	**Argentina**	**US**
Growth Rates		
Standard Deviation	0.60	0.53
Skewness	-0.02	-0.31
Perc. 10	-37.63	-43.45
Perc. 50	4.14	2.02
Perc. 90	61.62	47.43
Log-Levels		
Standard Deviation	1.05	0.91
Skewness	-0.49	0.57
Min minus Perc. 50	-3.19	-3.24
Max minus Perc. 50	5.08	5.55
Perc. 1 minus Perc. 50	-2.91	-2.84
Perc. 5 minus Perc. 50	-2.19	-1.90
Perc. 10 minus Perc. 50	-1.61	-1.30
Perc. 25 minus Perc. 50	-0.63	-0.54
Perc. 75 minus Perc. 50	0.55	0.44
Perc. 90 minus Perc. 50	1.07	0.85
Perc. 99 minus Perc. 50	2.16	1.97

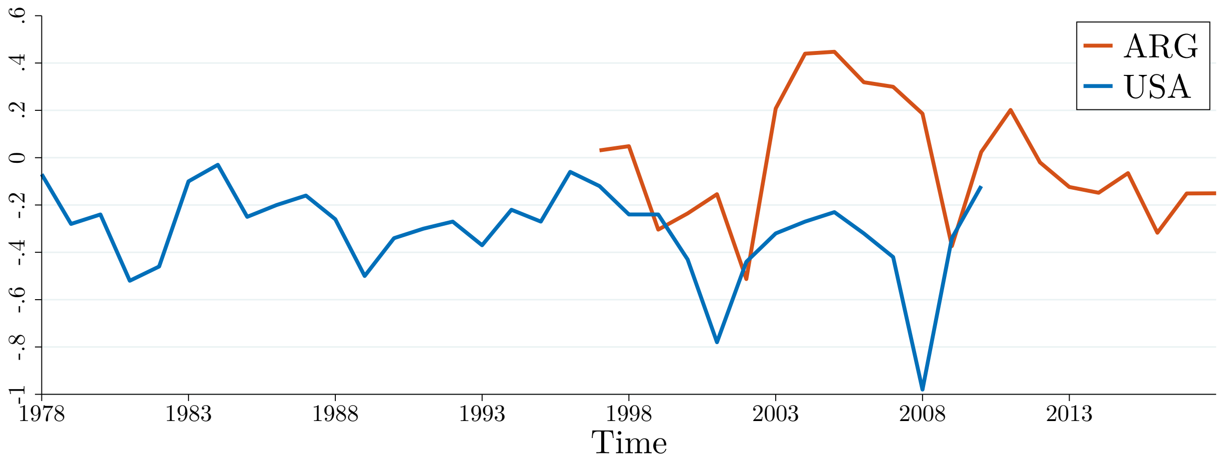
Notes: The table describes the average moments of yearly labor income for working-age males in Argentina and the US. Data for the US are from Guvenen *et al.* (2014). We set up the minimum annual income each year in Argentina to match the difference between minimum and median income in the US.

Figure A.4 – Moments of Annual Income Growth: Argentina and the U.S.



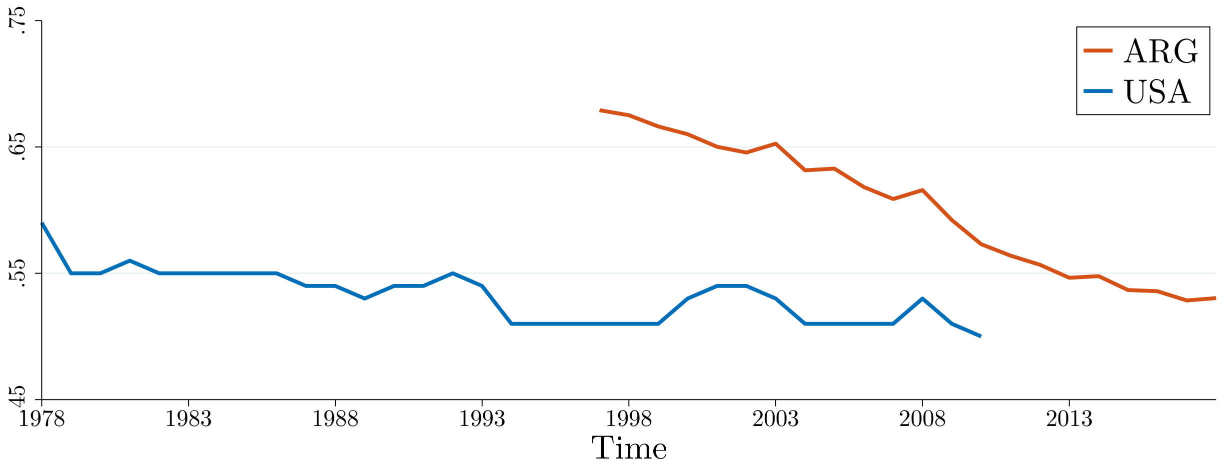
Notes: Panel A plots the log difference of the 50th and 10th percentiles of the annual income growth distribution for the U.S. and Argentina. Panel B plots the log difference of the 90th and 50th percentiles of the annual income growth distribution for the U.S. and Argentina. Workers in the distribution are formal private sector male workers aged 25-65. Percentiles are multiplied by 100. The source for U.S. data is Guvenen *et al.* (2014).

Figure A.5 – Skewness of Annual Income Growth: Argentina and the U.S.



Notes: The figure presents the skewness of the annual income growth distribution for workers in the U.S. and Argentina. Workers in the sample are male, aged 25-65, and work in the formal private sector. The source for U.S. data is Guvenen *et al.* (2014).

Figure A.6 – Standard Deviation of Annual Income Growth: Argentina and the U.S.



Notes: The figure presents the standard deviation of the annual income growth distribution for workers in the U.S. and Argentina. Workers in the sample are male, aged 25-65, and work in the formal private sector. The source for U.S. data is Guvenen *et al.* (2014).

B Cross-Country Analysis: Additional Results

Robustness analysis. This section describes the subsamples of episodes we consider to show that our results are not driven by particular recessions or devaluations.

Table B.1 lists the different subsamples we analyze. We consider the first four subsamples to isolate the effect of devaluations contemporaneous with sovereign or banking crises. Half of the recession episodes also feature a banking crisis, while approximately 40% of devaluations coincided with a banking crisis. Almost none of the recessions feature a sovereign default, with Greece's 2009-2013 recession being the only exception. For this reason, we do not consider the subsample of defaults and focus instead on episodes without a default. In almost 75% of the large devaluations, there is no sovereign default. It could also be the case that devaluations are not preceded by or do not lead to contractions in output. Thus, the comparison with recessions might not be appropriate. Therefore, we analyze a subsample of devaluations surrounded by recessions. We keep almost 60% of our devaluations in this subsample.

Inequality can be measured with consumption or income data. Because we are ultimately interested in labor income inequality, we consider a subsample in which we only include episodes in which the Gini coefficient is computed using households' income. In this subsample, we keep almost 90% of recession episodes and almost 75% of devaluations.

Our devaluation events are short. Because we do not restrict recessions based on their length, the sample of recessions might include long recessions, which might reduce comparability across types of episodes. We consider a subsample in which the only recessions included are those that last a year. In this subsample, the total number of recession episodes is 24.

Our sample of recessions has almost no episodes before the 2000s, while our devaluations sample includes several episodes from the late 1990s. To remedy this, we consider a subsample of recent episodes, in which we only keep those that occurred after 2000. This sample contains 38 recessions and 10 devaluations.

Four of our episodes occur during periods of high inflation or hyperinflation. These events are known to have different dynamics, which could render our analysis less representative of the rest of the sample. For that reason, we consider a sample without one recession (Argentina 1995) and three devaluations (Brazil 1990 and 1993 and Georgia 1999).

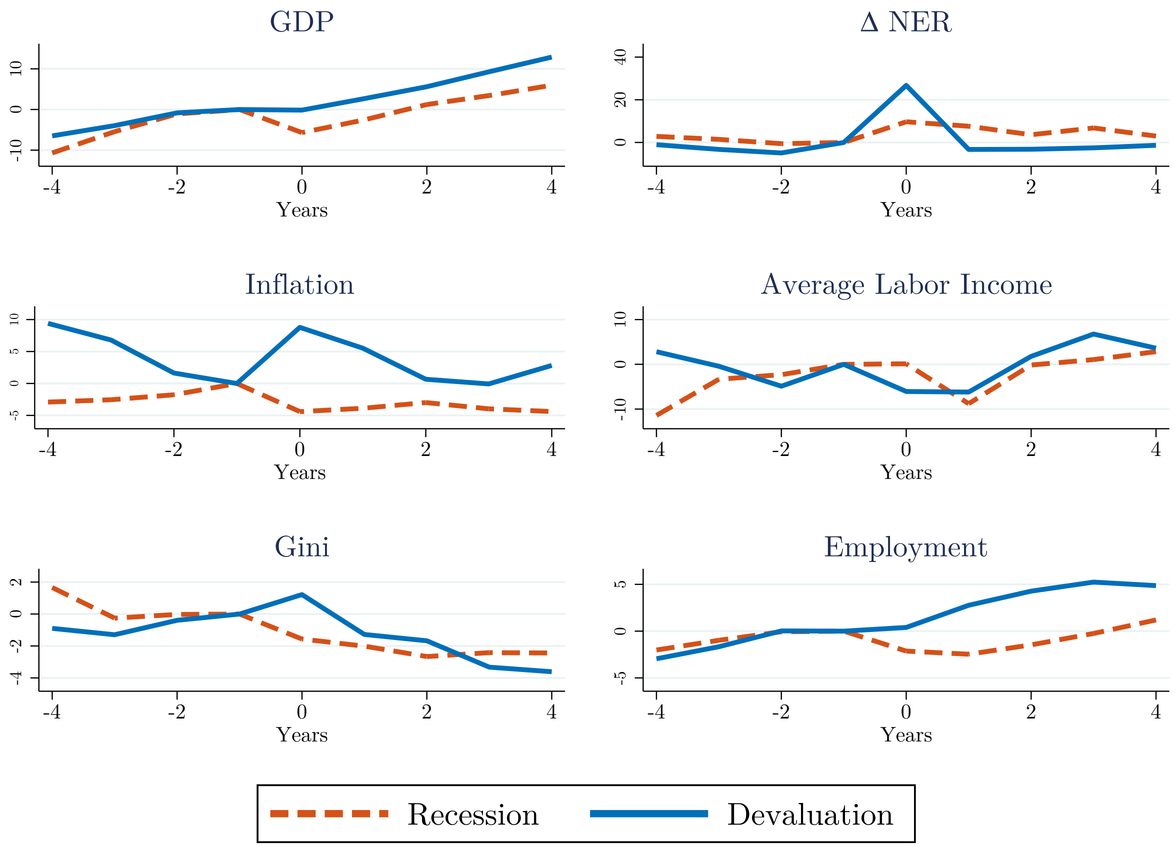
Our baseline sample includes episodes with available data on both the Gini coefficient and average real labor income. Here, we consider a slightly augmented sample in which we do not require the availability of data on labor income. This relaxed sample selection criterion increases the number of available episodes in which we can study the dynamics of inequality: It adds two recessions (Croatia 2014 and Turkey 2009) and three devaluations (Thailand 1998 and Russia 1999 and 2015).

Finally, we control for possible preexisting trends in the series by repeating the analysis in Section 3 with detrended variables. For this, we separately detrend the series for GDP, average real labor income, the Gini coefficient, and employment using an annual Hodrick–Prescott filter and data from all available years in each country in the panel. Figure B.4 shows similar results obtained with the HP-detrended variables (we also consider a linear and a quadratic trend with similar qualitative results).

Table B.1 – Samples of Episodes

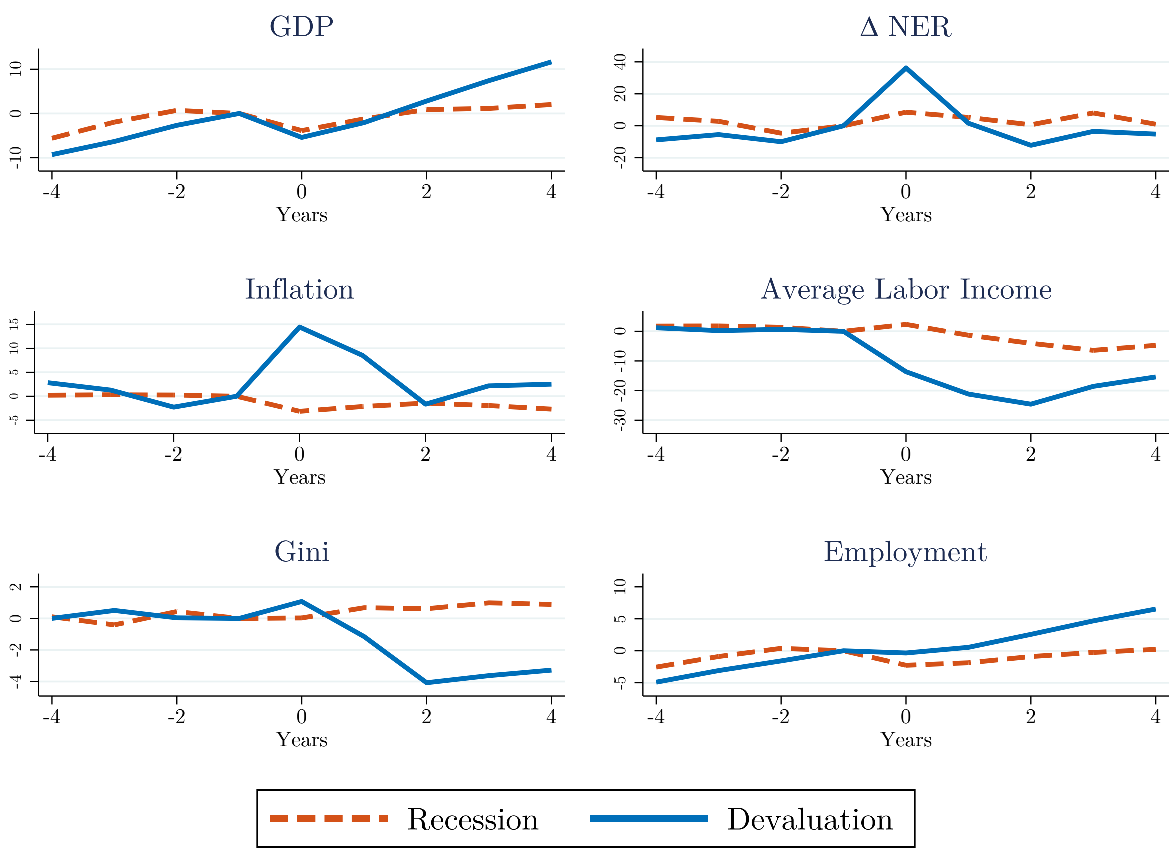
Sample	Recessions	Devaluations
Full sample	40	19
No banking crisis	20	8
Banking crisis	20	11
No sovereign default	39	13
Recessions: all devaluations are also recessions	40	11
Income inequality	35	14
Short recessions	24	19
Episodes from 2000 onwards	38	10
No hyperinflation	39	16
Gini Sample	42	22
Detrended sample	40	19

Figure B.1 – Macroeconomic Facts After Large Devaluations - No Banking Crisis



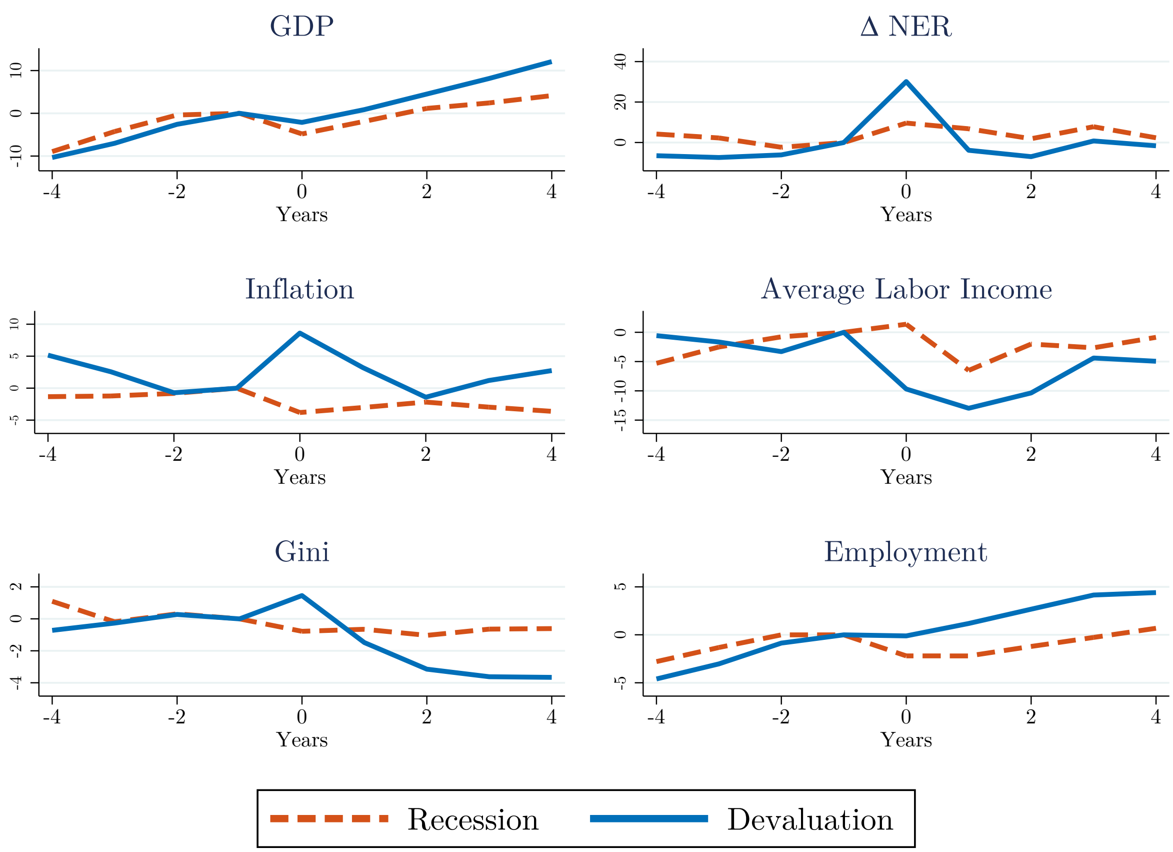
Notes: The figure plots (in the following order) the change in real GDP, NER, inflation, average real labor income, Gini, and employment at an annual frequency. Δ NER and inflation are computed as annual log differences in the nominal exchange rate and the CPI ($\times$ 100). We winsorize the normalized change in NER and inflation at the 2.5% and 97.5% percentiles across all 59 episodes in our sample. Real GDP, average labor income, employment, and the Gini coefficient are measured in log points $\times$ 100. All variables are normalized to zero in year -1. The solid blue line plots the average of each variable across episodes in an 8-year window around a large devaluation. The dotted red line plots the same variables for recessions without devaluations. The year zero corresponds to either the year of the devaluation or the year of the recession. When our filters identify either large devaluations or recessions without devaluations in 2 or more consecutive years, we center the window of the event around the last year. None of the episodes feature a banking crisis as defined by Laeven and Valencia (2018). Large devaluation episodes include Argentina (2014), Brazil (1999), Brazil (2015), Colombia (2015), Costa Rica (1991), Georgia (1999), Moldova (1999), and Paraguay (2002). Episodes of recessions without devaluations include Argentina (2009), Armenia (2009), Bulgaria (2009), Cyprus (2014), Czech Republic (2009), El Salvador (2009), Estonia (2009), Finland (2009), Finland (2014), Georgia (2009), Greece (2013), Honduras (2009), Italy (2014), Lithuania (2009), Mexico (2009), Moldova (2009), Montenegro (2009), Romania (2010), Russia (2009), and Slovenia (2013).

Figure B.2 – Macroeconomic Facts After Large Devaluations - Only Banking Crisis



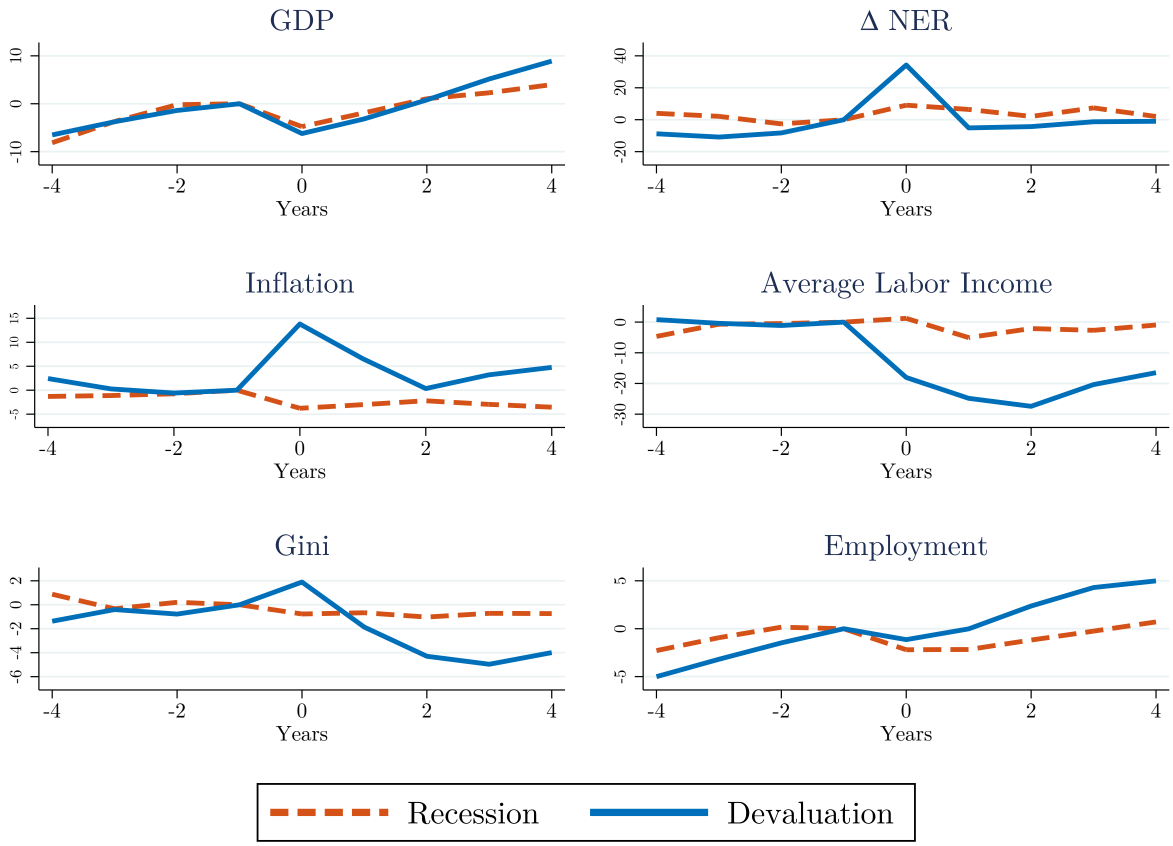
Notes: The figure plots (in the following order) the change in real GDP, NER, inflation, average real labor income, Gini, and employment at annual frequency. Δ NER and inflation are computed as annual log differences in the nominal exchange rate and the CPI ($\times$ 100). We winsorize the normalized change in NER and inflation at 2.5% and the 97.5% percentiles across all 59 episodes in our sample. Real GDP, average labor income, employment, and the Gini coefficient are measured in log-points $\times$ 100. All variables are normalized to zero in year -1. The solid blue line plots the average of each variable across episodes in an 8-year window around a large devaluation. The dotted red line plots the same variables for recessions without devaluations. The year zero corresponds to either the year of the devaluation or the year of the recession. When our filters identify either large devaluations or recessions without devaluations in 2 or more consecutive years, we center the window of the event around the last year. All episodes feature a banking crisis as defined by Laeven and Valencia (2018). Large devaluation episodes include Argentina (2002), Brazil (1990), Brazil (1993), Dominican Republic (2003), Iceland (2008), Indonesia (1998), Mexico (1995), Moldova (2015), South Korea (1998), Ukraine (2009), and Uruguay (2002). Episodes of recessions without devaluations include Argentina (1995), Austria (2009), Belgium (2009), Colombia (1999), Denmark (2009), France (2009), Germany (2009), Hungary (2009), Ireland (2009), Italy (2009), Latvia (2010), Luxembourg (2009), Netherlands (2009), Portugal (2009), Portugal (2013), Spain (2009), Spain (2013), Sweden (2009), Switzerland (2009), and the United Kingdom (2009).

Figure B.3 – Macroeconomic Facts After Large Devaluations - No Defaults



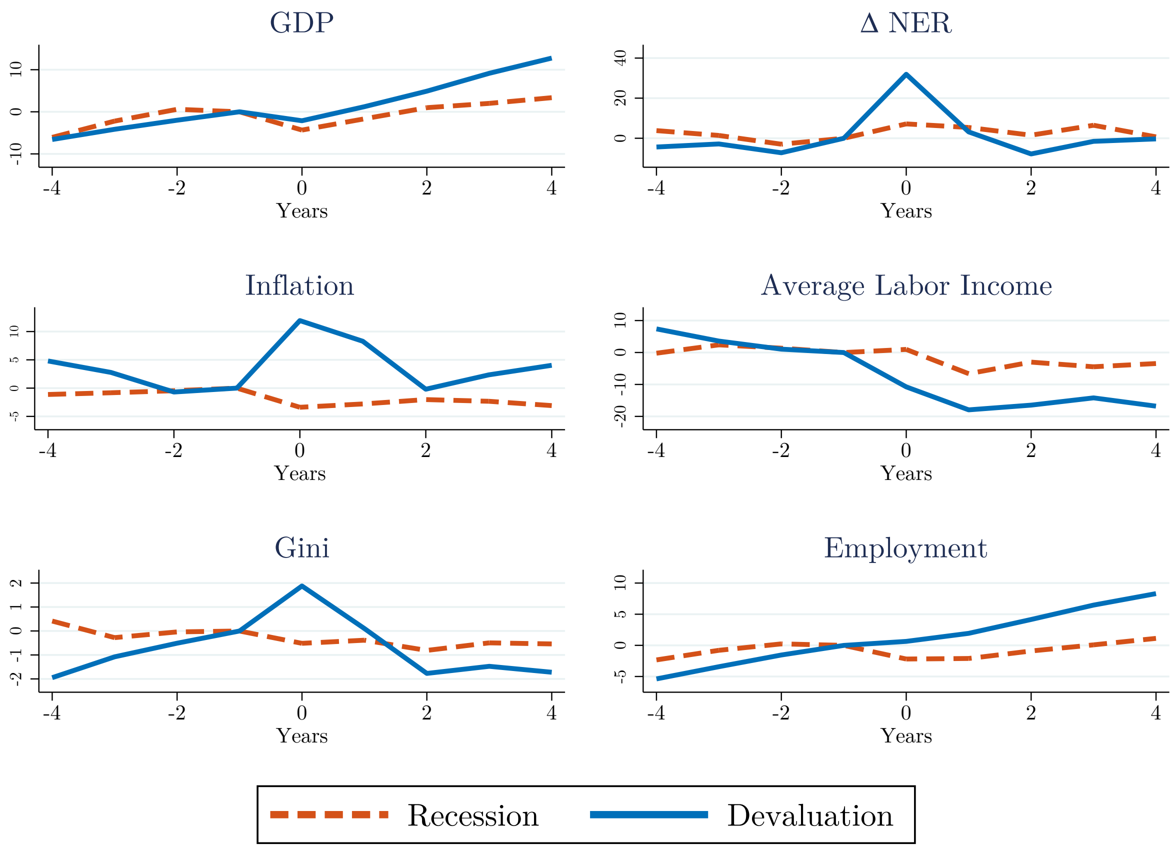
Notes: The figure plots (in the following order) the change in real GDP, NER, inflation, average real labor income, Gini, and employment at annual frequency. Δ NER and inflation are computed as annual log differences in the nominal exchange rate and the CPI (× 100). We winsorize the normalized change in NER and inflation at the 2.5% and 97.5% percentiles across all 59 episodes in our sample. Real GDP, average labor income, employment, and the Gini coefficient are measured in log-points × 100. All variables are normalized to zero in year −1. The solid blue line plots the average of each variable across episodes in an 8-year window around a large devaluation. The dotted red line plots the same variables for recessions without devaluations. The year zero corresponds to either the year of the devaluation or the year of the recession. When our filters identify either large devaluations or recessions without devaluations in 2 or more consecutive years, we center the window of the event around the last year. None of the episodes feature a Default as defined by Laeven and Valencia (2018). Large devaluation episodes include Brazil (1990), Brazil (1999), Brazil (2015), Colombia (2015), Costa Rica (1991), Georgia (1999), Iceland (2008), Mexico (1995), Moldova (1999), Moldova (2015), Paraguay (2002), South Korea (1998), and Ukraine (2009). Episodes of recessions without devaluations include Argentina (1995), Argentina (2009), Armenia (2009), Austria (2009), Belgium (2009), Bulgaria (2009), Colombia (1999), Cyprus (2014), Czech Republic (2009), Denmark (2009), El Salvador (2009), Estonia (2009), Finland (2009), Finland (2014), France (2009), Georgia (2009), Germany (2009), Honduras (2009), Hungary (2009), Ireland (2009), Italy (2009), Italy (2014), Latvia (2010), Lithuania (2009), Luxembourg (2009), Mexico (2009), Moldova (2009), Montenegro (2009), Netherlands (2009), Portugal (2009), Portugal (2013), Romania (2010), Russia (2009), Slovenia (2013), Spain (2009), Spain (2013), Sweden (2009), Switzerland (2009), and the United Kingdom (2009).

Figure B.4 – Macroeconomic Facts After Large Devaluations - All Recessions



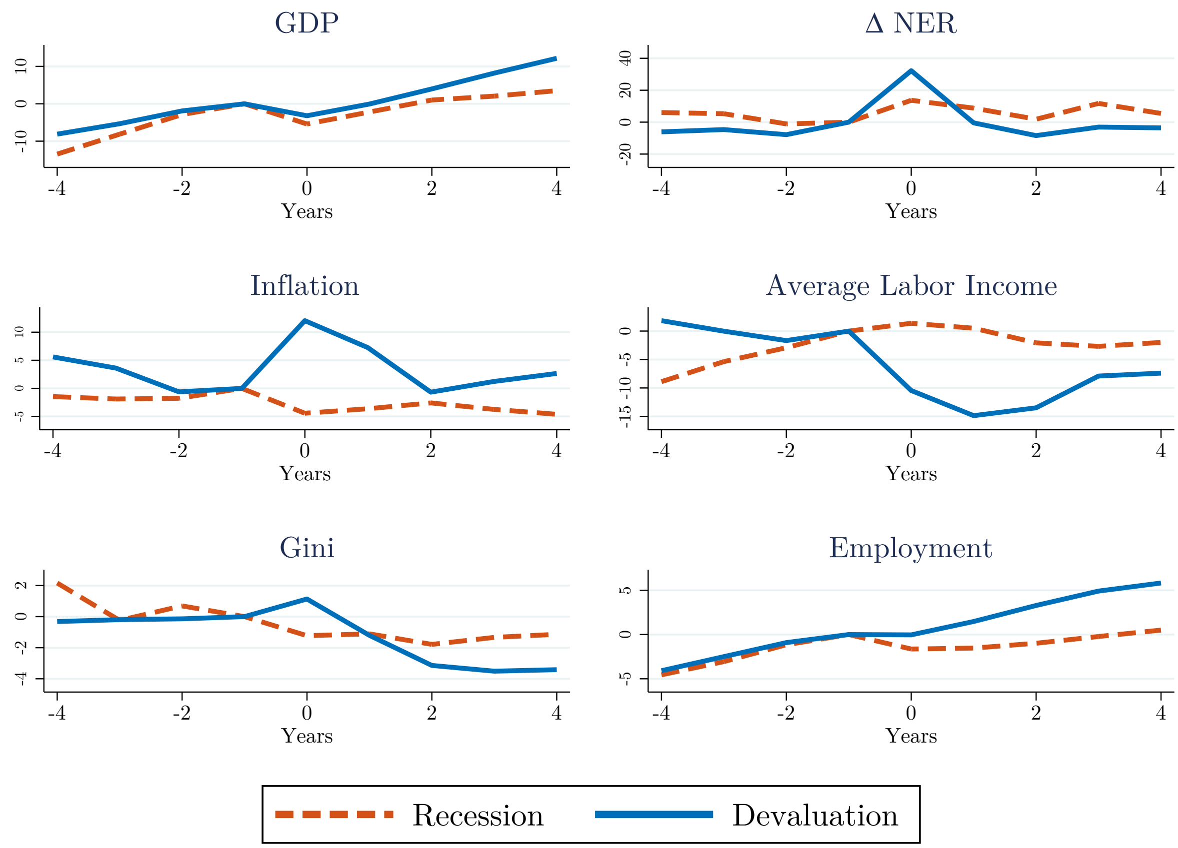
Notes: The figure plots (in the following order) the change in real GDP, NER, inflation, average real labor income, Gini, and employment at annual frequency. Δ NER and inflation are computed as annual log differences in the nominal exchange rate and the CPI ($\times$ 100). We winsorize the normalized change in NER and inflation at the 2.5% and 97.5% percentiles across all 59 episodes in our sample. Real GDP, average labor income, employment, and the Gini coefficient are measured in log-points $\times$ 100. All variables are normalized to zero in year -1. The solid blue line plots the average of each variable across episodes in an 8-year window around a large devaluation. The dotted red line plots the same variables for recessions without devaluations. The year zero corresponds to either the year of the devaluation or the year of the recession. When our filters identify either large devaluations or recessions without devaluations in 2 or more consecutive years, we center the window of the event around the last year. All devaluation episodes in this sample also qualify as recessions. Large devaluation episodes include Argentina (2002), Argentina (2014), Brazil (1990), Iceland (2008), Indonesia (1998), Mexico (1995), Moldova (1999), Paraguay (2002), South Korea (1998), Ukraine (2009), and Uruguay (2002). Episodes of recessions without devaluations include Argentina (1995), Argentina (2009), Armenia (2009), Austria (2009), Belgium (2009), Bulgaria (2009), Colombia (1999), Cyprus (2014), Czech Republic (2009), Denmark (2009), El Salvador (2009), Estonia (2009), Finland (2009), Finland (2014), France (2009), Georgia (2009), Germany (2009), Greece (2013), Honduras (2009), Hungary (2009), Ireland (2009), Italy (2009), Italy (2014), Latvia (2010), Lithuania (2009), Luxembourg (2009), Mexico (2009), Moldova (2009),Montenegro (2009), Netherlands (2009), Portugal (2009), Portugal (2013), Romania (2010), Russia (2009), Slovenia (2013), Spain (2009), Spain (2013), Sweden (2009), Switzerland (2009), and the United Kingdom (2009).

Figure B.5 – Macroeconomic Facts After Large Devaluations - Income Inequality



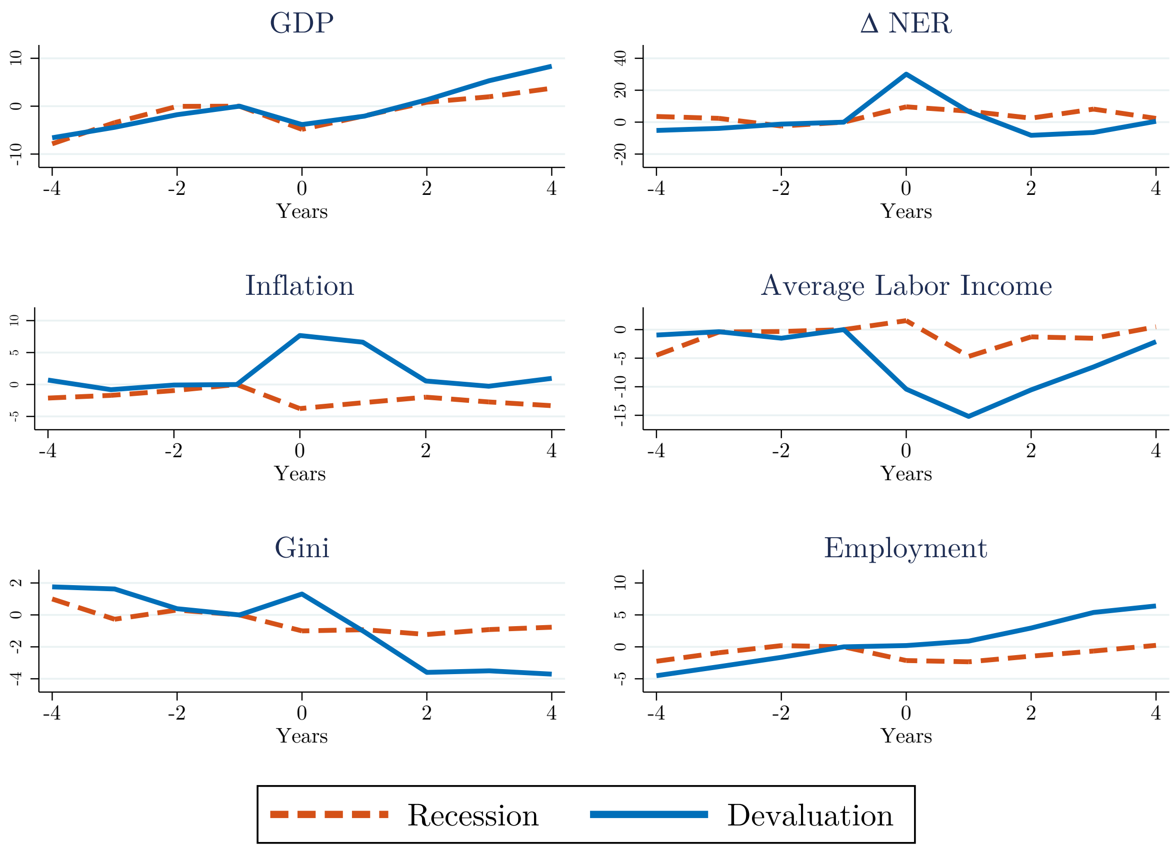
Notes: The figure plots (in the following order) the change in real GDP, NER, inflation, average real labor income, Gini, and employment at annual frequency. Δ NER and inflation are computed as annual log differences in the nominal exchange rate and the CPI ($\times$ 100). We winsorize the normalized change in NER and inflation at the 2.5% and 97.5% percentiles across all 59 episodes in our sample. Real GDP, average labor income, employment, and the Gini coefficient are measured in log-points $\times$ 100. All variables are normalized to zero in year -1. The solid blue line plots the average of each variable across episodes in an 8-year window around a large devaluation. The dotted red line plots the same variables for recessions without devaluations. The year zero corresponds to either the year of the devaluation or the year of the recession. When our filters identify either large devaluations or recessions without devaluations in 2 or more consecutive years, we center the window of the event around the last year. In all of these episodes the Gini coefficient measures income inequality. Large devaluation episodes include Argentina (2002), Argentina (2014), Brazil (1990), Brazil (1993), Brazil (1999), Brazil (2015), Colombia (2015), Costa Rica (1991), Dominican Republic (2003), Iceland (2008), Mexico (1995), Paraguay (2002), South Korea (1998), and Uruguay (2002). Episodes of recessions without devaluations include Argentina (1995), Argentina (2009), Austria (2009), Belgium (2009), Bulgaria (2009), Colombia (1999), Cyprus (2014), Czech Republic (2009), Denmark (2009), El Salvador (2009), Estonia (2009), Finland (2009), Finland (2014), France (2009), Germany (2009), Greece (2013), Honduras (2009), Hungary (2009), Ireland (2009), Italy (2009), Italy (2014), Latvia (2010), Lithuania (2009), Luxembourg (2009), Mexico (2009), Netherlands (2009), Portugal (2009), Portugal (2013), Romania (2010), Slovenia (2013), Spain (2009), Spain (2013), Sweden (2009), Switzerland (2009), and the United Kingdom (2009).

Figure B.6 – Macroeconomic Facts After Large Devaluations - Short Recessions



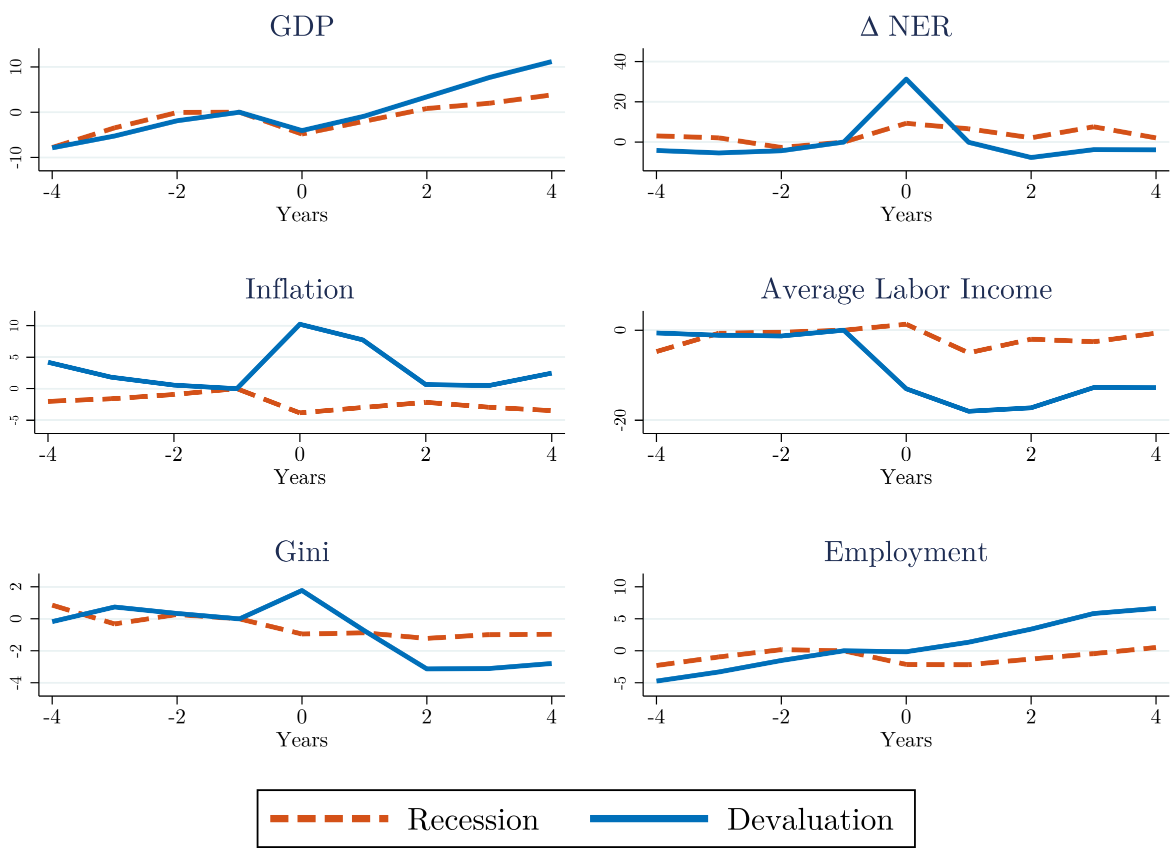
Notes: The figure plots (in the following order) the change in real GDP, NER, inflation, average real labor income, Gini, and employment at annual frequency. Δ NER and inflation are computed as annual log differences in the nominal exchange rate and the CPI (× 100). We winsorize the normalized change in NER and inflation at the 2.5% and 97.5% percentiles across all 59 episodes in our sample. Real GDP, average labor income, employment, and the Gini coefficient are measured in log-points × 100. All variables are normalized to zero in year -1. The solid blue line plots the average of each variable across episodes in an 8-year window around a large devaluation. The dotted red line plots the same variables for recessions without devaluations. The year zero corresponds to either the year of the devaluation or the year of the recession. When our filters identify either large devaluations or recessions without devaluations in 2 or more consecutive years, we center the window of the event around the last year.All the recession episodes lasted only one year. Large devaluation episodes include Argentina (2002), Argentina (2014), Brazil (1990), Brazil (1993), Brazil (1999), Brazil (2015), Colombia (2015), Costa Rica (1991), Dominican Republic (2003), Georgia (1999), Iceland (2008), Indonesia (1998), Mexico (1995), Moldova (1999), Moldova (2015), Paraguay (2002), South Korea (1998), Ukraine (2009), and Uruguay (2002). Episodes of recessions without devaluations include Argentina (1995), Argentina (2009), Armenia (2009), Austria (2009), Belgium (2009), Bulgaria (2009), Colombia (1999), Czech Republic (2009), El Salvador (2009), Finland (2009), France (2009), Georgia (2009), Germany (2009), Honduras (2009), Hungary (2009), Lithuania (2009), Mexico (2009), Moldova (2009), Montenegro (2009), Netherlands (2009), Portugal (2009), Russia (2009), Spain (2009), and Switzerland (2009).

Figure B.7 – Macroeconomic Facts After Large Devaluations - 2000 Onwards



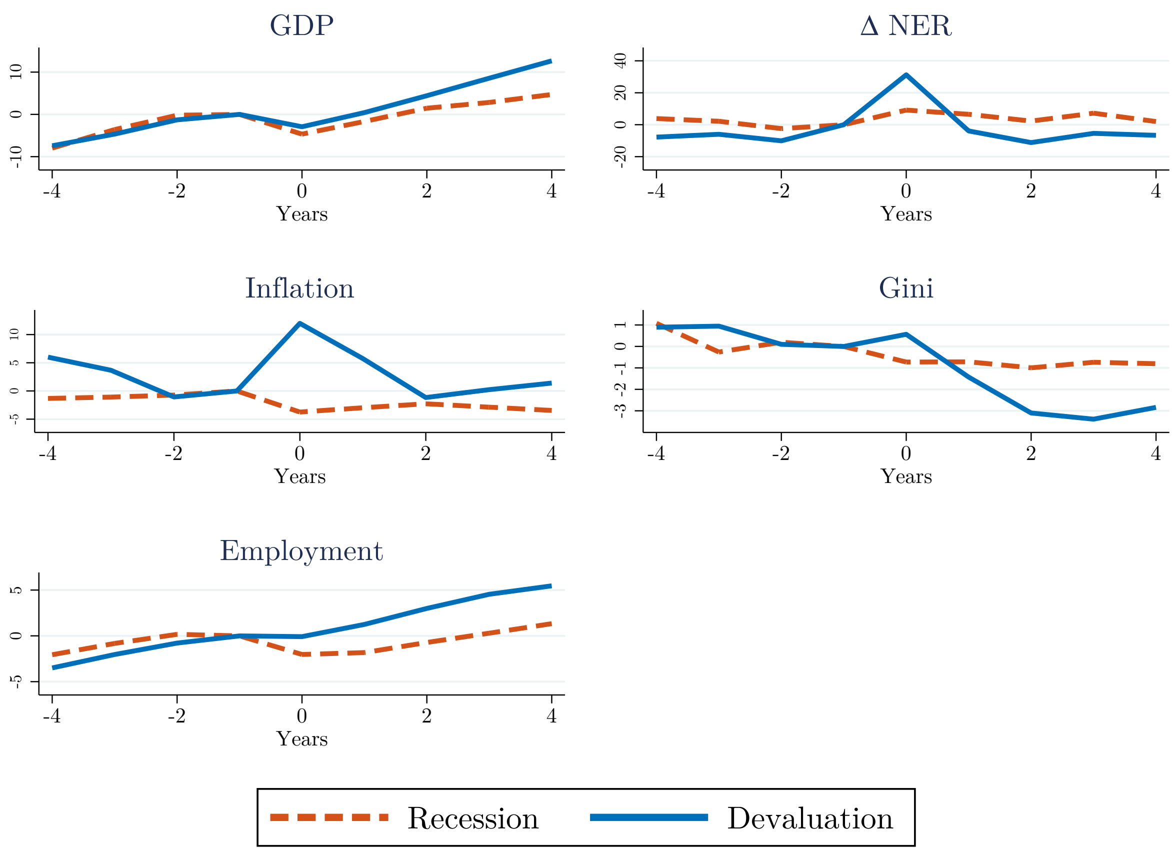
Notes: The figure plots (in the following order) the change in real GDP, NER, inflation, average real labor income, Gini, and employment at an annual frequency. Δ NER and inflation are computed as annual log differences in the nominal exchange rate and the CPI ($\times$ 100). We winsorize the normalized change in NER and inflation at the 2.5% and 97.5% percentiles across all 59 episodes in our sample. Real GDP, average labor income, employment, and the Gini coefficient are measured in log-points $\times$ 100. All variables are normalized to zero in year -1. The solid blue line plots the average of each variable across episodes in an 8-year window around a large devaluation. The dotted red line plots the same variables for recessions without devaluations. The year zero corresponds to either the year of the devaluation or the year of the recession. When our filters identify either large devaluations or recessions without devaluations in 2 or more consecutive years, we center the window of the event around the last year. All of the episodes happened from 2000 onward. Large devaluation episodes include Argentina (2002), Argentina (2014), Brazil (2015), Colombia (2015), Dominican Republic (2003), Iceland (2008), Moldova (2015), Paraguay (2002), Ukraine (2009), and Uruguay (2002). Episodes of recessions without devaluations include Argentina (2009), Armenia (2009), Austria (2009), Belgium (2009), Bulgaria (2009), Cyprus (2014), Czech Republic (2009), Denmark (2009), El Salvador (2009), Estonia (2009), Finland (2009), Finland (2014), France (2009), Georgia (2009), Germany (2009), Greece (2013), Honduras (2009), Hungary (2009), Ireland (2009), Italy (2009), Italy (2014), Latvia (2010), Lithuania (2009), Luxembourg (2009), Mexico (2009), Moldova (2009), Montenegro (2009), Netherlands (2009), Portugal (2009), Portugal (2013), Romania (2010), Russia (2009), Slovenia (2013), Spain (2009), Spain (2013), Sweden (2009), Switzerland (2009), and the United Kingdom (2009).

Figure B.8 – Macroeconomic Facts After Large Devaluations - No Hyperinflations



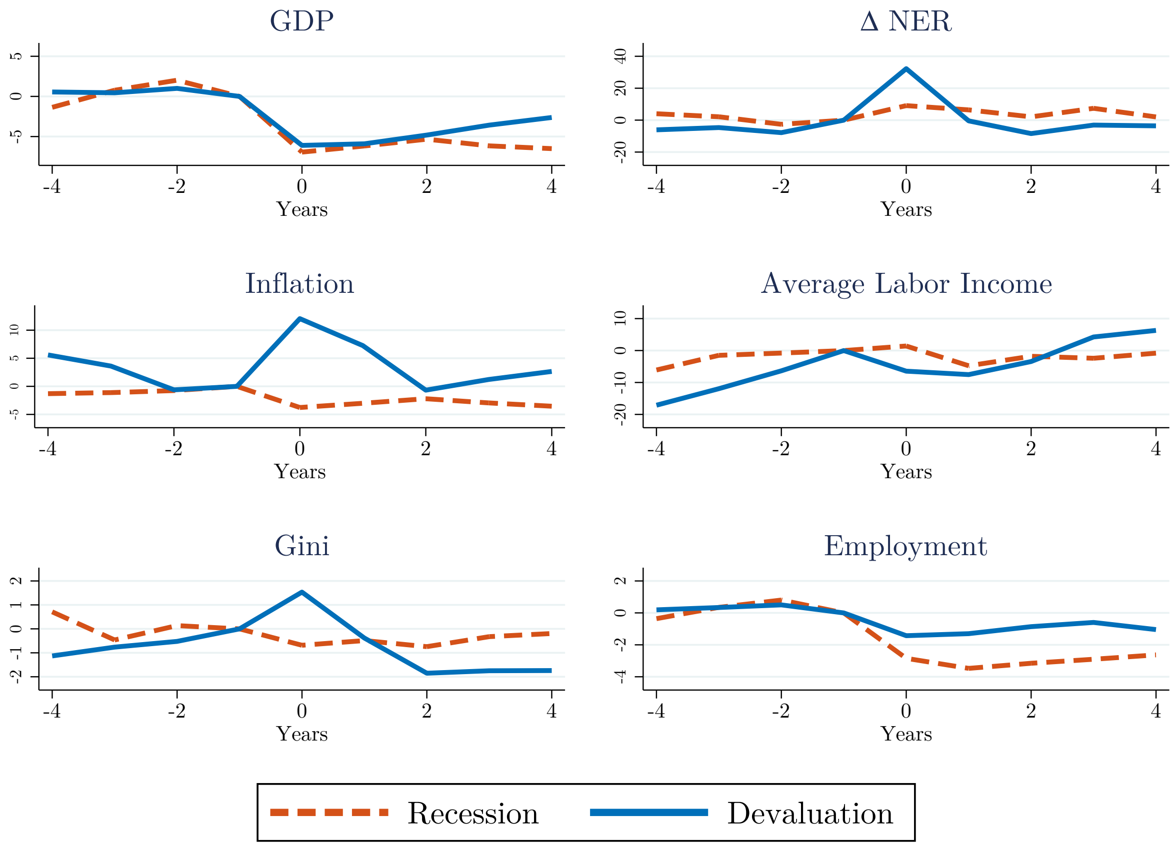
Notes: The figure plots (in the following order) the change in real GDP, NER, inflation, average real labor income, Gini, and employment at annual frequency. Δ NER and inflation are computed as annual log differences in the nominal exchange rate and the CPI ($\times$ 100). We winsorize the normalized change in NER and inflation at the 2.5% and 97.5% percentiles across all 59 episodes in our sample. Real GDP, average labor income, employment, and the Gini coefficient are measured in log-points $\times$ 100. All variables are normalized to zero in year -1. The solid blue line plots the average of each variable across episodes in an 8-year window around a large devaluation. The dotted red line plots the same variables for recessions without devaluations. The year zero corresponds to either the year of the devaluation or the year of the recession. When our filters identify either large devaluations or recessions without devaluations in 2 or more consecutive years, we center the window of the event around the last year. None of the episodes feature a hyperinflation. Large devaluation episodes include Argentina (2002), Argentina (2014),Brazil (1999) Brazil (2015), Colombia (2015), Costa Rica (1991), Dominican Republic (2003), Iceland (2008), Indonesia (1998), Mexico (1995), Moldova (1999), Moldova (2015), Paraguay (2002), South Korea (1998), Ukraine (2009), and Uruguay (2002). Episodes of recessions without devaluations include Argentina (2009), Armenia (2009), Austria (2009), Belgium (2009), Bulgaria (2009), Colombia (1999), Cyprus (2014), Czech Republic (2009), Denmark (2009), El Salvador (2009), Estonia (2009), Finland (2009), Finland (2014), France (2009), Georgia (2009), Germany (2009), Greece (2013), Honduras (2009), Hungary (2009), Ireland (2009), Italy (2009), Italy (2014), Latvia (2010), Lithuania (2009), Luxembourg (2009), Mexico (2009), Moldova (2009), Montenegro (2009), Netherlands (2009), Portugal (2009), Portugal (2013), Romania (2010), Russia (2009), Slovenia (2013), Spain (2009), Spain (2013), Sweden (2009), Switzerland (2009), and the United Kingdom (2009).

Figure B.9 – Macroeconomic Facts After Large Devaluations - Gini Sample



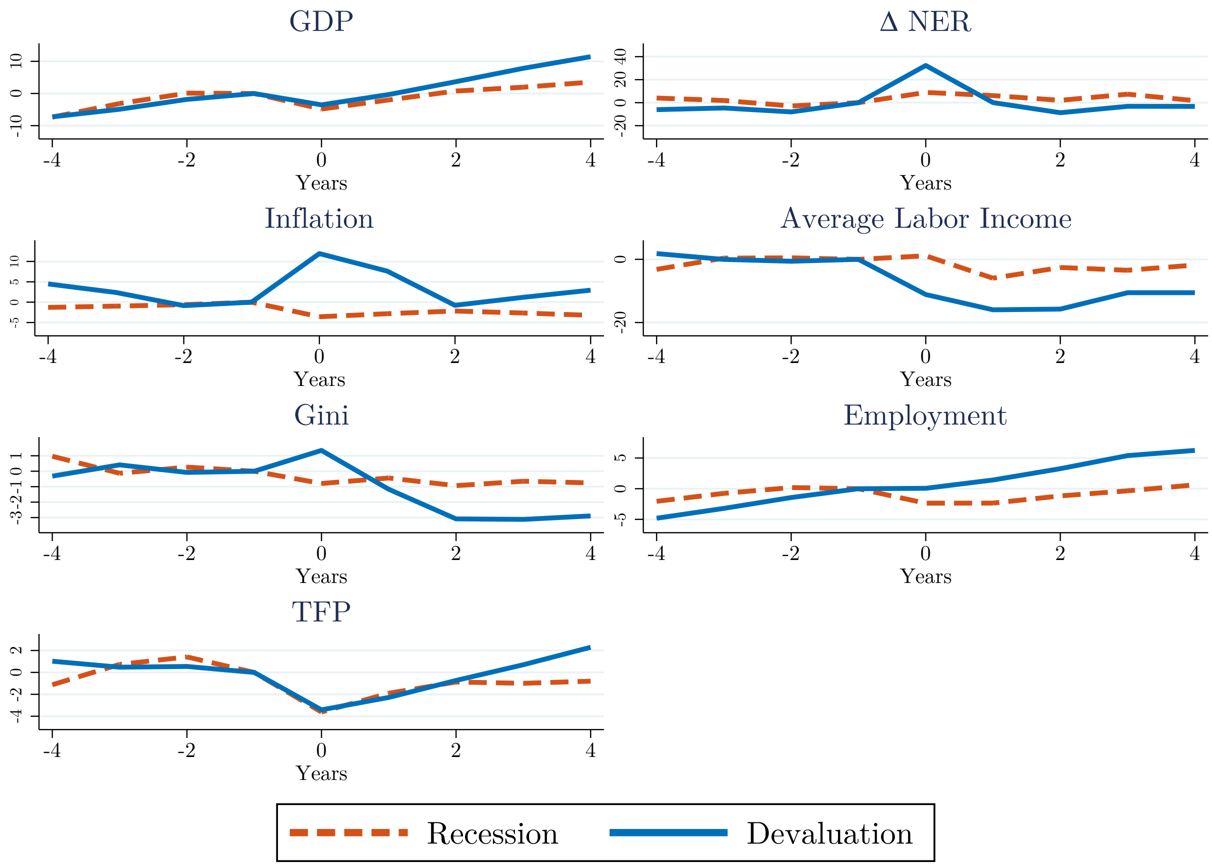
Notes: The figure plots (in the following order) the change in real GDP, NER, inflation, average real labor income, Gini, and employment at annual frequency. Δ NER and inflation are computed as annual log differences in the nominal exchange rate and the CPI (× 100). We winsorize the normalized change in NER and inflation at the 2.5% and 97.5% percentiles across all 59 episodes in our sample. Real GDP, average labor income, employment, and the Gini coefficient are measured in log-points × 100. All variables are normalized to zero in year -1. The solid blue line plots the average of each variable across episodes in an 8-year window around a large devaluation. The dotted red line plots the same variables for recessions without devaluations. The year zero corresponds to either the year of the devaluation or the year of the recession. When our filters identify either large devaluations or recessions without devaluations in 2 or more consecutive years, we center the window of the event around the last year. This plot omits the dynamics of average labor income as this variable is not available for all episodes. Large devaluation episodes include Argentina (2002), Argentina (2014), Brazil (1990), Brazil (1993), Brazil (1999), Brazil (2015), Colombia (2015), Costa Rica (1991), Dominican Republic (2003), Georgia (1999), Iceland (2008), Indonesia (1998), Mexico (1995), Paraguay (2002), Russia (1998), Russia (2015), South Korea (1998), Thailand (1998), Ukraine (2009), and Uruguay (2002). Episodes of recessions without devaluations include Argentina (1995), Argentina (2009), Austria (2009), Belgium (2009), Bulgaria (2009), Colombia (1999), Cyprus (2014), Czech Republic (2009), Denmark (2009), El Salvador (2009), Estonia (2009), Finland (2009), Finland (2014), France (2009), Georgia (2009), Germany (2009), Greece (2013), Honduras (2009), Hungary (2009), Ireland (2009), Italy (2009), Italy (2014), Latvia (2010), Lithuania (2009), Luxembourg (2009), Mexico (2009), Moldova (2009), Montenegro (2009), Netherlands (2009), Portugal (2009), Portugal (2013), Romania (2010), Russia (2009), Slovenia (2013), Spain (2009), Spain (2013), Sweden (2009), Switzerland (2009), Turkey (2009), and the United Kingdom (2009).

Figure B.10 – Macroeconomic Facts After Large Devaluations - HP Detrended Series



Notes: The figure plots (in the following order) the change in real GDP, NER, inflation, average real labor income, Gini, and employment at annual frequency. Δ NER and inflation are computed as annual log differences of the nominal exchange rate and the CPI (× 100). We winsorize the normalized change in NER and inflation at the 2.5% and 97.5% percentiles across all 59 episodes in our sample. Real GDP, average labor income, employment, and the Gini coefficient are measured in log-points × 100. The series of GDP, average labor income, the Gini coefficient, and employment are individually detrended using an annual Hodrick–Prescott filter and data from all available years in each country in the panel. All variables are normalized to zero in year −1. The solid blue line plots the average of each variable across episodes in an 8-year window around a large devaluation. The dotted red line plots the same variables for recessions without devaluations. The year zero corresponds to either the year of the devaluation or the year of the recession. When our filters identify either large devaluations or recessions without devaluations in 2 or more consecutive years, we center the window of the event around the last year. Large devaluation episodes include Argentina (2002), Argentina (2014), Brazil (1990), Brazil (1993), Brazil (1999), Brazil (2015), Colombia (2015), Costa Rica (1991), Dominican Republic (2003), Georgia (1999), Iceland (2008), Indonesia (1998), Mexico (1995), Moldova (1999), Moldova (2015), Paraguay (2002), South Korea (1998), Ukraine (2009), and Uruguay (2002). Episodes of recessions without devaluations include Argentina (1995), Argentina (2009), Armenia (2009), Austria (2009), Belgium (2009), Bulgaria (2009), Colombia (1999), Cyprus (2014), Czech Republic (2009), Denmark (2009), El Salvador (2009), Estonia (2009), Finland (2009), Finland (2014), France (2009), Georgia (2009), Germany (2009), Greece (2013), Honduras (2009), Hungary (2009), Ireland (2009), Italy (2009), Italy (2014), Latvia (2010), Lithuania (2009), Luxembourg (2009), Mexico (2009), Moldova (2009),Montenegro (2009), Netherlands (2009), Portugal (2009), Portugal (2013), Romania (2010), Russia (2009), Slovenia (2013), Spain (2009), Spain (2013), Sweden (2009), Switzerland (2009), and the United Kingdom (2009).

Figure B.11 – Macroeconomic Facts After Large Devaluations - TFP Sample



Notes: The figure plots (in the following order) the change in real GDP, NER, inflation, average real labor income, Gini, employment and TFP at an annual frequency. Δ NER and inflation are computed as annual log differences in the nominal exchange rate and the CPI (× 100). We winsorize the normalized change in NER and inflation at the 2.5% and 97.5% percentiles across all 59 episodes in our sample. Real GDP, average labor income, employment, the Gini coefficient, and TFP are measured in log points × 100. All variables are normalized to zero in year -1. The solid blue line plots the average of each variable across episodes in an 8-year window around a large devaluation. The dotted red line plots the same variables for recessions without devaluations. The year zero corresponds to either the year of the devaluation or the year of the recession. When our filters identify either large devaluations or recessions without devaluations in 2 or more consecutive years, we center the window of the event around the last year. Large devaluation episodes include Argentina (2002), Argentina (2014), Brazil (1999), Brazil (1990), Brazil (1993), Brazil (1999), Brazil (2015), Colombia (2015), Costa Rica (1991), Dominican Republic (2003), Iceland (2008), Indonesia (1998), Mexico (1995), Moldova (1999), Moldova (2015), Paraguay (2002), South Korea (1998), Ukraine (2009), and Uruguay (2002). Episodes of recessions without devaluations include Argentina (1995), Argentina (2009), Armenia (2009), Austria (2009), Belgium (2009), Bulgaria (2009), Colombia (1999), Cyprus (2014), Czech Republic (2009), Denmark (2009), Estonia (2009), Finland (2009), Finland (2014), France (2009), Germany (2009), Greece (2013), Honduras (2009), Hungary (2009), Ireland (2009), Italy (2009) Italy (2014), Latvia (2010), Lithuania (2009), Luxembourg (2009), Mexico (2009), Moldova (2009), Netherlands (2009), Portugal (2009), Portugal (2013), Romania (2010), Russia (2009), Slovenia (2013), Spain (2009), Spain (2013), Sweden (2009), Switzerland (2009), and United Kingdom (2009).

B.1 The Synchronicity Between Large Devaluations and Inflation

This section documents the fact that large inflation events in the absence of large devaluations are infrequent. To show this, we identify inflation events similar to how we identify devaluation events. Focusing on the years 1990-2015, we classify a country-year pair as an inflation event if the annual inflation rate is larger than 15% and also 7% larger than in the previous year. As with devaluation episodes, if adjacent years satisfy these criteria, we focus on the last year. We choose a threshold of 15%, which closely corresponds to the 85th percentile of the distribution of annual inflation and would usually be considered a high level of inflation.

Below, we report the occurrence of two types of episodes: those that occurred in isolation and simultaneously. We use the criteria outlined above to define isolated devaluation and inflation episodes. We define episodes with both large devaluation and inflation rates as those occurring simultaneously within a 2-year window from each other. Moreover, some devaluation (resp. inflation) episodes feature high inflation (resp. large devaluation) without satisfying all criteria to be classified as an inflation (resp. devaluation) episode.[31] Because these cases are more appropriately described as episodes of both high inflation and devaluation, we make the following choice: If an inflation episode occurs around a devaluation larger than 30%, then we also classify it as a devaluation episode. Conversely, all devaluation episodes featuring an inflation rate larger than 15% are classified as inflation episodes. Finally, because of the rolling window procedure for classifying joint events, it is not clear how to treat years without high inflation and devaluation rates. Thus, we do not report the number of country-year pairs without any episode. This procedure yields 80 episodes of high inflation; around 25% of countries experienced at least one episode, with a mean of 0.53 episodes per country.[32]

Table B.2 provides the cross-tabulation of inflation and devaluation episodes and shows that only 25% (20 out of 80) of inflation episodes are not surrounded by a large devaluation. In addition, these episodes, while satisfying the selection criteria, do not exhibit the same characteristics of inflation episodes brought on by large devaluations: In the former, the median inflation rate is less than half of the median inflation in the latter (21% vs. 49%, respectively).[33] Thus, this table suggests that episodes of sudden and large increases in inflation typically occur in the context of large devaluations and vice versa. Although the paper's main results could arguably be extrapolated to other inflationary contexts, isolated large increases in inflation are rare, which motivates our analysis of labor market dynamics during large devaluations.

[31] For example, Turkey fulfills all the criteria of a devaluation episode in 1996. In that year, it experienced an inflation rate of 80%, but it is not classified as an inflation episode because the country was going through an extended period of high inflation.

[32] We exclude 14 episodes that occurred during wars, civil wars, and transitions to capitalist economies (as we do in Table B.1).

[33] A closer inspection of these episodes of large inflation without a devaluation reveals that most occurred under special circumstances: the increase in global commodity prices around 2007/2008, climate disasters, civil wars, and transitions to a capitalist economy. This strengthens our claim that the typical inflation episode occurs around a large devaluation.

Table B.2 – Devaluation and Inflation Events

		Inflation	
		Yes	No
Devaluation	Yes	60 (49, 95)	28 (9, 41)
	No	20 (21, 3.8)	-

Notes: The table shows the cross-tabulation of inflation and devaluation episodes. The median inflation and devaluation rates, respectively, are shown in parentheses. Due to the rolling window design used to classify episodes, the "No-No" category is omitted. Episodes are classified according to the criteria described in Sections A.1 and B.1.

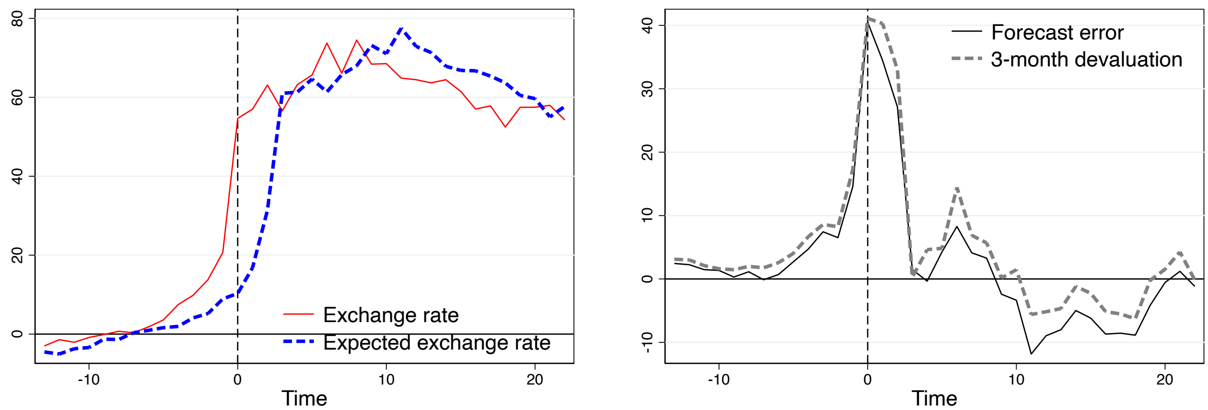
B.2 Predictability of the Nominal Exchange Rate Around Large Devaluations

This section shows that large devaluations typically are unexpected events. For this, we use data on nominal exchange rate expectations from a survey of professional forecasters compiled by Consensus Economics. Founded in 1989, Consensus Economics is the world's leading international economic survey organization. Each month, they solicit more than 700 economists, banks, and consulting companies for their latest forecasts on a set of macroeconomic variables. While the dataset contains information from 1990, it does not cover all of the large devaluations described in the main text.[34] The dataset includes information on average expectations for the domestic nominal exchange rate vis-a-vis the U.S. dollar e_t. From these data, we compute: (a) the log normalized exchange rate in month t, $\log(e_t) - \log(\bar{e}_{t_0})$, where $\bar{e}_{t_0}$ is the average NER during the year before the devaluation; (b) the log normalized expected nominal exchange rate $\log(\mathbb{E}_{t-3}[e_t]) - \log(\bar{e}_{t_0})$, where $\log(\mathbb{E}_{t-3}[e_t])$ is the 3-month-lagged average forecast; (c) the 3-month-ahead forecast error of the nominal exchange rate $\log(e_t) - \log(\mathbb{E}_{t-3}[e_t])$; and (d) the 3-month change in the NER $\log(e_t) - \log(e_{t-3})$. Figure B.12 plots the average of these variables across episodes of large devaluation on the y-axis as a function of the number of months from the month of the devaluation on the x-axis. We plot all figures in log percentage points.

A clear fact emerges from Figure B.12-Panel A: The size and timing of large nominal devaluations are largely unexpected. On average, professional forecasters anticipated a small increase in the nominal exchange rate during the months before the devaluation. However, their forecasts largely missed the size of the on-impact devaluation rate. This can be seen more clearly in Figure B.12-Panel B, in which the average 3-month devaluation rate around the first 3 months after the sudden increase in the NER closely tracks the forecast error. This implies that $\mathbb{E}_{t-3}[e_t] \approx e_{t-3}$. Thus, even though professional forecasters were on average aware of an upcoming increase in the nominal exchange rate, they could not predict its size. Figure B.13 shows a similar plot for the 2002 Argentinean devaluation episode separately.

[34] The Consensus dataset does not include data for the following episodes of large devaluations: Brazil-1990, Costa Rica-1991, Georgia-1999, Iceland-2008, and Moldova-1999.

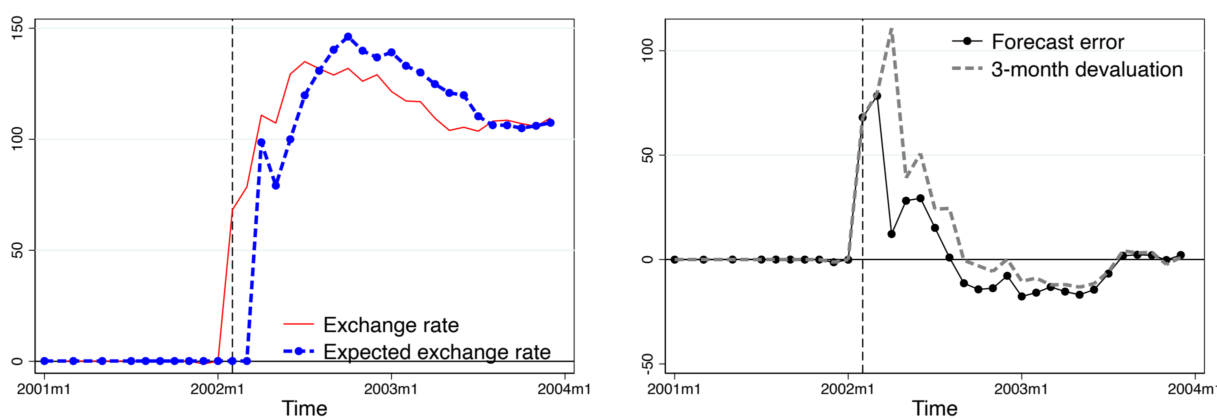
Figure B.12 – Predictability of the NER across Large Devaluation



(a) NER and NER expectation **(b)** NER forecast error and change in NER

Notes: Panel (a) shows the log-normalized average NER and the log-normalized 3-month-ahead average expected NER. Averages are taken across all devaluation episodes. We normalize the NER and its expectation by the average NER during the year before the devaluation episode. Panel (b) shows the 3-month-ahead forecast error and the 3-month-ahead change in the NER. All variables are expressed as percentage points.
Source: Consensus Economics and additional sources described in Table A.4.

Figure B.13 – Predictability of the NER: Argentina 2002



(a) NER and NER expectation **(b)** NER forecast error and change in NER

Notes: Panel (a) shows the log-normalized NER and the log-normalized 3-month-ahead expected NER. We normalize the NER and its expectation by the average NER during the year before the devaluation episode. Panel (b) shows the 3-month-ahead forecast error and the 3-month-ahead change in the NER. All variables are expressed as percentage points.
Source: Consensus Economics and additional sources described in Table A.4.

B.3 A Synthetic Control Approach

An alternative approach for causal inference in settings in which large units (i.e., countries) are affected by a policy is the pioneering synthetic control methodology developed by Abadie and Gardeazabal (2003) and Abadie *et al.* (2010). This methodology is a generalization of the difference-in-differences framework, and its main benefit is that it allows us to control for regional or global factors that simultaneously affect multiple economies, including those that experience large devaluations. In a nutshell, this method constructs an appropriate counterfactual benchmark for each country that experienced a large devaluation, which describes what would have happened to the "treated" country in the absence of the devaluation. To obtain the estimate of interest, the method first creates a "synthetic" control country from a subgroup of countries that experienced similar trends in inequality before the year of the devaluation. Then, it uses this synthetic counterfactual to compare the evolution of inequality in the country of interest in the post-devaluation period.

In what follows, we describe the synthetic control methodology applied to a particular devaluation event. Below, we explain how we aggregate the results across events. The exposition is brief, since it closely tracks the description in Abadie (2021). We have data for $J+1$ countries: $j = 1, 2, \ldots, J+1$. Assume that the first country ($j = 1$) is the treated unit (i.e., the country that experienced a large devaluation). The "donor pool"—that is, the set of potential comparisons, $j = 2, \ldots, J+1$—is a collection of countries not affected by the devaluation. The data span T periods, and the first T_0 periods are before the intervention (i.e., the intervention occurs in period $T_0 + 1$). For each country j and time t, we observe the outcome Y_{jt} (i.e., the Gini coefficient). We also observe a set of k predictors of the outcome $X_{1j}, \ldots, X_{kj}$. The $k \times 1$ vectors $X_1, \ldots, X_{J+1}$ contain the values of the predictors for countries $j = 1, \ldots, J+1$, respectively. The $k \times J$ matrix, $X_0 = [X_2 \cdots X_{J+1}]$, collects the values of the predictors for the J untreated countries. For each country j and time period t, we define Y_{jt}^N to be the potential response in the absence of the intervention (i.e., the devaluation). For the country affected by the intervention, $j = 1$, and a post-intervention period $t > T_0$, we define Y_{jt}^I to be the potential response under the intervention. The effect of the intervention for $t > T_0$ is thus given by

$$\tau_{1t} = Y_{1t}^I - Y_{1t}^N.$$

The goal is to obtain an estimate of τ_{1t}. However, the main issue is that for the country that experienced the intervention $Y_{1t}^I = Y_{1t}$—that is, the potential outcome under the intervention is observed—but we do not observe Y_{1t}^N for $t > T_0$—that is, the potential outcome in the absence of the intervention. The solution offered by the synthetic control method is to construct a "synthetic" control, which is defined as a weighted average of the countries in the donor pool. Given a set of weights $W = (w_2, \ldots, w_{J+1})$, the synthetic control and the estimate of the effect are

$$\hat{Y}_{1t}^N = \sum_{j=2}^{J+1} w_j Y_{jt}$$

and

$$\hat{\tau}_{1t} = Y_{1t}^I - \hat{Y}_{1t}^N,$$

respectively. Thus, this methodology provides a data-driven method to replace Y_{1t}^N with the estimate $\hat{Y}_{1t}^N$ based on a weighted average of the outcome of donor countries. To choose these weights, the method minimizes the distance between the treated country's predictors X_1 and the resulting average of predictors across donor countries $X_0 W$:

$$(w_2^*, \ldots, w_{J+1}^*) \equiv \arg\min \left(\sum_{h=1}^{k} v_h \left(X_{h1} - w_2 X_{h2} - \cdots - w_{J+1} X_{hJ+1} \right)^2 \right)^{1/2}$$

subject to $w_j \in [0,1]$ and $\sum_{j=2}^{J+1} w_j = 1$ (to avoid extrapolation). The positive constants $v_1, \ldots, v_k$ reflect the relative importance of the synthetic control reproducing the values of each of the k predictors of the outcome variable. To chose $V = (v_1, \ldots, v_k)$, we follow Abadie and Gardeazabal (2003) and Abadie *et al.* (2010) and choose the vector V that minimizes the mean squared prediction error of the outcome variable during the pre-devaluation period ($t \leq T_0$):

$$V^* = \arg\min \sum_{t \in \mathcal{T}_0} \left(Y_{1t} - w_2(V)Y_{2t} - \cdots - w_{J+1}(V)Y_{J+1t}\right)^2$$

for some set $\mathcal{T}_0 \subseteq \{1, 2, \ldots, T_0\}$ of the pre-treatment periods. Then, the estimate of the effect of interest is given by

$$\hat{\tau}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}.$$

Our setting differs from previous applications of the synthetic control method, since we analyze multiple events with large devaluations. Thus, to provide the average effect of devaluations on inequality, we follow Cavallo, Galiani, Noy and Pantano (2013) and average estimates across events. Then, we want to estimate the average effect $\bar{\tau}_t$, which is given by

$$\bar{\tau}_t \equiv \frac{1}{G} \sum_{g=1}^{G} \hat{\tau}_{g,t}, \tag{B.2}$$

where each event is denoted by $g \in \{1, \ldots, G\}$ and $\hat{\tau}_{g,t}$ denotes the estimated effect in event g at time t.

In our application, the outcome variable is the Gini coefficient. Since we want to compare outcomes across events, we first rescale the outcome variable in the same way we normalized it in Section 3 (i.e., the log difference with respect to inequality in period T_0). The set of predictor variables includes pre-devaluation averages of real GDP per capita, the (level of) Gini coefficient, the share of manufacturing output in GDP, trade openness (measured by the sum of exports and imports over GDP), the GDP share of private consumption, and the GDP share of investment. Data on the Gini coefficient were obtained from the same sources used in Section 3. Data on GDP per capita, the share of manufacturing, and trade openness were obtained from the World Bank. Data on the GDP share of private consumption and investment were obtained from the Penn World Tables. As highlighted by Abadie (2021), matching outcomes during a long pre-treatment period helps control for observed and unobserved factors that affect inequality. Therefore, we use all available data on inequality from 1985 to 2019 and set the window of analysis to 10 years before and 4 years after the year of each devaluation event (for South Korea, the pre-period only includes 8 years, due to data limitations). This choice trades off the method's requirements of long pre-treatment periods and relatively large sizes of donor pools. Predictor variables are averaged between $T_0 - 9$ and $T_0 - 4$ to reduce the influence of large changes in these variables in the narrow window around large devaluations and to better capture the "average" characteristics of each country. Finally, to maximize the size of the donor pool and improve the quality of synthetic controls, we include all countries with available data. Table B.3 shows the number of donor countries included in each event.

Figure B.14 report the estimates of the average inequality gap between treated and synthetic countries, $\bar{\tau}_t$, over time. First, notice that before the year of the devaluation (normalized to year 0 in the figure and highlighted with the dashed vertical line), the average inequality gap fluctuates around zero, which indicates that synthetic countries track the evolution of the inequality of treated countries on average. More importantly, the figure shows that during the 4 years after the devaluation, there is a decline in inequality of up to 2.5 percentage points relative to the synthetic control.

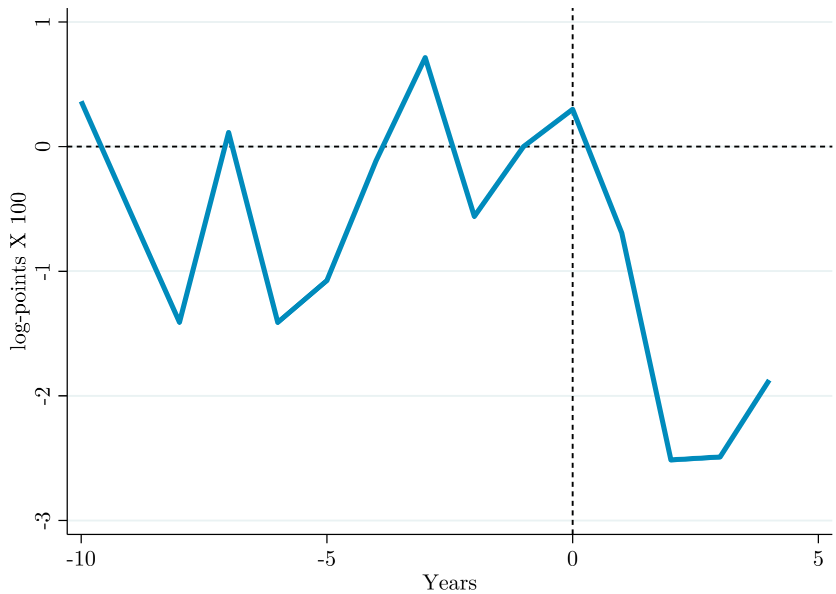
Although Figure B.14 shows that the average inequality gap closely fluctuates around zero in the pre-devaluation period, these fluctuations might not seem small. Therefore, we pursue an alternative approach used in the literature (see, e.g., Cunningham and Shah, 2017) and replace the previous set of predictors with the evolution of inequality in the pre-devaluation period. That is, we construct a synthetic control by directly matching the evolution of the outcome in the pre-treatment period. Figure B.15 reports the results. Not surprisingly, the synthetic countries generated by this alternative approach track the evolution of inequality of the treated countries before period 0 more closely. However, we still find a large decline in the inequality gap after the devaluation. In fact, we find that the Gini coefficient dropped by more than 3 percentage points, which is slightly larger than the estimate reported in Figure B.14 and closer to the average decline documented in Section 3. To summarize, the synthetic control analysis, which allows us to control for regional or global shocks, generates results similar to those documented in Section 3.

Table B.3 – Summary statistics by event

	Window length		
Episode	Pre	Post	Donors
Argentina 2002	10	4	68
Argentina 2014	10	4	55
Brazil 1993	10	4	23
Brazil 1999	10	4	48
Brazil 2015	10	4	18
Colombia 2015	10	4	18
Costa Rica 1991	10	4	23
Dominican Republic 2003	10	4	75
Indonesia 1998	10	4	38
Mexico 1995	10	4	24
Paraguay 2002	10	4	68
South Korea 1998	8	4	43
Thailand 1998	10	4	38
Ukraine 2009	10	4	83
Uruguay 2002	10	4	68

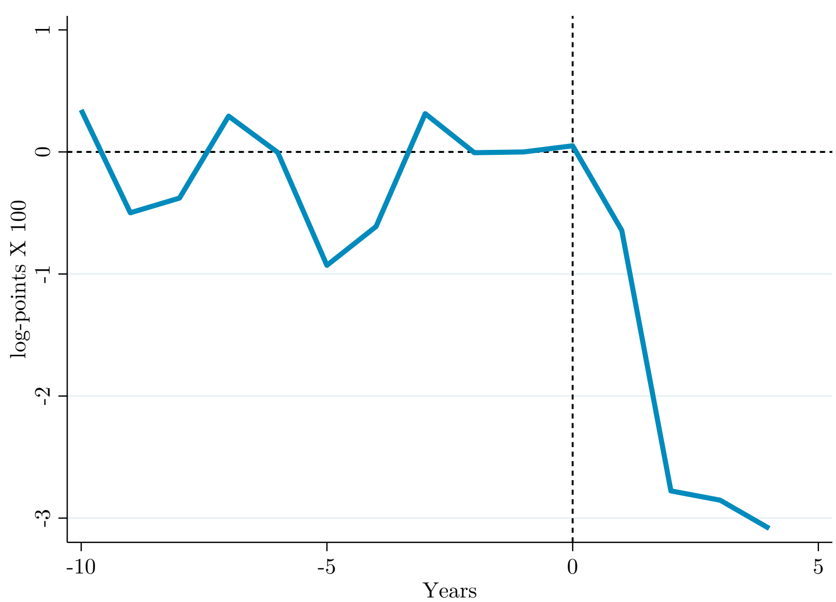
Before finishing this section, we want to state a caveat. The validity of the synthetic control method hinges on the availability of data for treated countries and donor countries for a large pre-treatment window of time (see Abadie, 2021). In our application, the same reason our sample of devaluations does not include all episodes of large devaluations (mainly, the lack of widely available inequality data) might also have an impact on the synthetic control analysis (which requires not only data for multiple countries but also for an extended period of time).

Figure B.14 – Average Inequality Gap



Notes: The figure plots estimates of $\bar{\tau}_t$ from equation (B.2). The set of predictor variables includes pre-devaluation averages of real GDP per capita, the (level of) Gini coefficient, the share of manufacturing output in GDP, trade openness (measured by the sum of exports and imports over GDP), the GDP share of private consumption, and the GDP share of investment.

Figure B.15 – Average Inequality Gap: Alternative Approach



Notes: The figure plots estimates of $\bar{\tau}_t$ from equation (B.2). The set of predictor variables includes the evolution of inequality in the pre-devaluation period.

C Additional Aggregate Facts in Argentina

C.1 Additional Aggregate Variables

This section describes additional macroeconomic and labor market variables that were not included in the main text.

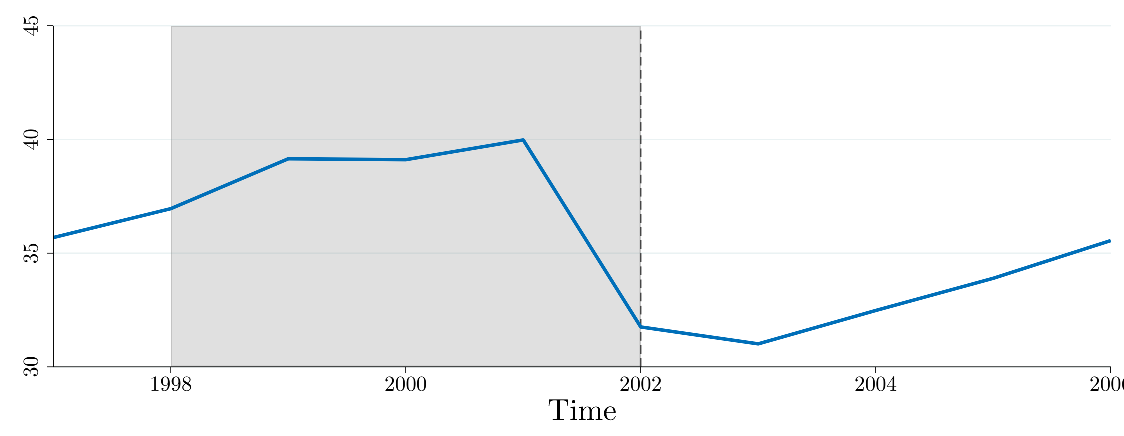
Labor share. The main text characterizes the dynamics of real labor income across workers with different permanent incomes. Here, we characterize the division of revenues between workers and firms—i.e., the labor share—during the 2002 devaluation. Figure C.1 shows the labor share in Argentina during the 1997-2006 period. The labor share falls during the 2002 devaluation, which implies a redistribution of real income from workers to firms.

There is a direct relationship between average labor income, the labor share, and output per worker. The labor share (LS) in a country is given by the average income per worker $\left(\frac{\sum_i y_i}{n}\right)$ times the inverse of output per worker $\left(\frac{n}{Y}\right)$:

$$LS = \frac{\sum y_i}{Y} = \frac{\sum y_i}{n}\frac{n}{Y} = \text{average labor income} \times \text{inverse of output per worker.} \tag{C.3}$$

In the main text, we characterize average income $\frac{\sum y_i}{n}$ in the private sector and show that it decreased significantly following the devaluation. While the average labor income does not fully characterize the labor share, the quantitative magnitude of its changes relative to labor productivity provides a clear direction for labor–share fluctuations in 2002.

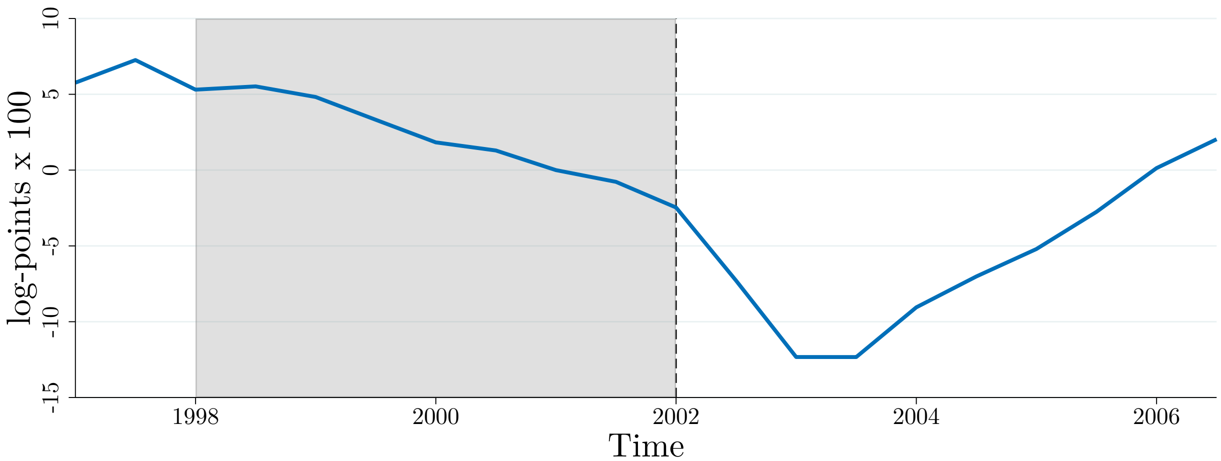
Figure C.1 – Labor Share in Argentina



Notes: The figure shows the annual labor share in Argentina from 1997 to 2006. Data were obtained from Feenstra *et al.* (2015) (Penn World Tables 9.1).

Output per worker. The main text characterizes the recovery of labor income across percentiles of the income distribution. Thus, we compare the relative recovery across different workers. However, we did not analyze an important driver of real labor income, i.e., labor productivity. Figure C.2 shows the evolution of quarterly log output per worker (a simple measure of labor productivity) in Argentina from 1997 to 2006. The figure exhibits two patterns. First, output per worker decreased considerably in Argentina before the 2002 devaluation (i.e., 10% between 1997-2001), while average real labor income remained constant or weakly increasing. Second, there was a strong recovery of output per worker after 2003, as highlighted in the main text.

Figure C.2 – Output per Worker in Argentina

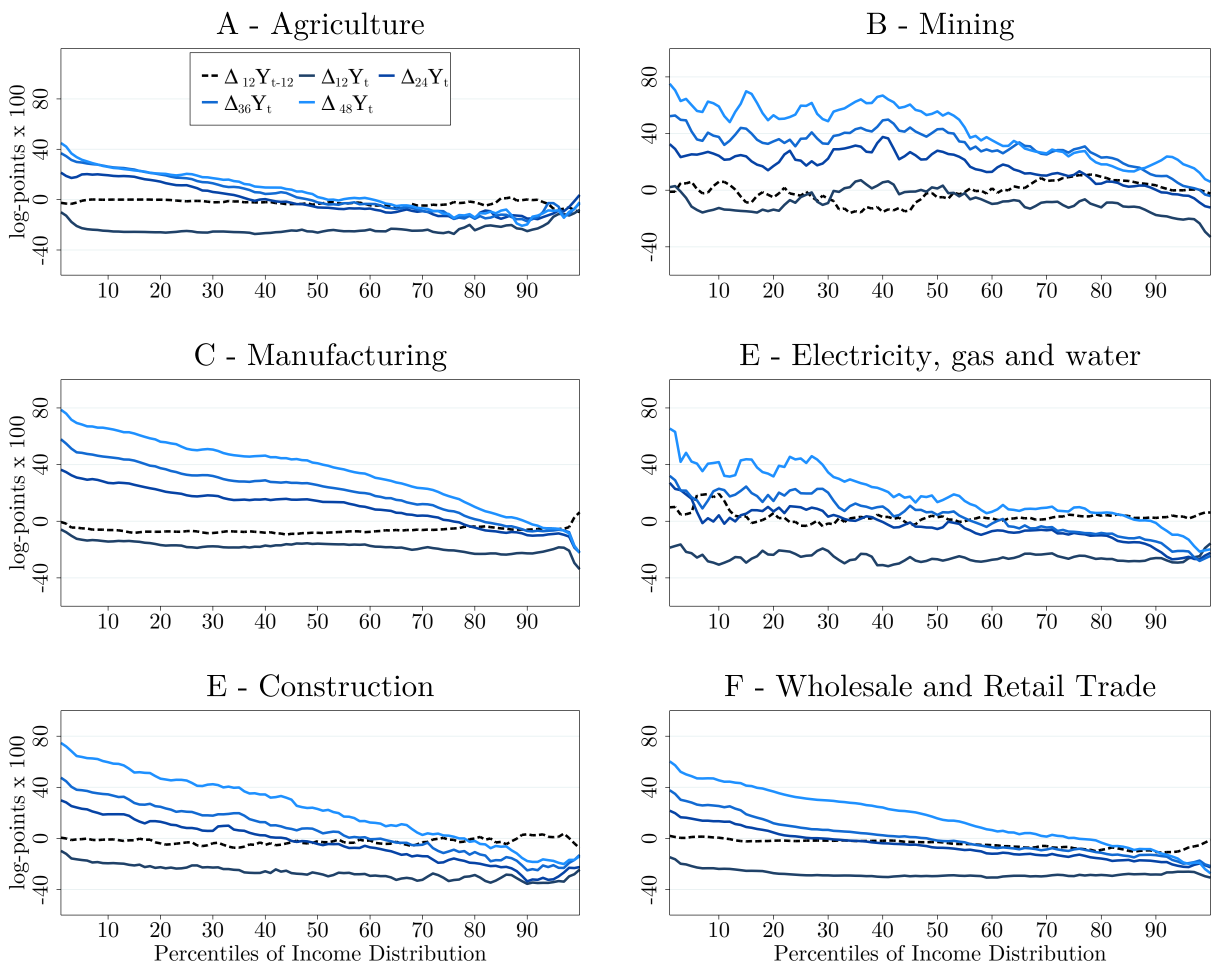


Notes: The figure shows output per worker in Argentina from 1997 to 2006. The series is normalized to its value in the first semester of 2001 and expressed in log points $\times 100$. We compute output per worker as the ratio between real GDP and total employment from the Permanent Household Survey.

D Mechanisms Behind the Fall in Inequality: Additional Results

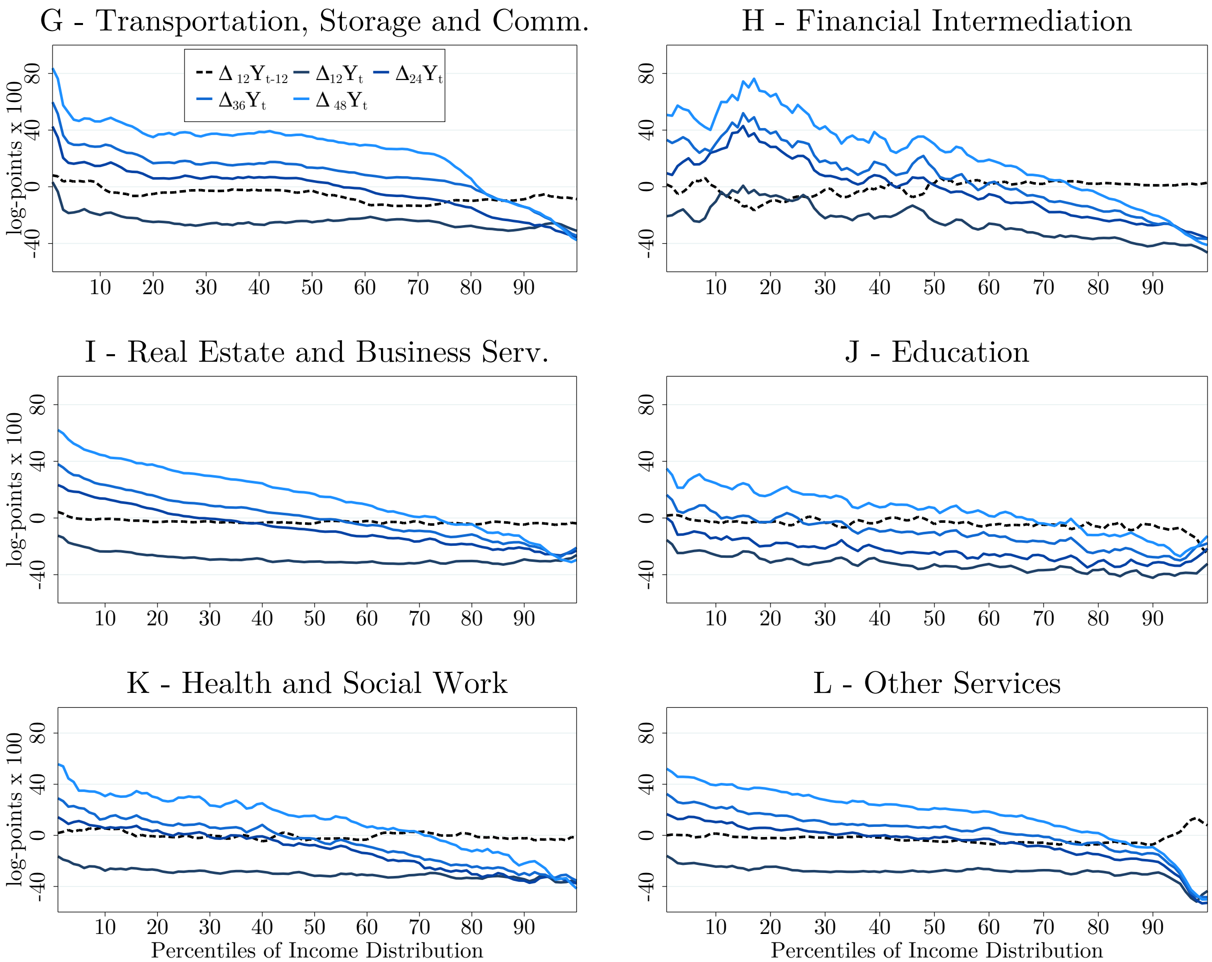
D.1 Robustness Analysis of Parallel Drop and Pivoting

Figure D.1 – Avg. income growth conditional on average income in 2000-2001 by sector



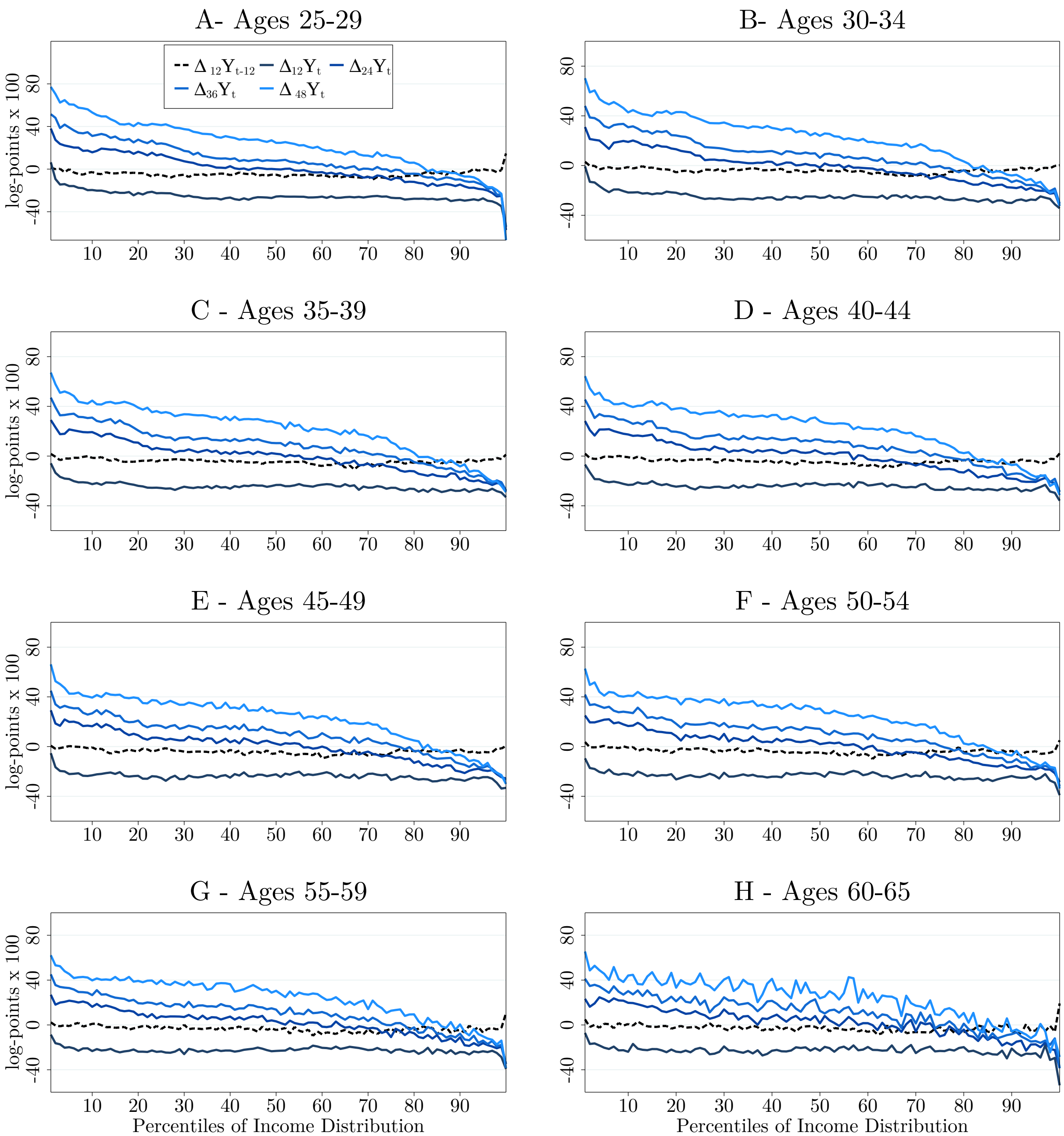
Notes: The figure plots average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. The figures are split according to the sector of employment in December 2001.

Figure D.1 – Avg. income growth conditional on average income in 2000-2001 by sector



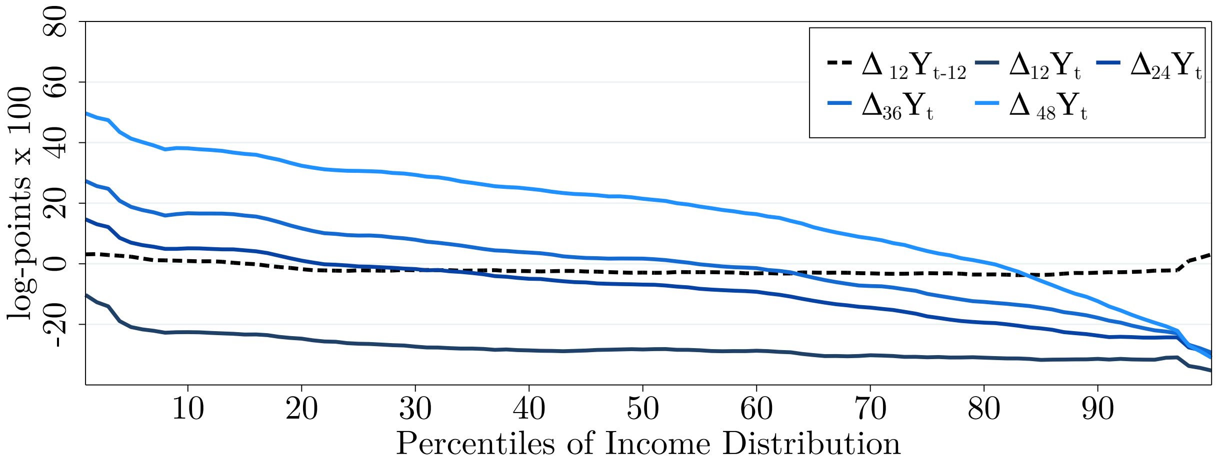
Notes: The figure plots average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. The figures are split according to the sector of employment in December 2001.

Figure D.2 – Avg. income growth conditional on average income in 2000-2001 by age



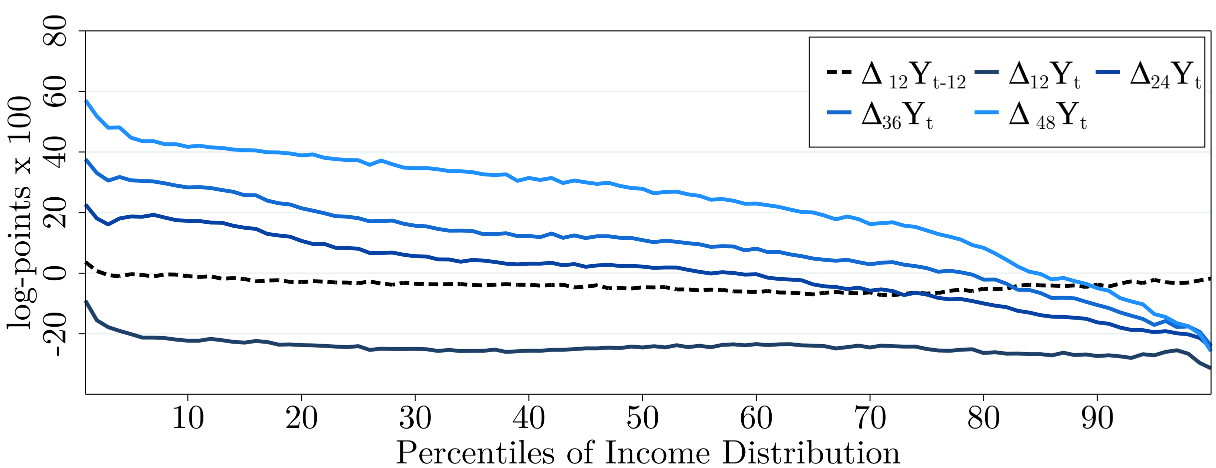
Notes: The figure plots average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. The figures are split according to the age group in December 2001.

Figure D.3 – Avg. income growth conditional on average income in 2000-2001: Women



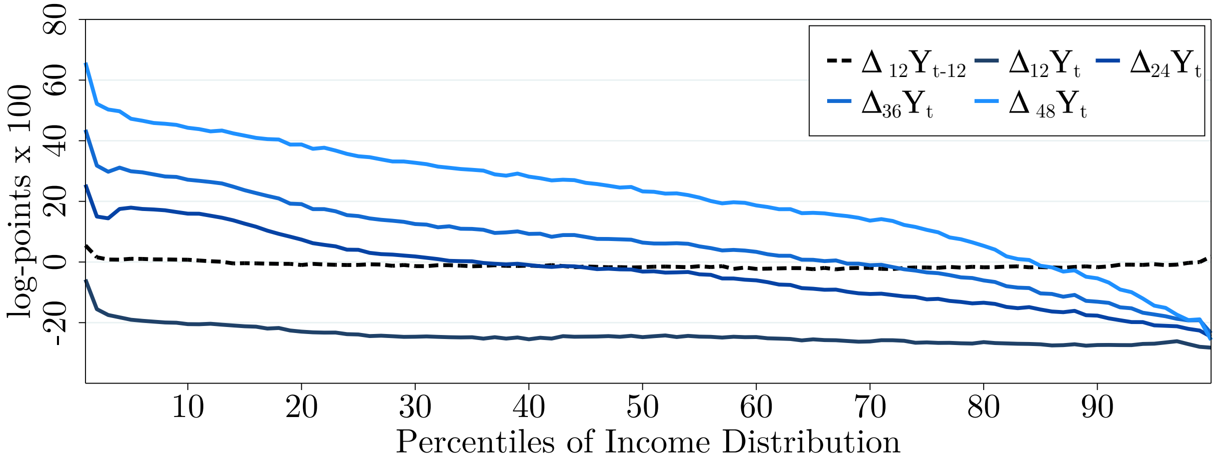
Notes: The figure plots average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period.

Figure D.4 – Avg. income growth conditional on average income in 1997-2001



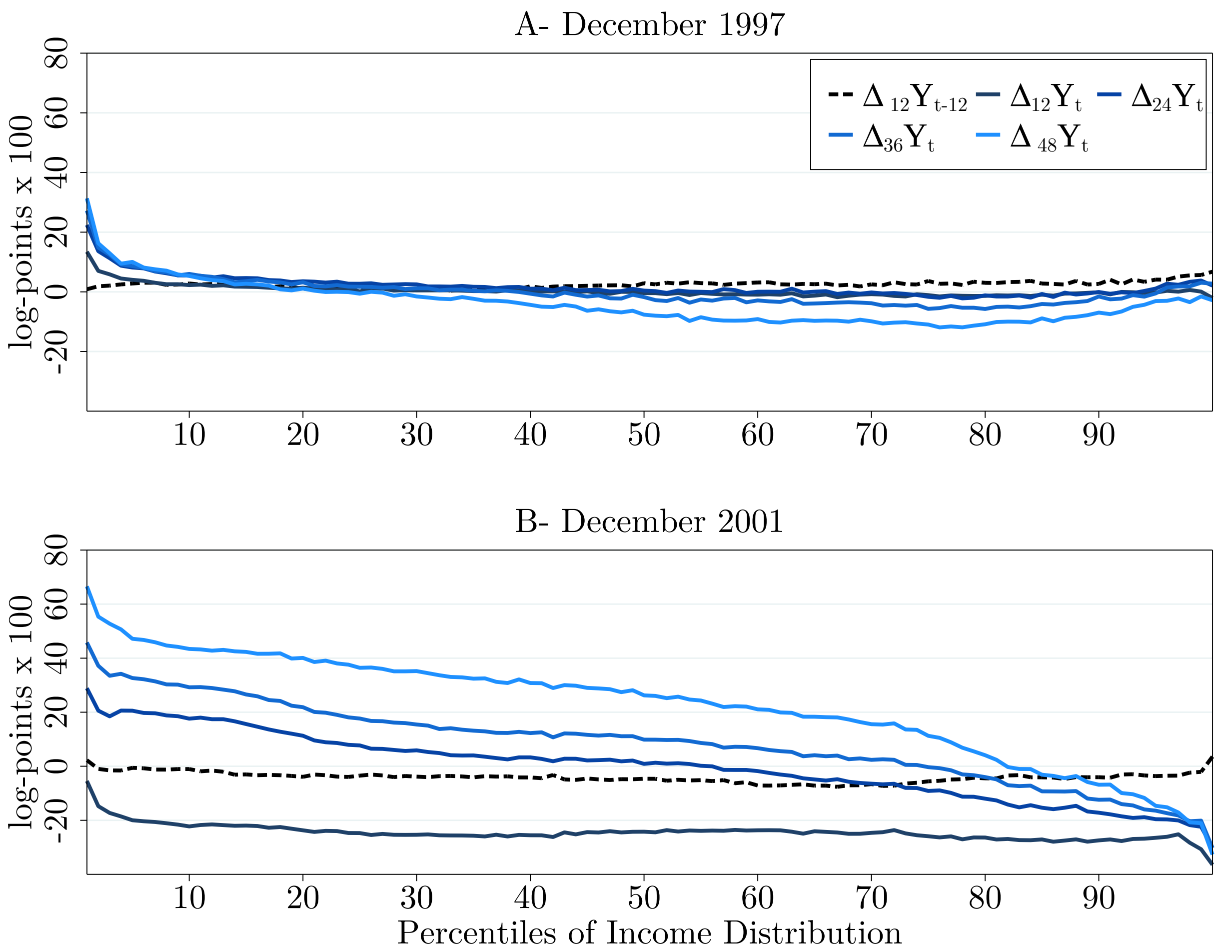
Notes: The figure plots average income growth conditional on the percentile of the distribution of average monthly real income during 1997-2001. The sample is restricted to workers who had at least 6 months of employment during the 1997-2001 period.

Figure D.5 – Avg. income growth conditional on average income in 2000-2001: Quarterly income



Notes: The figure plots average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. Average income growth is constructed using data on the average monthly income in the last quarter of each year.

Figure D.6 – Average income growth conditional on average income: 1997 vs 2001



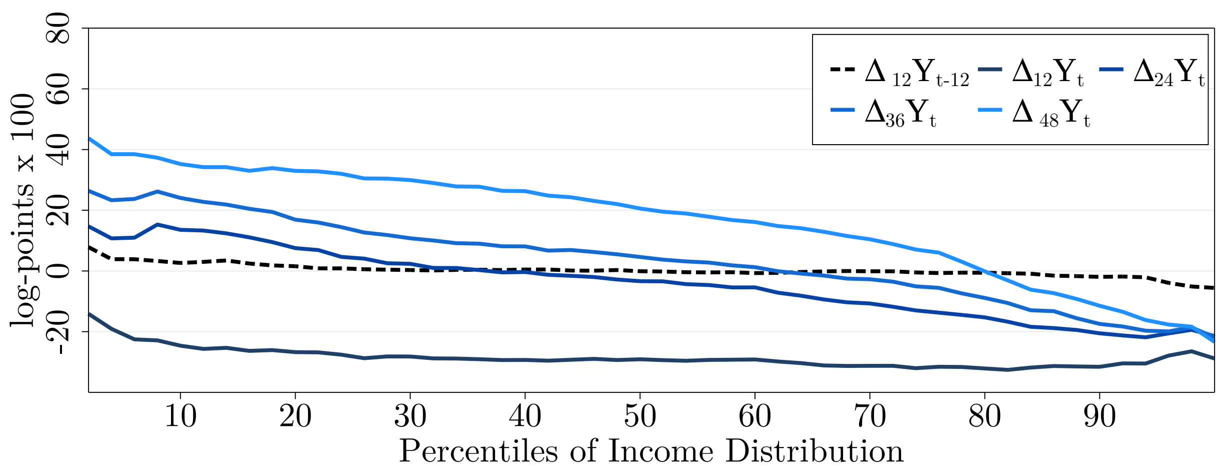
Notes: Panel A (B resp.) plots average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001 (1996-1997 resp.). The sample is restricted to workers who had at least 6 months of employment during the 1996-1997 and 2000-2001 periods.

Pre-devaluation trends in income growth. Here, we control for workers' pre-devaluation trends in income growth to verify whether our main fact could be driven by mean reversion in growth rates. For this exercise, we follow Guvenen *et al.* (2014). In addition to controlling for age and the pre-devaluation *level* of income $\bar{Y}_t^i$, as we did in our baseline analysis, we add a control for a worker's income *growth* 5 years before the devaluation $\Delta\bar{Y}_t^i \equiv \bar{Y}_t^i - \bar{Y}_{t-59}^i$ (where t denotes the month prior to the devaluation). To do this, we sort workers within an age group (25-29, 30-24, ..., 60-65) by their $\bar{Y}_t^i$ and $\Delta\bar{Y}_t^i$, separately, and compute 50th- and 40th-quantile thresholds, respectively. With these thresholds in hand, we categorize workers into groups according to their age, pre-devaluation level of income (indexed by l), and pre-devaluation income growth (indexed by g). Then, we compute the average income ($y_{t+k}^{l,g}$ for $k \in \{-12, 0, 12, 24, 36, 48\}$) across all workers within each of these 2,000 cells. Finally, we estimate the following equation via OLS:

$$y_{t+k}^{l,g} - y_t^{l,g} = \sum_{l=1}^{50} \alpha_l \mathbb{1}_{\bar{Y}}\{l\} + \sum_{g=1}^{50} \beta_g \mathbb{1}_{\Delta\bar{Y}}\{g\} + \varepsilon_t^{l,g}, \tag{D.4}$$

where $\mathbb{1}_{\bar{Y}}\{l\}$ is a dummy variable equal to one if the observation belongs to a group of workers in the l-th quantile of the pre-devaluation income distribution, and $\mathbb{1}_{\Delta\bar{Y}}\{g\}$ is a dummy variable equal to one if the observation belongs to a group of workers in the g-th quantile of the pre-devaluation distribution of income growth. Figure D.7 plots the estimated values of α_l at different horizons as a function of workers' position in the pre-devaluation income distribution. Controlling for workers' pre-devaluation income growth does not affect our main fact about the heterogeneous recovery after the 2002 devaluation. Thus, our main fact is not driven by mean reversion in growth rates.[35]

Figure D.7 – Avg. income growth conditional on average income in 2000-2001: Controls for past trends



Notes: The figure plots average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. The figure plots the coefficients α_l from an OLS estimation of equation (D.4).

[35]We inspected the estimated values of β_g and found evidence of mean reversion in income growth, as in Guvenen *et al.* (2014). However, we find that this mean reversion has no sizable impact on the main fact documented in the paper.

D.2 The Role of Sectors, Firms, and Workers

D.2.1 Anatomy of the Recovery: A Simple Variance Decomposition

We decompose the overall cross-sectional variance of log real income into between and within components across sectors and firms. Let y_{ijst} be the log real income of worker i employed in firm j in 4-digit sector s in period t. This can be rewritten as follows:

$$y_{ijst} \equiv \bar{y}_{st} + [\bar{y}_{jst} - \bar{y}_{st}] + [y_{ijst} - \bar{y}_{jst}],$$

where $\bar{y}_{st}$ is the average log real income in sector s, and $\bar{y}_{jst}$ is the average log real income in firm j in sector s. Then, the variance of y_{ijst} can be decomposed into three components:

$$\text{var}(y_{ijst}) \equiv \underbrace{\text{var}_s(\bar{y}_{st})}_{\text{Between-sector dispersion}} + \underbrace{\sum_s \omega_{st}\text{var}_j[\bar{y}_{jst}|j \in s]}_{\text{Between-firm dispersion}} + \underbrace{\sum_j \omega_{jt}\text{var}[y_{ijst}|i \in (j,s)]}_{\text{Within-firm dispersion}}, \tag{D.5}$$

where ω_{st} is the employment share of sector s in the sample and ω_{jt} is the employment share of firm j. The first term captures the between-sector variance of sectoral average log real income. The second term is the weighted average of the within-sector and between-firm variance of firm average log real income. The last term is the weighted average of the within-sector and within-firm variance of workers' log real incomes.

Figure D.8, Panels A and B, plot the results of the decomposition for each month between January 2000 and December 2006. From the peak in December 2001, the cross-sectional variance of log real income decreased by 21.4 log points. Of this total decrease, a decrease of 7.4 log points was due to the between-sector component, a decrease of 6.9 log points was due to the between-firm component, and a decrease of 7.1 log points was due to the within-firm component. That is, each component almost equally accounts for 33% of the decline in labor income inequality.

A natural follow-up question is: How important is the reallocation of workers to explain the between-sector component? To answer this question, we further decompose the change in the between-sector component in equation (D.5):

$$\Delta\text{var}_s(\bar{y}_{st}) = \underbrace{\sum_s \omega_{st}\left[(\bar{y}_{st} - \bar{y}_t)^2 - (\bar{y}_{st-1} - \bar{y}_{t-1})^2\right]}_{\text{Fixed weights}} + \underbrace{\sum_s (\omega_{st} - \omega_{st-1})(\bar{y}_{st-1} - \bar{y}_{t-1})^2}_{\text{Fixed dispersion}}. \tag{D.6}$$

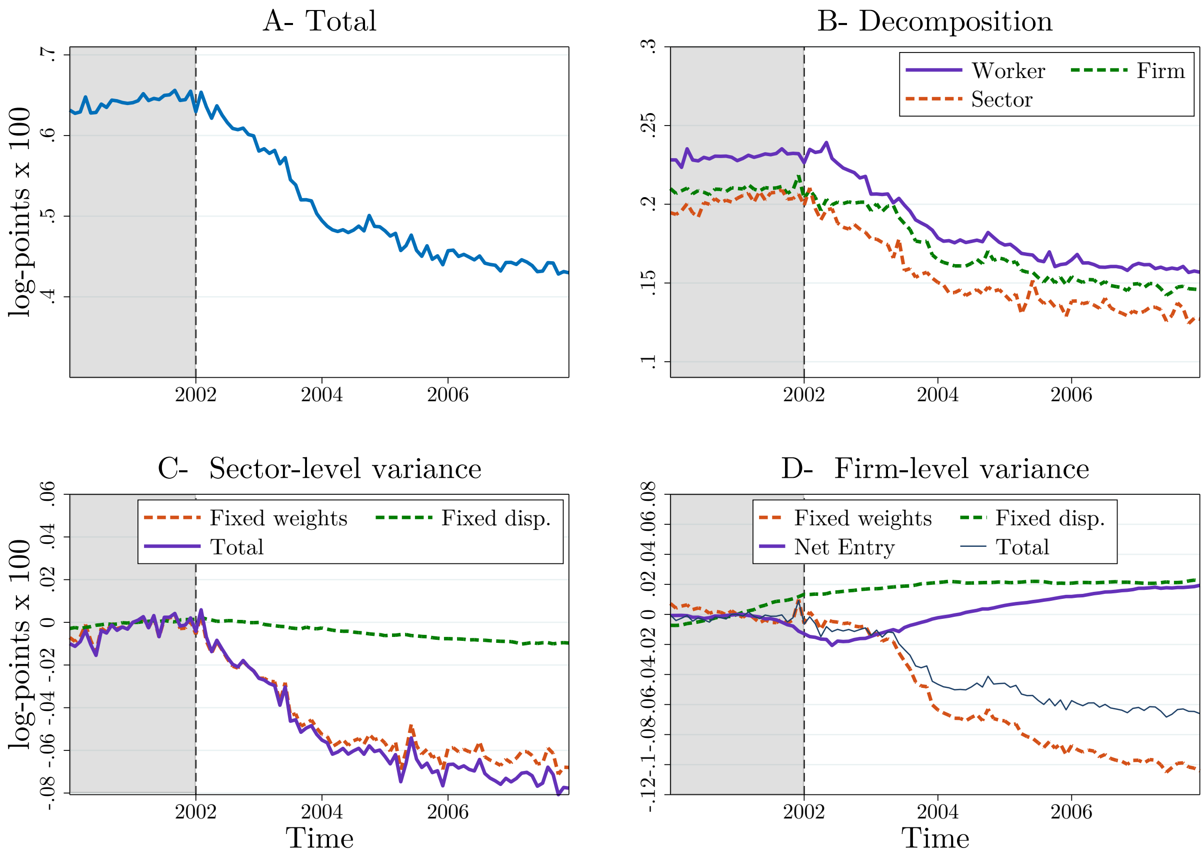
Here Δ denotes the difference operator, i.e., $\Delta y_t = y_t - y_{t-1}$. The first term captures changes in the between-sector component due to changes in sectoral squared deviations from the average labor income. The second term captures the contribution of changes in the weight of each sector. Figure D.8-Panel C plots the results of this decomposition. Of the overall decline in the between-sector component of 7.4 log points, 1 log point is accounted for by the reallocation of workers across sectors and 6.4 log points by within-sector changes in deviations from the average labor income. Thus, only 13% of the decline in the between-sector component is due to the reallocation of workers across sectors.

We repeat a similar exercise for between-firm dispersion and find that the variance across firms' wages decreases despite the reallocation of workers. We decompose changes in between-firm dispersion in three terms according to the following identity:

$$\Delta \sum_s \omega_{st} \text{var}_j \left[\bar{y}_{jst} | j \in s \right] = \underbrace{\sum_{s,j \in \mathcal{J}_{st} \& \mathcal{J}_{st-1}} \omega_{st}\omega_{jst} \left[\left(\bar{y}_{jst} - \bar{y}_{st} \right)^2 - \left(\bar{y}_{jst-1} - \bar{y}_{st-1} \right)^2 \right]}_{\text{Fixed weights}}$$
$$+ \underbrace{\sum_{s,j \in \mathcal{J}_{st} \& \mathcal{J}_{st-1}} \left[\omega_{st}\omega_{jst} - \omega_{st-1}\omega_{jst-1} \right] \left(\bar{y}_{jst} - \bar{y}_{st} \right)^2}_{\text{Fixed dispersion}}$$
$$+ \underbrace{\sum_{s,j \in \mathcal{J}_{st} / \mathcal{J}_{st-1}} \omega_{st}\omega_{jst} \left(\bar{y}_{jst} - \bar{y}_{st} \right)^2 - \sum_{s,j \in \mathcal{J}_{st-1} / \mathcal{J}_{st}} \omega_{st-1}\omega_{jst-1} \left(\bar{y}_{jst-1} - \bar{y}_{st-1} \right)^2}_{\text{Net entry}} . \tag{D.7}$$

Here $\mathcal{J}_{st}$ denotes the set of firms in sector s at time t. The first two terms have the same economic interpretation as in the decomposition of the between-sector component. The third term measures the change in the variance due to the entry and exit of firms. Figure D.8-Panel D plots the decomposition in equation (D.7). The variance increases due to changes in the weights of each firm and net entry. The overall increment since December 2001 is around 0.3 log points. The increase in the variance across firms' mean labor income due to the reallocation of workers between survival and new firms is overshadowed by the decline in the dispersion of mean labor income across firms. Therefore, the variance across firms' wages decreases despite the reallocation of workers between survival and new firms.

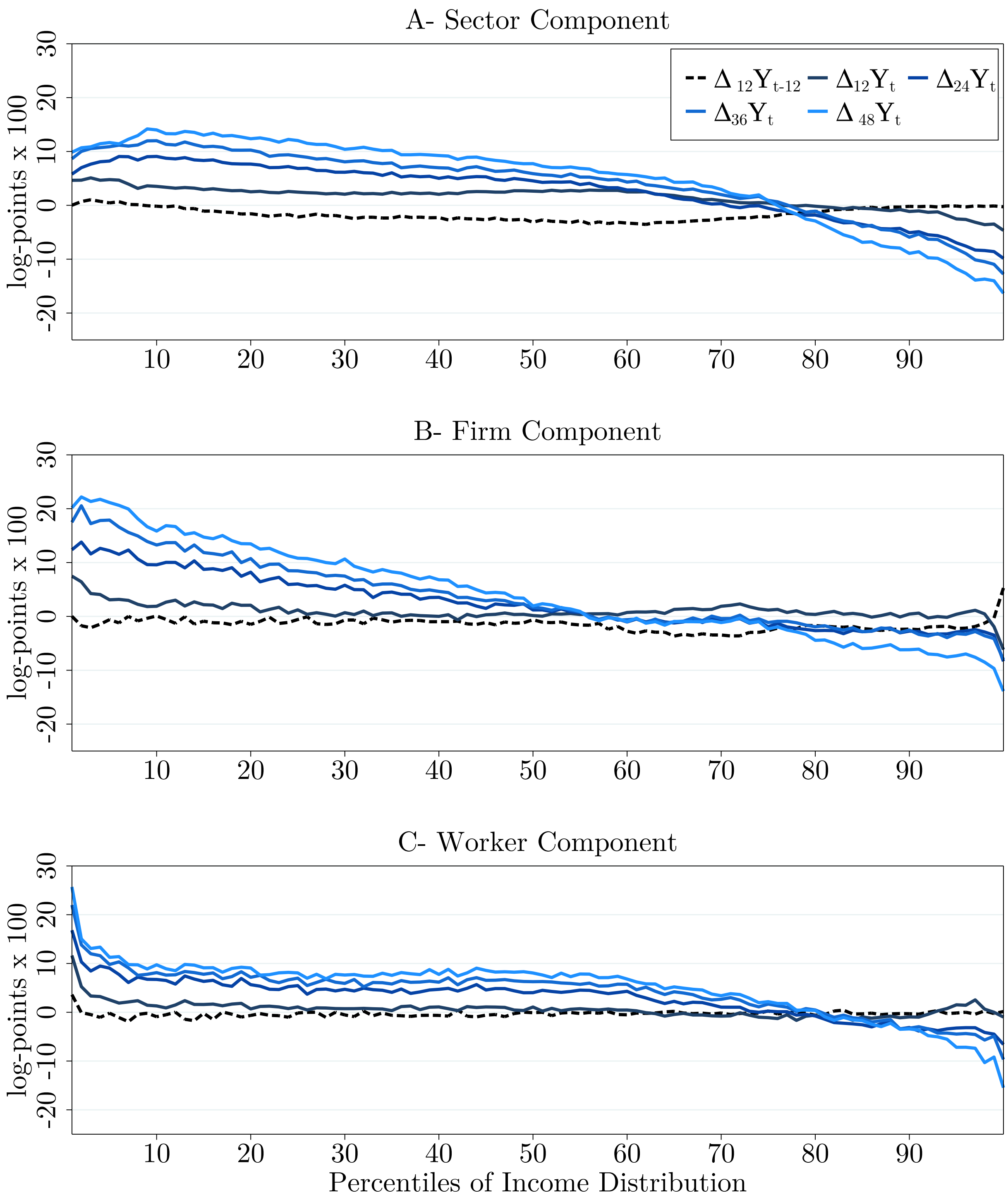
Figure D.8 – Variance decomposition across sectors, firms, and workers



Notes: The figure plots the total variance and its decomposition according to (D.5) from January 2000 to December 2006. The sector component is $var_s[\bar{y}_{st}]$, where $\bar{y}_{st}$ is the average income at sector s defined at 4-digit ISIC level. The firm component is $\sum_s \omega_{st} var_s[\bar{y}_{jst}]$, where $\bar{y}_{jst}$ is the average income at firm j in sector s and ω_{st} is its workers' share. The worker component is $\sum_j \omega_{jt} var_j[\bar{y}_{ijst}]$, where $\bar{y}_{ijst}$ is the labor income of worker i at firm j in sector s and ω_{jt} is firm's j workers' share. Panels C and D report the decomposition of the sector and firm components in equations (D.6) and (D.7).

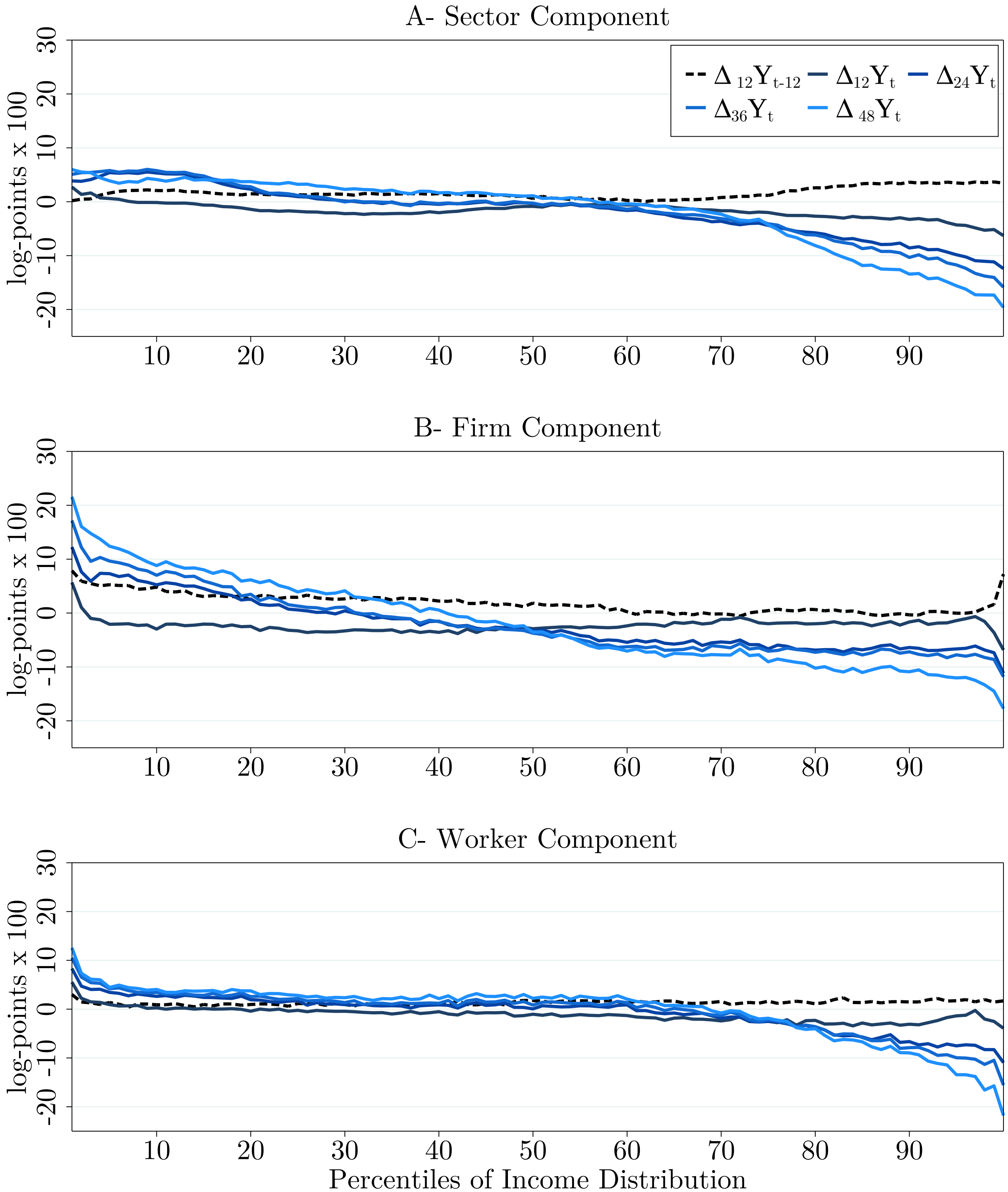
D.2.2 Additional Figures

Figure D.9 – Decomposition of average income growth conditional on average income in 2000-2001: Workers employed in firms with at least 10 employees



Notes: The figure plots average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. Relative to the baseline analysis, the sample is further restricted to workers who, in December 2001, were employed in firms with an average size (during the 2000-2001 period) of at least 10 employees. Panel A replaces a worker's labor income with the average labor income in the sector of employment net of the overall average labor income in the given year. Panel B replaces a worker's labor income with the average labor income in the firm of employment net of the sectoral average labor income. Panel C replaces a worker's labor income with the worker's labor income net of the firm's average labor income.

Figure D.10 – Decomposition of average income growth conditional on average income in 2000-2001: Averages conditional on being an employed worker in December 2001



Notes: The figure plots average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. Relative to the baseline analysis, here we only use data on workers who were employed in December 2001 when computing the average income within sectors and firms. Panel A replaces a worker's labor income with the average labor income in the sector of employment net of the overall average labor income in the given year. Panel B replaces a worker's labor income with the average labor income in the firm of employment net of the sectoral average labor income. Panel C replaces a worker's labor income with the worker's labor income net of the firm's average labor income.

D.3 Mechanism II: Heterogeneous Income Floors Set by Unions

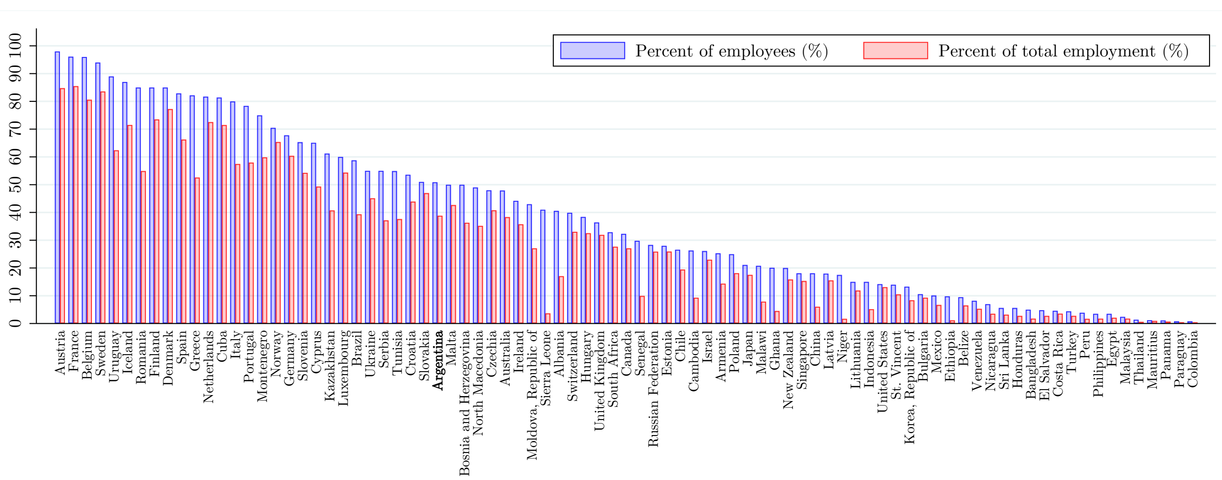
D.3.1 The Union System in Argentina

This section complements the analysis in the main text in several dimensions. First, we present the unionization system in Argentina within an international context. Second, we describe the institutional background of the union system in Argentina. Third, we describe the timing of collective bargaining to understand the interaction between unions, the 2002 devaluations, and the significant drop in real income during this episode.

International comparison. Collective bargaining is a negotiation process between unions and employers to determine terms and conditions of employment. Most workers in the OECD, outside the United States, have their wages determined by collective bargaining agreements (see Galiani and Gerchunoff, 2003). Collective bargaining agreements across countries can differ in three dimensions: (i) the coverage rate, (ii) the distinction between union membership and coverage, and (iii) the level of bargaining. We now compare the union system in Argentina with the rest of the world across these dimensions.

The coverage rate refers to the fraction of employees the collective bargaining agreement covers regardless of their individual membership status. Figure D.11 shows the coverage rate across countries in 2005 among all workers (e.g., including informal employment) and employees. As Figure D.11 shows, Argentina's coverage rate is between those observed in higher-coverage countries—e.g., France and Germany—and lower-coverage countries—e.g., Canada and Chile. In conclusion, Argentina is the "median" country regarding coverage rates.

Figure D.11 – Worldwide Coverage Rates

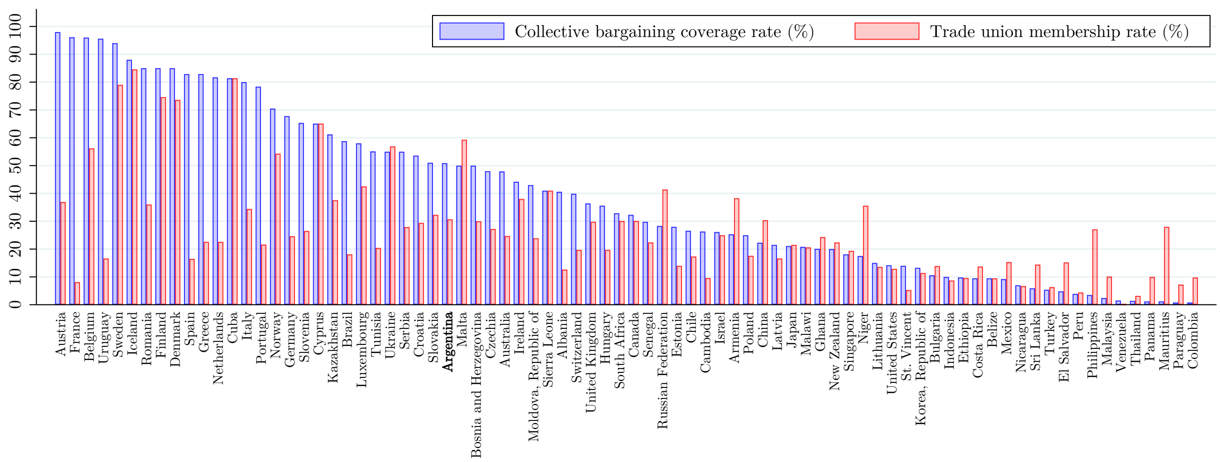


Notes: The figure plots coverage rates across 85 countries using the first observation available over the period 2000-2017 (year 2006 on average). Red bars show coverage rates as a percentage of total employment (e.g., including informal employment). Blue bars show coverage rates as a percentage of total employees. Source: ILO (2015).

The unionization (or union membership) rate is different from the coverage rate. The unionization rate is defined as the share of employees who are union members. For example, workers in a subset of occupations and firms in the U.S. automotive manufacturing sector are unionized (e.g., GM and Ford workers). Nevertheless, there are also workers in the same occupations and industries who are not unionized (e.g., those employed by Toyota and Tesla). Therefore, coverage and unionization rates are closely related in the

U.S. In Argentina, as in most countries, all workers in the formal sector are covered if there is a union that covers that particular occupation and sector. For example, all workers within a subset of occupations in the automotive sector are covered by the collective bargaining agreement regardless of the firm they work for and their individual membership status. Thus, coverage rates are usually larger than unionization rates. Figure D.12 shows coverage and unionization rates across countries in 2006.

Figure D.12 – Comparison between Coverage and Unionization Rates across Countries



Notes: The figure plots unionization and coverage rates across 80 countries using the first observation available over the period 2000-2017 (year 2006 on average). Blue bars show coverage rates as a percentage of total employees. Red bars show union membership rates as a percentage of total employees. Source: ILO (2015).

Finally, unions could bargain at the national, sector, or firm level. In the majority of countries with high coverage rates, the most common level of bargaining is at national or sectoral level. As ILO (2015) shows, for the 57 countries in which data are available, that 33% have a national or intersectoral bargaining level, 22% have sectoral or firm-level bargaining, and 45% have firm-level bargaining. Argentina is in the middle category, since most relevant bargaining occurs at the sectoral level, but there is room for additional bargaining with large firms.

Institutional background in Argentina.[36] The union system in Argentina, which originated in the 1950s and followed the model of Continental Europe, is characterized by three features: (i) unions are centralized, (ii) negotiations occur at the industry level, and (iii) there is a high rate of coverage. In Argentina, a single union that has a special status ("personeria gremial") can sign CBAs, call a strike, and collect fees. This status can be obtained when a union organization proves that it affiliates at least 20% of all workers within its scope and has been active for at least 6 months. Typically, the scope of a union is delimited by the group of workers who work in a specific industry and region and work in certain occupations (see Figures **??**, **??**, and **??** for examples of how unions specify the occupations covered by an agreement).

The regulatory system in Argentina provides that CBAs that are approved by the National Ministry of Labor will apply to all workers in the industry or region included in the scope of the agreement, regardless of whether the worker or employer is affiliated with representative organizations of workers or employers.

[36] The following description is based on Laws 14,250, 23,546, and 23,551, which regulate the union system in Argentina.

However, the agreements may exclude certain groups of workers from their scope. Since unions are traditionally blue-collar organizations, this last situation is common among white-collar workers (e.g., management, hierarchical, or supervisory personnel), who thus remain outside the scope of coverage of the agreement. Thus, the union system in Argentina—as in Europe and Latin America—establishes an important distinction between union coverage and membership. While the worker can choose whether to become a union member or not (to receive additional benefits from the union), the worker cannot opt out of the coverage of a CBA if her occupation/industry falls within the scope of the agreement.

Regarding the content of these agreements, unions typically negotiate a wide range of aspects related to employment contracts: wages (which first requires specifying the categories of covered workers and their responsibilities on the job), working hours, performance-based and other bonuses, payment of overtime, health and safety conditions, training, and mechanisms for dispute-resolution, among others. Thus, collective bargaining regulates not only workers' labor compensation, but also their employment conditions and the rules that govern the employer-employee relationship.

It is worth noting, that trade unions negotiate wage floors for workers covered by CBAs, but the law give firms the ability to pay wages above those lower bounds. Thus, it is possible that similar workers (e.g., those with the same occupation) will have their wages affected by the same income floors and still earn different wages because firms pay them above those floors. In any case, the floors serve as reference points during the wage-bargaining process. Importantly, while regulation that sets a minimum wage exists in Argentina, it applied to only 1% of workers before the 2002 devaluation. Instead, the most relevant income floors in Argentina are set by trade unions, which differ by sector and occupation.

Timing of collective bargaining. The importance of CBAs changed during our period of analysis. During the 1990s, a macroeconomic context of a privatization program, a wide-ranging trade liberalization, and a low and stable inflation process considerably reduced the power of unions. Within this context, salary negotiation ceased to be the main point of negotiations, and clauses that aimed to make labor relationships more flexible prevailed in the content of the CBAs.[37] Given the lack of new collective bargaining agreements, the Argentinian law allows expired contracts to remain valid until a new contract is signed by the union and the firms. The result of this law was that during the 1990s, a large proportion of the wages remained determined by contracts negotiated at the beginning of the decade that were not renegotiated after their expiration.

This changed dramatically after the 2002 devaluation, when the government promoted collective bargaining for wages to compensate for the strong transfer of income in favor of companies generated by the devaluation and the abrupt increase in domestic prices, which sharply reduced the real wage. As Figure C.1 shows, the labor share decreased by 10% during the year of the devaluation. During the first year, there was not much bargaining, consistent with real income falling by an amount similar to the rise in inflation. Arguably, this was because unions and firms needed time to reinstate the labor institutions through which bargaining occurs, which had not been used in more than a decade. In mid-2003, union bargaining resumes across many industries, with a slight variation of a few months across agreements.[38] Since then, unions

[37] Additionally, several laws were passed to limit the power of unions within the boundaries of constitutional law. For example, Law 1334/91 required wage increments in new CBAs to follow improvements in productivity:

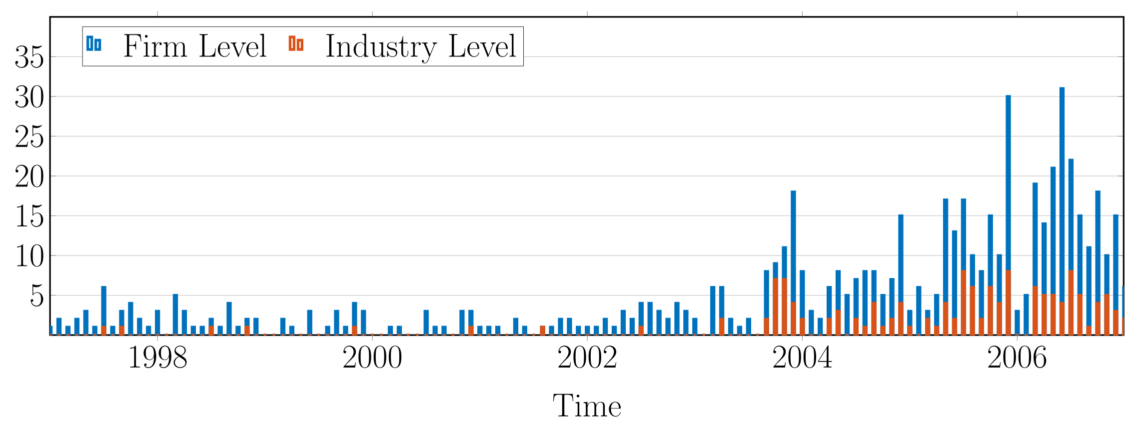
> "For the purposes of homologation, the Ministry [of Labor]... must take into account whether...a set of criteria in productivity, investments, technology incorporations, and vocational training system were taken into account..."

[38] Analysis of the determinants of the timing of union bargaining and its outcomes is outside the scope of this paper. However, previous literature has discussed some relevant factors: (i) the size itself of the

renegotiated the wage scales in previous agreements on a regular annual basis (although an agreement could specify wage scales for multiple periods in the year—typically, one for the first and another for the second half of the year). This change in focus was further precipitated by another piece of regulation in Argentina: Given Argentina's history of inflation, the law prohibits the indexation of most contracts, including labor contracts.

Additional evidence for the effects of unionization on the compression of the income distribution is presented in Panel A of Figure D.13, which shows the number of contracts negotiated by unions and firms in 12 sectors between 1996 and 2008. As the figure shows, after the increase in inflation brought about by the 2002 devaluation there is a rapid increase in the number of contracts renegotiated, especially at the industry level, which has the largest coverage.

Figure D.13 – Number of Contracts Negotiated by Unions

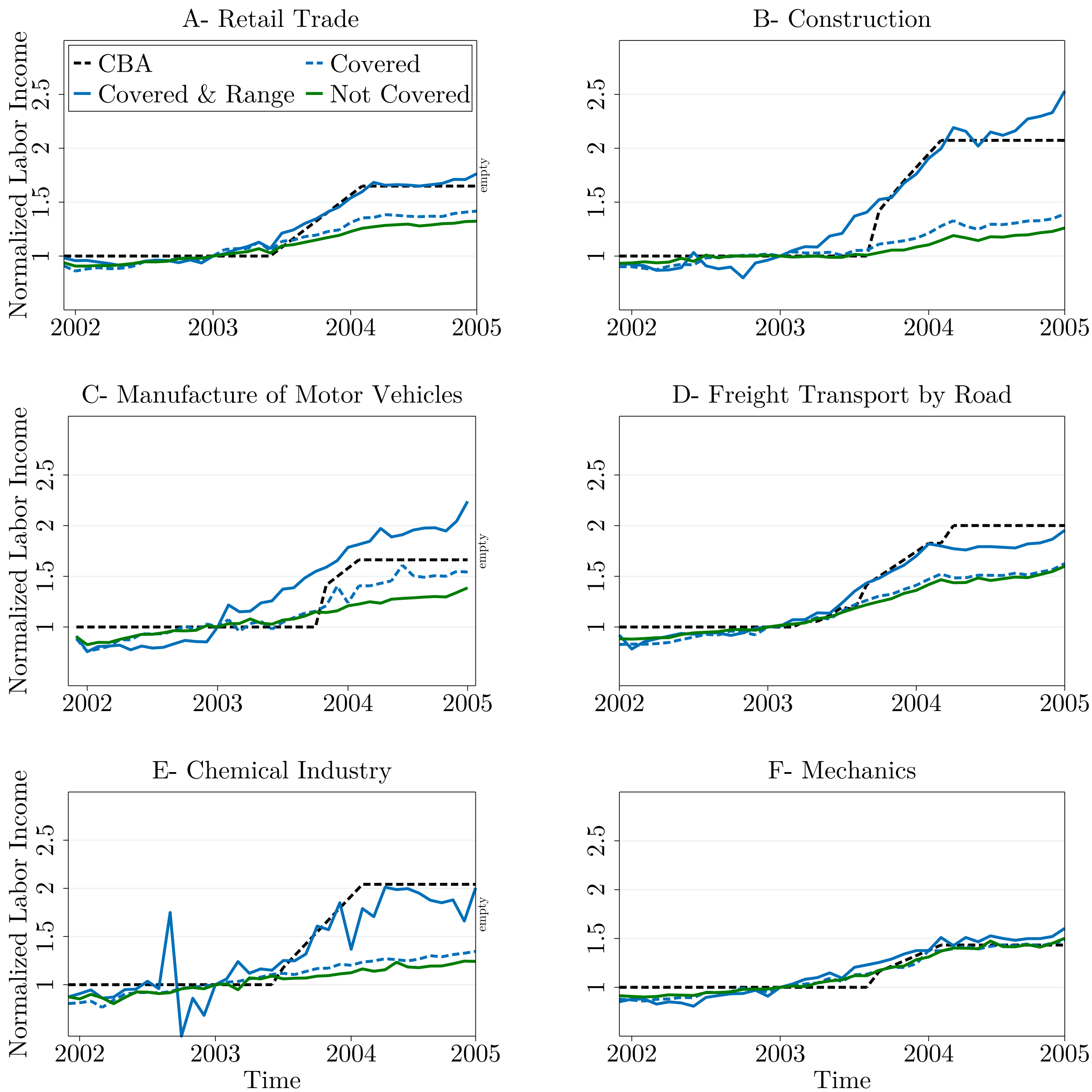


Notes: The figure shows the number of contracts negotiated by unions per month for a subset of industries. The sample of contracts includes only contracts that modified the scale of basic wages of workers. The source of these data are the original documents signed by the parties in each collective bargaining contract approved by the Argentinian Ministry of Labor.

union, which is presumably related to the consequences of its strikes, (ii) the ability of employers to absorb higher labor costs, which is influenced by the market power of an industry and the firms' ability to pass cost increases to final consumers, and (iii) the existence of outside options for workers (e.g., the informality rate is heterogeneous across industries), which could influence the bargaining power of the union.

D.3.2 Additional figures

Figure D.14 – Normalized labor income by union coverage and labor income in CBAs



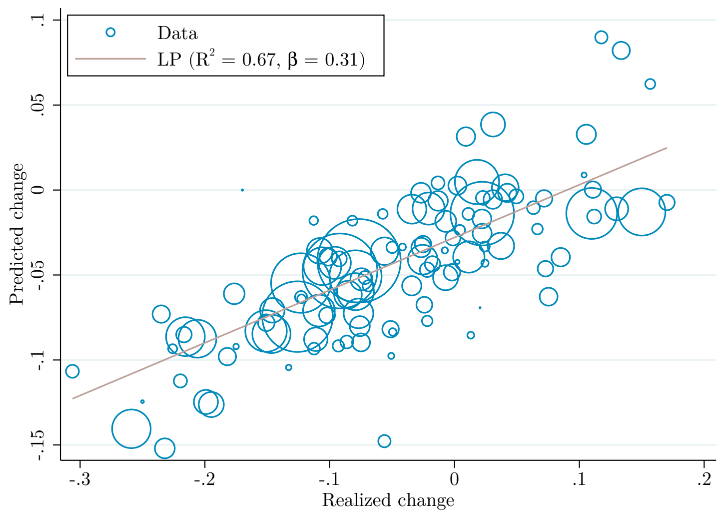
Notes: Panels A to F plot nominal income for the lowest paid occupation in each CBA and the average nominal income of workers covered and non-covered by the CBA across six sectors (i.e., retail trade, construction, manufacture of motor vehicles, freight transport by road, chemical manufacturing and mechanics). A worker belongs to the group "Covered" if she is covered by a CBA at any point in 2003 according to the SIPA dataset. A worker belongs to the group "Covered & Range" if she is covered in 2003 and her labor income is within 0-10% above the income of the lowest occupation established by the CBA in October 2002. A worker belongs to the group "Not Covered" if she is not covered by a CBA during 2003 in the SIPA dataset. Average nominal income is normalized to one in January 2003.

D.4 Mechanism III: Heterogeneous Trade Exposure

This section presents additional results on the role of trade in Argentina's labor market to complement our analysis in Section 5.3.3.

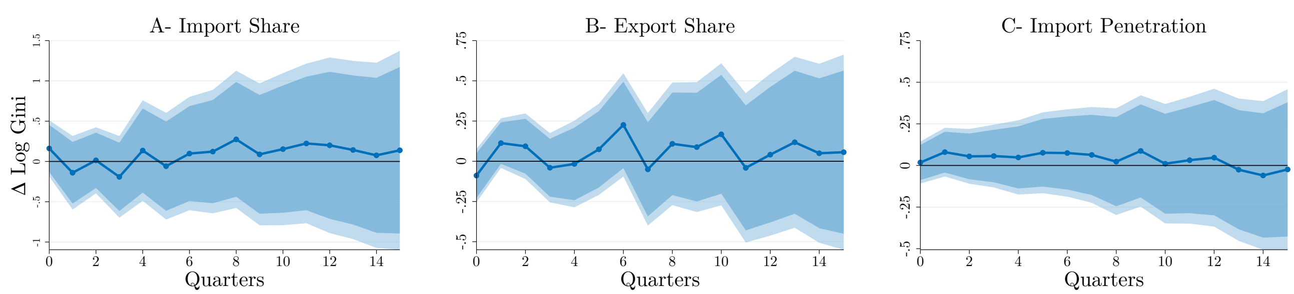
D.4.1 Additional Figures

Figure D.15 – Sample and predicted 3-year sectoral income growth



Notes: The figure plots the realized real income growth over 3 years from the last quarter in 2001 to the last quarter in 2004 by sector on the x-axis and the predicted real income growth from the projection in (1). The size of each circle reflects the number of workers employed in each sector. The red line shows the linear fit between the predicted and realized sectoral growth rates.

Figure D.16 – Trade Exposure and Within-Sector Inequality

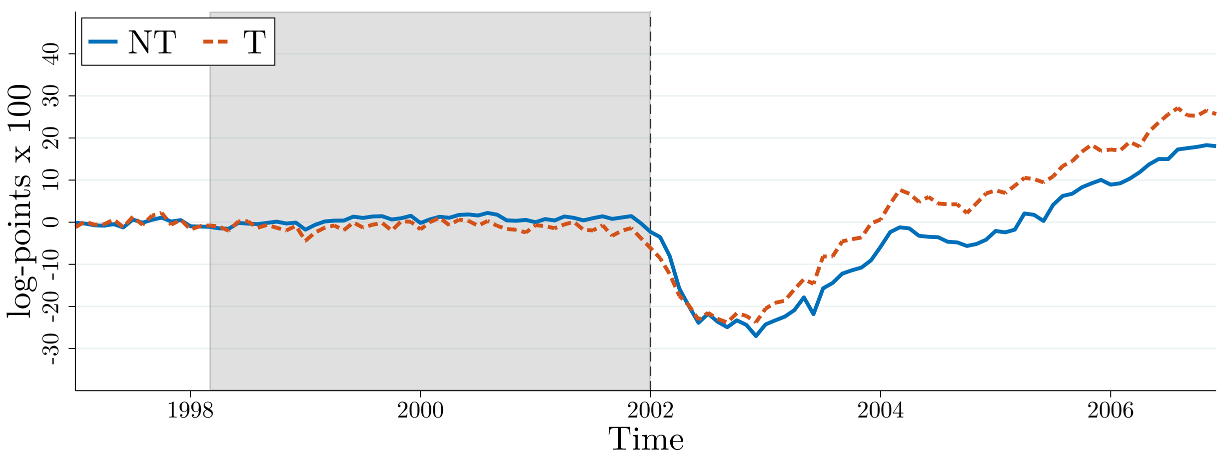


Notes: This figure reports the estimates of equation (1). The dependent variable is the quarterly growth rate of log sectoral Gini coefficient. Independent variables include the interaction of the quarterly change in the NER with the export share, the share of imported intermediate inputs and import penetration by sector, and time and sector fixed effects. Solid lines depict cumulative sums $\sum_{j=0}^{n} \phi_j$, $\sum_{j=0}^{n} \gamma_j$, and $\sum_{j=0}^{n} \delta_j$ for $n \in [0, 12]$. Shaded areas depict 90% and 95% confidence intervals based on robust standard errors. The estimation method is OLS and the equation is estimated using data over the 1997-2006 period.

D.4.2 Labor Markets in the Tradable and Nontradable Sectors

We first present a time-series analysis of tradable and nontradable sectors to show the reallocation of labor and trends of sectoral labor income.[39] Figure D.17 plots the average real labor income across sectors, normalized by the average income in the nontradable sector in January 2001. We can see two clear patterns around the 2002 devaluation. First, between December 2000 and 2001, there is a small difference in sectoral wages of 2.3% in favor of the nontradable sector. Second, following the 2002 devaluation, there is a faster recovery of labor income in the tradable sector relative to the nontradable sector. The tradable-sector wage premia over the course of 4 years are, in chronological order, 4%, 7%, 10%, and 8%. Thus, there is a significant difference in labor income dynamics across the tradable and nontradable sectors that follows the increase in revenue in tradable sectors relative to nontradable sectors.

Figure D.17 – Labor income by sector



Notes: The figure shows monthly average (log) real income from January 1997 to December 2006 for the tradable and nontradable sectors. The variables are seasonally adjusted and normalized by the average income in January 2001 in the nontradable sector. Recession periods are in gray, and monthly devaluations larger than 30% are marked with dotted black lines.

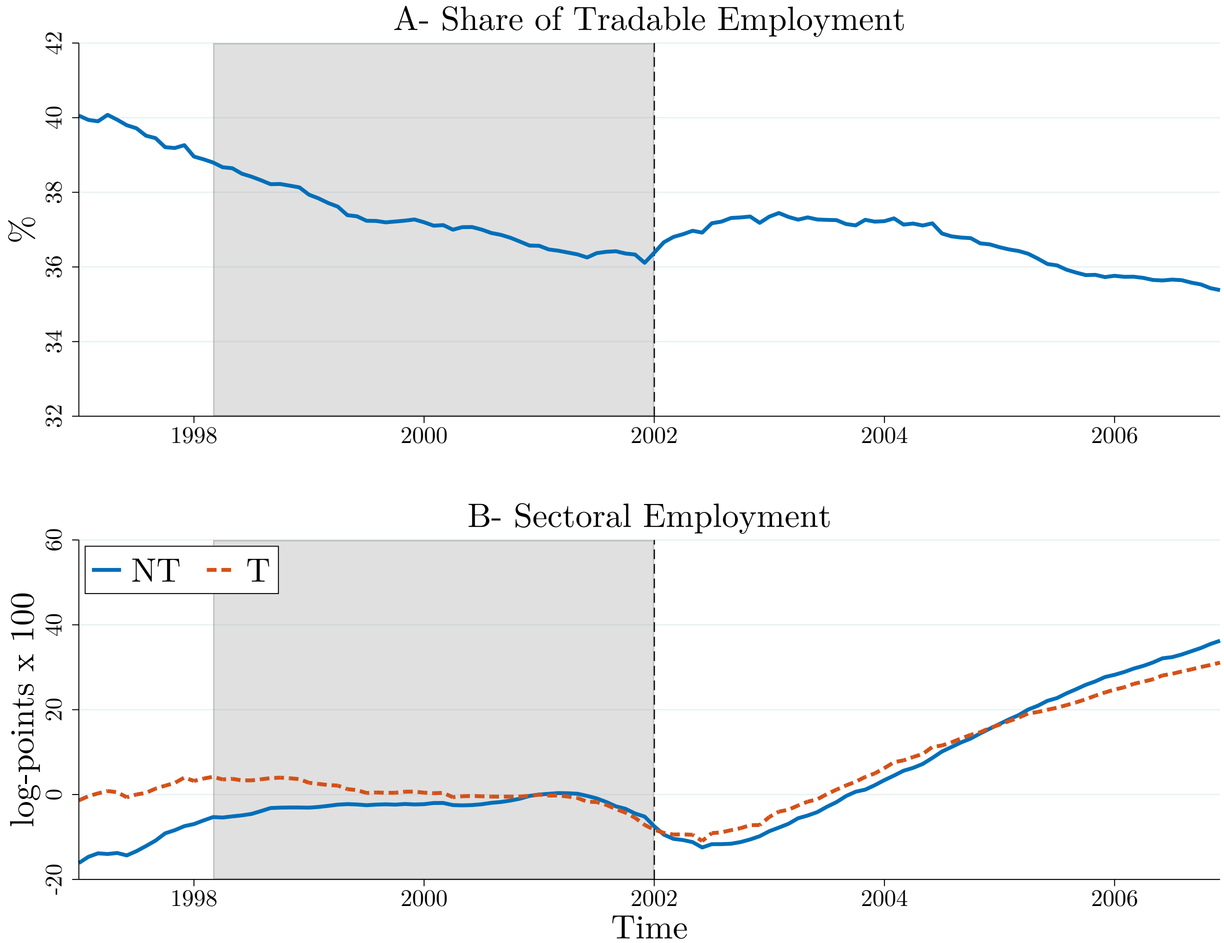
It is a well-known fact in the literature on structural change that there is a worldwide secular decline in employment in the tradable sector (see Buera and Kaboski, 2012). Argentina is no exception. Figure D.18-Panel A shows the share of tradable employment from 1997 to 2006. This share declined from 40% to 36% over 10 years. Within the context of a low-frequency reallocation of labor as part of structural change, we find a small reallocation of labor toward the tradable sector after large devaluations. During 2002, when the currency devalued by more than 100 log points, the share of tradable employment increased by only 1%.

Given the timing of the origination of the persistent income gap between sectors, we want to understand whether the workers driving this gap are at the bottom or the top of the distribution, or whether the gap is uniform across the distribution. Figure D.19 shows, in Panels A and B, the normalized percentiles and, in Panels C and D, the interquartile range and the standard deviation of the income distribution in each sector.

The first noteworthy pattern in Figure D.19 is the lack of dynamics in the income distribution across percentiles in each sector before the devaluation. Thus, the interquartile range and the standard deviation

[39] The tradable sector includes agriculture, livestock, and hunting, fishing and related services, mining, and the manufacturing industry.

Figure D.18 – Sectoral employment

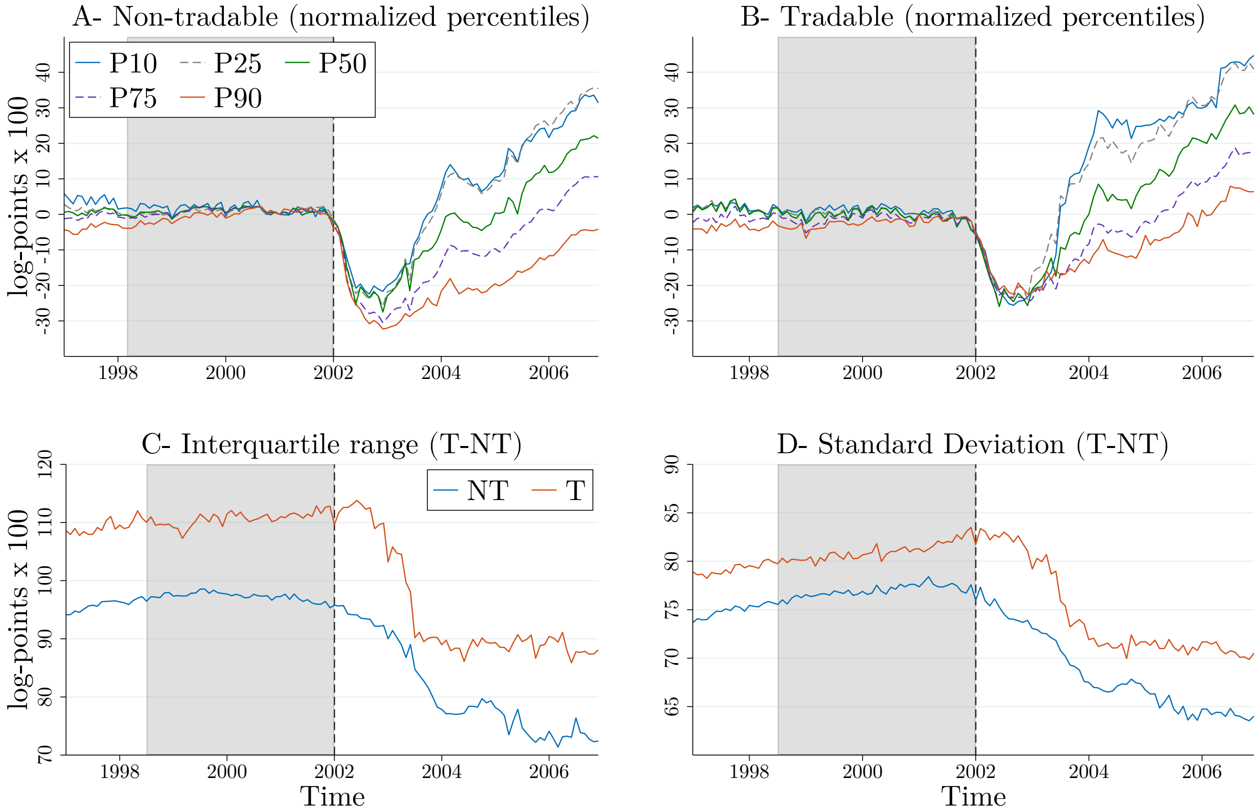


Notes: Panels A and B show the employment share in the tradable sector and the (log) total employment from January 1997 to December 2006 in the tradable and nontradable sectors, respectively. Total employment in each sector is normalized to zero in January 2001. Recession periods are in gray, and monthly devaluations larger than 30% are marked with dotted black lines.

are almost constant before 2002. These facts do not imply that the income distributions are equal across sectors. The interquartile range and the standard deviation are larger in the tradable sector. The second pattern is easier to visually appreciate 5 years after the devaluation. All of the normalized percentiles of the income distribution in the tradable sector are larger than the normalized percentiles in the nontradable sector. Thus, changes across the entire distribution are responsible for the observed gap in relative real income in tradable relative to nontradable sectors.

For this emerging tradable-sector wage premium to generate a fall in inequality, it has to be the case that tradable-sector workers were predominantly located at the bottom of the income distribution before the devaluation. Figure D.20-Panel A plots the share of tradable workers in each income bin in December 2001 and 2 and 4 years after. The largest share of tradable workers across the distribution, which is almost 15 percentage points higher than the average share across the income distribution, is in the 15th percentile. Since the gap in income growth between the tradable and nontradable sectors is also around 10%, being employed in the tradable sector can generate a difference in income growth across the distribution of around 1.5%, which is negligible relative to the heterogeneity in income growth shown in Figure 7. This is formalized

Figure D.19 – Percentiles of real labor income distribution by sector

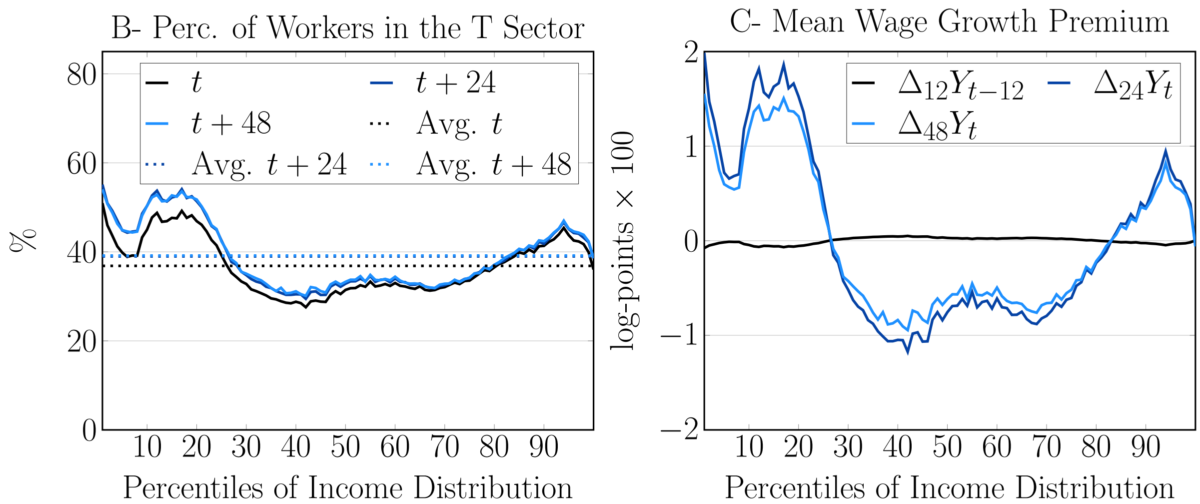


Notes: The figure plots statistics for monthly real income from January 1997 to December 2006. Panel A (B resp.) plots the percentiles in the nontradable (tradable resp.) sector of the log income distribution ($\times$ 100) normalized by the average in January 2001. We use NT (T resp.) to denote the nontradable (tradable resp.) sector. We use Px to denote the xth percentile of the distribution. Panels C and D plot the interquartile range ($P75 - P25$) and the standard deviation of the income distribution for the same time period across sectors.

in Figure D.20-Panel B, which shows the average tradable-sector income growth premium by income bin.[40] As we can see, the overall size of this premium is small. Furthermore, this premium is positive for workers at both the bottom and top of the income distribution, which mimics the concentration of tradable employment at both ends of the income distribution.

[40] To construct this figure, we first compute the cumulative growth in average income in the tradable and nontradable sectors relative to December 2001; e.g., 12 months after the devaluation. This is denoted by $\Delta_{12}\bar{Y}_t^T$ and $\Delta_{12}\bar{Y}_t^{NT}$, where $\bar{Y}_t^j$ denotes the average income in sector j in period t. Then, for each income bin, we plot $share_i^T \times \left(\Delta_{12}\bar{Y}_t^T - \Delta_{12}\bar{Y}_t^{NT}\right)$, where $share_i^T$ denotes the share of workers in income bin i who in December 2001 were employed in the tradable sector. Finally, we remove the average values from each line. Thus, Panel C of Figure D.20 shows the differential growth across income bins generated by the fact that tradable-sector income recovered faster after the devaluation.

Figure D.20 – Predicted Average Income Growth Conditional on Average Income in 2000-2001 for Tradable and Nontradable Sectors



Notes: Panel A plots the percentage of workers employed in the tradable sector by percentiles of income in December 2001 (denoted by t), December 2003 ($t+24$), and December 2005 ($t+48$), together with the average across percentiles of the income distribution on those dates (dashed lines). The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. Panel B plots, for each income bin, the share of workers employed in the tradable sector in December 2001 multiplied by relative cumulative income growth in the tradable sector. Each line is normalized by the average across income bins in each year.

D.4.3 Indirect Trade Exposure and Inequality

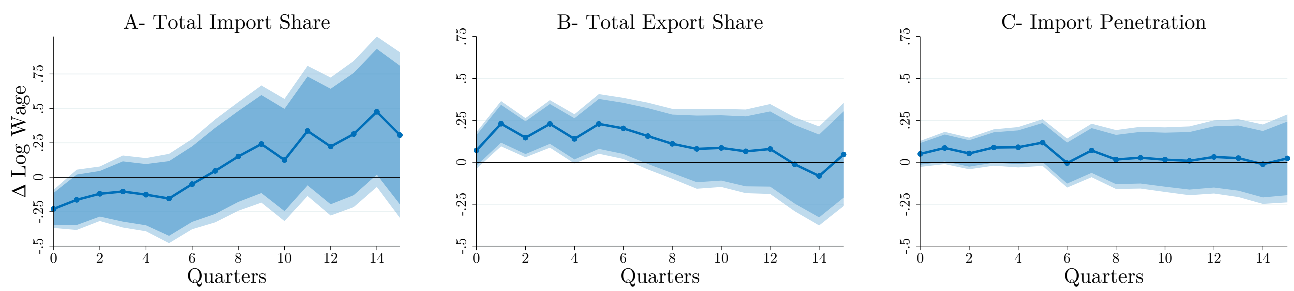
Recent evidence has documented the importance of firms' indirect trade exposure (see Dhyne *et al.*, 2021). Such exposure arises from the fact that although some firms do not directly buy foreign inputs or sell in foreign markets, they buy from or sell to domestic firms that import or export. Here, we show that our previous results are robust to incorporating such indirect trade exposure in the analysis.

To do so, we recompute our baseline trade-related variables, which only capture direct trade exposure, using the 1997 Input-Output matrix in Argentina. More specifically, we compute the total intermediate import share of a sector as the share of intermediate inputs purchased directly or indirectly (i.e., through other sectors) from abroad, and the export share as the total share of output it sells directly or indirectly (i.e., through other sectors) to foreign markets. We compute import penetration in the same way as in the baseline analysis. Then the new estimating equation becomes:

$$\begin{aligned}\Delta outcome_{st} = &\sum_{j=0}^{12} \phi_j \Delta NER_{t-j} \times \text{Total Import Share}_{s1997} \\ &+ \sum_{j=0}^{12} \gamma_j \Delta NER_{t-j} \times \text{Total Export Share}_{s1997} \\ &+ \sum_{j=0}^{12} \delta_j \Delta NER_{t-j} \times \text{Import Penetration}_{s1997} + \alpha_s + \beta_t + \varepsilon_{st}. \qquad \text{(D.8)}\end{aligned}$$

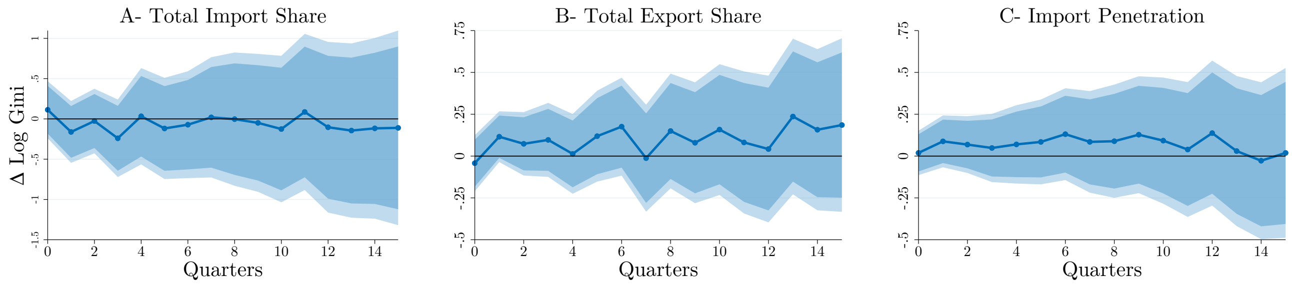
We estimate (D.8) using quarterly data around the 2002 devaluation from the first quarter in 1997 to the last quarter in 2006. Figures D.21 and D.23 reproduce the analysis in Figures 13 and 14 with the measures that capture total (i.e., direct and indirect) trade exposure. The figures show that in the short and medium run, sectoral income growth is negatively associated with a sector's total import share—and positively associated with a sector's total export share and degree of import penetration, as in our baseline analysis. With these alternative exposure measures, we still find that the predicted differences in sectoral income growth across the pre-devaluation income distribution are small (see Figure 14-Panel A). The reason is once again that winners ands losers from these trade-related channels are quite similarly distributed across the income distribution. Relative to our baseline analysis, there is only one difference: Both low- and high-income workers are employed in sectors with a higher total export share than the average worker (see Figure 14-Panel B). Finally, Figure D.16 reports the estimates of (D.8) when the dependent variable is the sectoral Gini coefficient. We do not find any statistically significant effect of exchange rates on within-sector inequality. To summarize, we find that our results are robust to taking into account a sector's indirect exposure to international trade.

Figure D.21 – Total Trade Exposure and Sectoral Wages



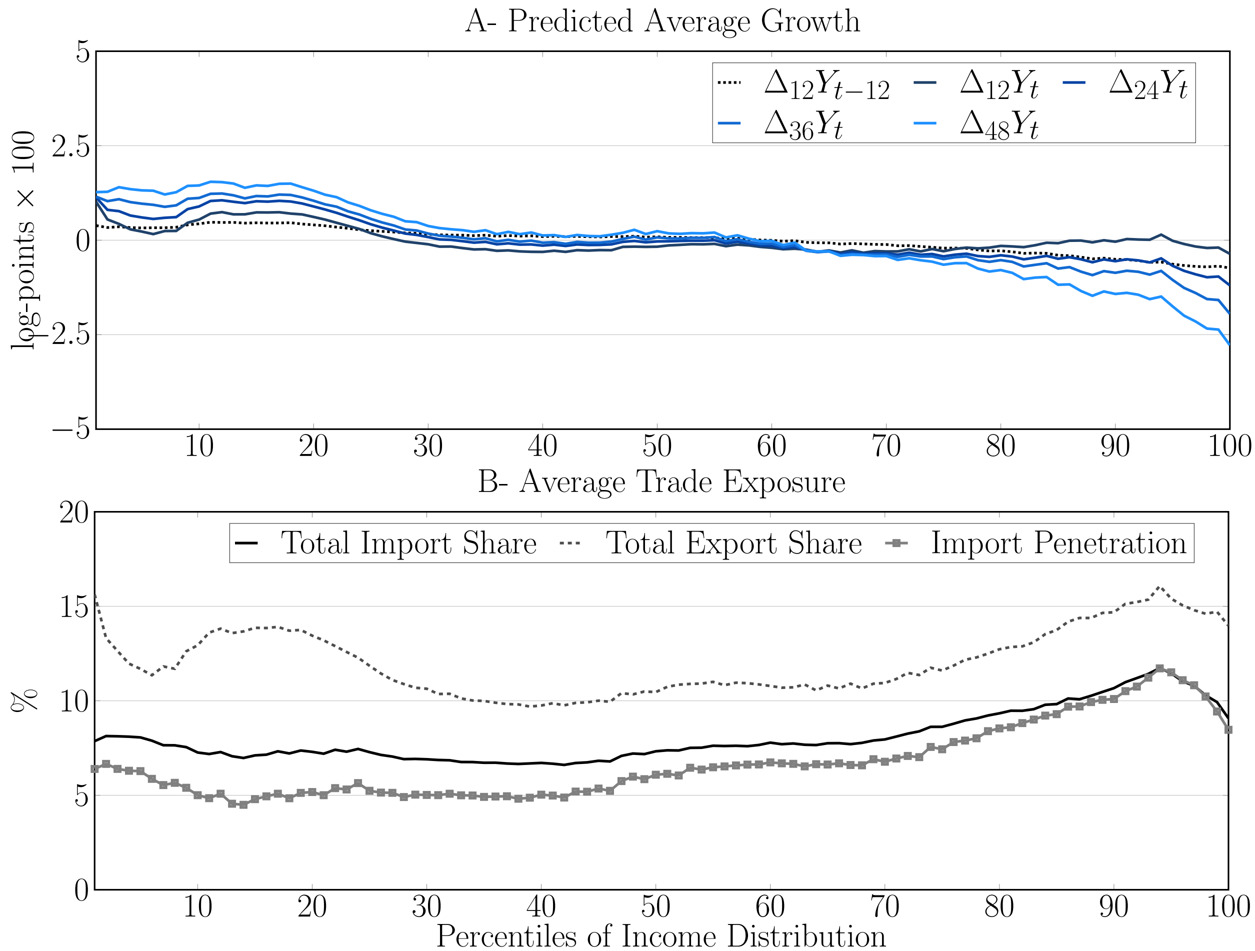
Notes: This figure reports the estimates of equation (D.8). The dependent variable is the quarterly growth rate of log average sectoral income. Independent variables include the interaction of the quarterly change in the NER with the total export share, the total share of imported intermediate inputs and import penetration by sector, and time and sector fixed effects. Solid lines depict cumulative sums $\sum_{j=0}^{n} \phi_j$, $\sum_{j=0}^{n} \gamma_j$, and $\sum_{j=0}^{n} \delta_j$ for $n \in [0, 12]$. Shaded areas depict 90% and 95% confidence intervals based on robust standard errors. The estimation method is OLS and the equation is estimated using data over the 1997-2006 period.

Figure D.22 – Total Trade Exposure and Within-Sector Inequality



Notes: This figure reports the estimates of equation (D.8). The dependent variable is the quarterly growth rate of log sectoral Gini coefficient. Independent variables include the interaction of the quarterly change in the NER with the total export share, the total share of imported intermediate inputs and import penetration by sector, and time and sector fixed effects. Solid lines depict cumulative sums $\sum_{j=0}^{n} \phi_j$, $\sum_{j=0}^{n} \gamma_j$, and $\sum_{j=0}^{n} \delta_j$ for $n \in [0, 12]$. Shaded areas depict 90% and 95% confidence intervals based on robust standard errors. The estimation method is OLS and the equation is estimated using data over the 1997-2006 period.

Figure D.23 – Total Trade Exposure and Heterogeneous Sectoral Income Growth



Notes: Panel A plots the predicted average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The lines show the weighted average of the predicted sectoral income growth from the estimates of equation (D.8). Weights are given by the within-bin sectoral composition in December 2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. Panel B shows the average total import share, total export share, and import penetration of the sector of employment of workers in each percentile of the distribution of average monthly real income during 2000-2001.

E Additional Mechanisms and Robustness

E.1 The Extensive and Intensive Margins of Employment

This section separately analyzes the importance of the extensive and intensive margins of employment—i.e., employment and hours of work, respectively—for the decline in inequality following the 2002 devaluation.

E.1.1 The Employment Margin

We first study the role of the extensive margin in shaping income inequality following the 2002 devaluations. The purpose of this section is twofold. First, we document that measures of inequality that incorporate the employment margin—e.g., the Gini coefficient that includes observations with zero income—drop by *more* than measures that do not include the extensive margin. The reason for this result is simple: Following the devaluation, there was a strong employment recovery. Thus, following the devaluation, the prevalence of workers with zero income decreased, further pushing inequality down. Second, when we focus on labor income inequality among workers with positive income (i.e., excluding the extensive margin), we find that inequality decreased despite—and not *because of*—strong recovery in the labor market. The reason is the same as before. Following the devaluation, the entry rate into employment of low-income workers increased and their exit rate decreased, both of which increased the mass of workers at the lower end of the distribution; thus selection arising from those two margins should have increased inequality among employed workers. In conclusion, taking the extensive margin into account magnifies the decline in total labor income inequality and masks the importance of the mechanisms we analyze in Sections 4 and 5.

The roadmap for this section is the following. First, we analyze the dynamics of aggregate employment and employment flows between formal employment and non-formal employment (i.e., flows into and out of our administrative dataset). The main takeaway is that following the devaluation, the labor market experienced a strong recovery, explained by an on-impact significant drop in the aggregate separation rate and a smooth recovery in the entry rate. Second, we analyze labor market flows between employment states across the income distribution. The main takeaway here is that the recovery of the entry rate and the drop in the separation rate is concentrated at the bottom of the income distribution. Third, after understanding these labor market dynamics, we compute the Gini coefficient for different subpopulations (including the subsample of informal and all workers) and find a more significant drop in inequality once we incorporate the extensive margin. Finally, we extend the analysis of individual income dynamics in Section 5 by incorporating the extensive margin of employment. We find that our measure of pivoting (i.e., the difference in income growth between the 10th and 90th percentiles) almost doubles.

Aggregate employment and labor market flows. As Figure 4 in the main text shows, the pre-devaluation downward trend in formal employment starts reverting in the first months after the devaluation, and employment experiences rapid growth thereafter. This should not be surprising, given the large drop in real income precipitated by the sharp increase in inflation. Using our administrative dataset, we decompose the dynamics of employment within the following accounting framework.[41] Let N_t be the stock of employed workers in period t. We write the law of motion of N_t in terms of the entry (N_t^{entry}) and

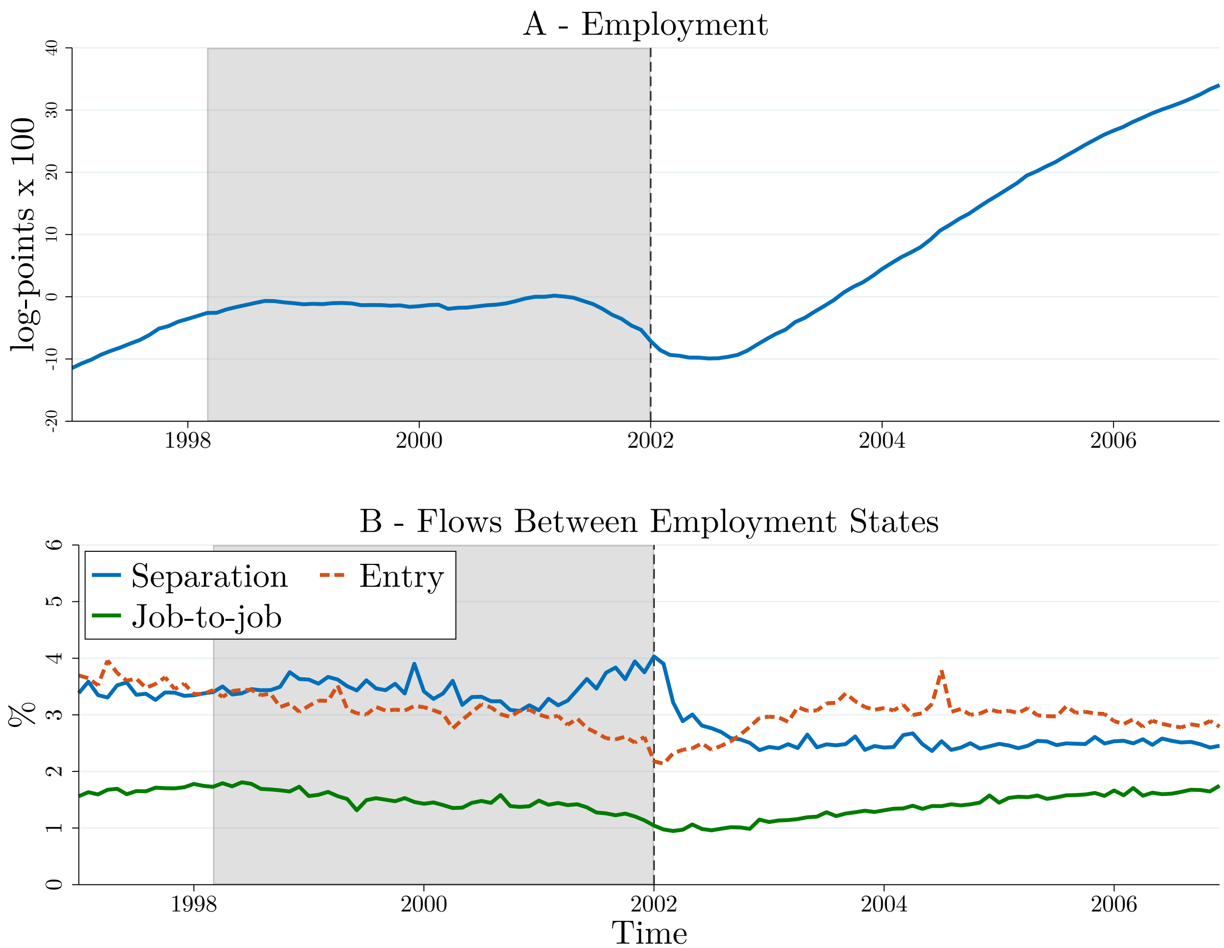
[41] The flow approach to the labor market (see Blanchard and Diamond, 1992) typically relies on measures of the job-finding rate, which requires information on the number of unemployed workers and the types of jobs (e.g., formal or informal) they are searching for. Data on the latter almost do not exist. Thus, our framework is motivated by the fact that we do not need to make assumptions about whether a worker is unemployed or working outside the formal private sector (e.g., in the informal or public sectors) if we do not observe her in our dataset—see also Davis and Haltiwanger (1992) for a similar approach.

exit flows (N_t^{exist}):

$$N_t = N_{t-1} + \underbrace{N_t^{entry}}_{\equiv e_t N_{t-1}} - \underbrace{N_{t-1}^{exit}}_{\equiv s_t N_{t-1}} = N_{t-1}(1 + e_t - s_t) \tag{E.9}$$

where e_t and s_t denote the entry and separation rates in period t, respectively.[42]

Figure E.1 – Aggregate Employment and Employment Flows



Notes: Panel A plots total employment in the formal private sector from SIPA. Panel B plots the entry and separation rates and the rate of job-to-job transitions. Total employment is expressed in log-points × 100 and normalized to zero in the first month of 2001. Recession periods are in gray, and monthly devaluations larger than 30% are marked with dotted black lines.

Figure E.1, Panels A and B, plot the dynamics of employment, entry rates, separation rates, and job-to-job transitions rates.[43] Since the beginning of the 1998 recession, there was almost zero employment growth and a steady decline in the entry rate (and the job-to-job transition rate). The labor market deteriorated further 1 year before the devaluation, when the entry rate collapsed and the separation rate rapidly increased.

[42]The entry rate is computed as the number of workers who became employed in the formal private sector in period t over the number of workers employed in the formal private sector in $t-1$. The exit rate is computed as the number of workers who were employed in the formal private sector in period $t-1$ but not in period t, over the number of workers employed in the formal private sector in $t-1$.

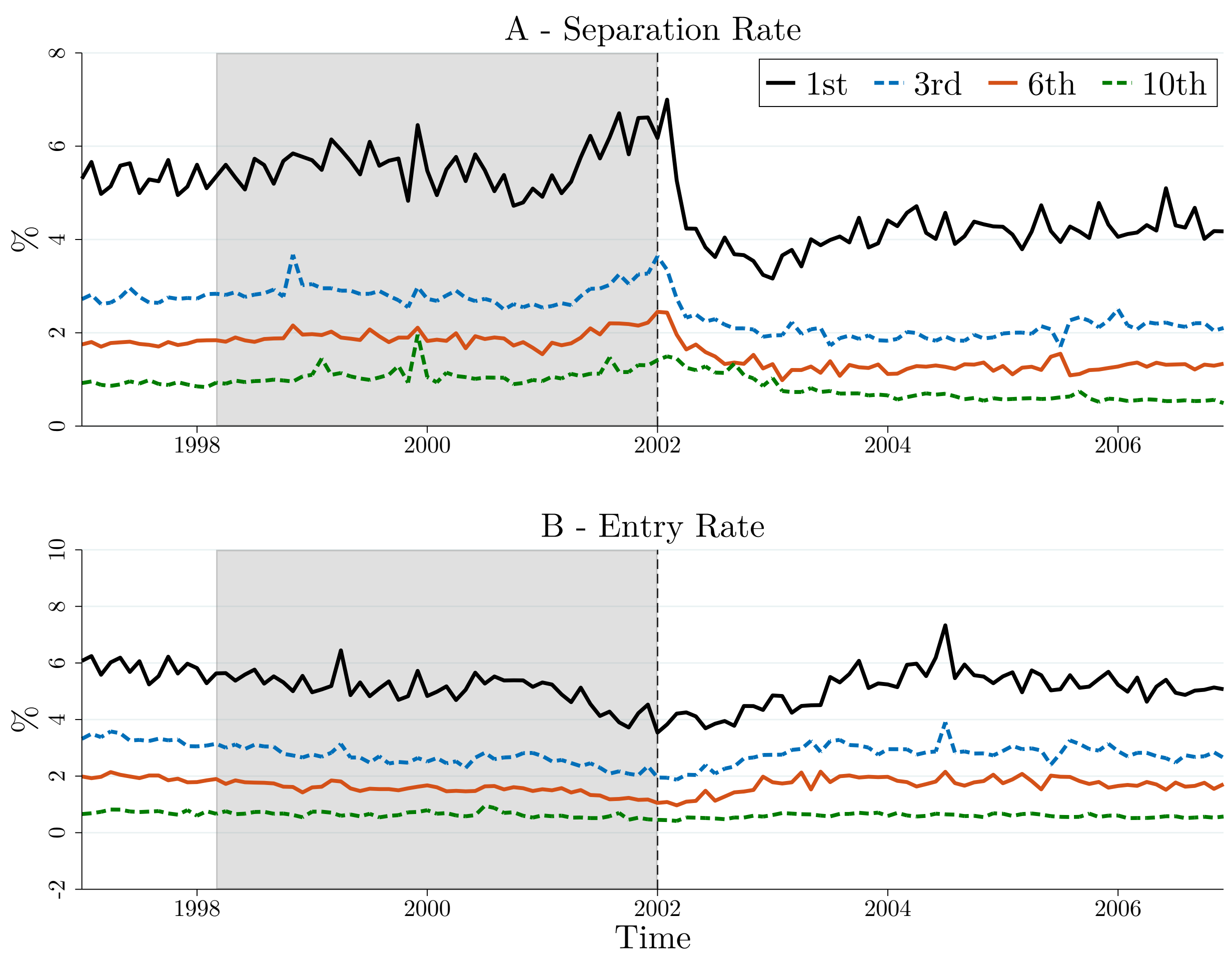
[43]We define a job-to-job transition as an event in which a worker is employed in a firm and then switches to another firm, with at most a month of non-employment in between.

In the first few months after the 2002 devaluation, we can see strong employment recovery, triggered first by a sharp drop in the separation rate and then accelerated by recovery of the entry rate. The job-to-job transition rate, another key labor market indicator, also recovered following the devaluation.

While these aggregate time series are informative of aggregate employment dynamics, they are silent on their potential effects on inequality without a deeper analysis of labor market flows across the income distribution.

Employment Flows by Income Levels. Now, we show that the decline in the separation rate, as well as the recovery in the entry rate, was concentrated among low-income workers.

Figure E.2 – Labor Market Flows by Income Levels



Notes: Panels A and B plot the separation and entry rates by deciles of the income distribution from January 1997 to December 2006. Recession periods are in gray, and monthly devaluations larger than 30% are marked with dotted black lines.

We compute the separation and entry rates by deciles of the income distribution in the following way. In each period t, we compute the deciles of the income distribution from the population of employed workers. Let N_{dt} be the stock of employed workers in period t in the dth-decile of the income distribution. By definition, $N_t = \sum_{d=1}^{10} N_{dt} = 10N_{1t}$. Similarly, we define N_{dt-1}^{exit} as the exit flow out of formal employment with income in the dth-decile (the worker's income and decile are measured in $t-1$) and N_{dt}^{entry} as the entry flow into formal employment with income in the dth-decile (the worker's income and decile are measured in

t). With these definitions, we decompose the law of motion of aggregate formal employment as

$$
\begin{aligned}
N_t &= N_{t-1} + \sum_{d=1}^{10} N_{dt}^{entry} - \sum_{d=1}^{10} N_{dt-1}^{exit} \\
&= N_{t-1} + N_{t-1}(1+g_t^N) \sum_{d=1}^{10} \underbrace{\frac{N_{dt}^{entry}}{N_{dt}}}_{=e_{dt}} \frac{N_{dt}}{N_t} - N_{t-1} \sum_{d=1}^{10} \underbrace{\frac{N_{dt-1}^{exit}}{N_{dt-1}}}_{=s_{dt}} \underbrace{\frac{N_{dt-1}}{N_{t-1}}}_{=1/10} \\
&= N_{t-1} + \left[\underbrace{(1+g_t^N) \sum_{d=1}^{10} \frac{e_{dt}}{10}}_{=e_t} - \underbrace{\sum_{d=1}^{10} \frac{s_{dt}}{10}}_{=s_t} \right] N_{t-1},
\end{aligned}
\tag{E.10}
$$

where $g_t^N \equiv N_t/N_{t-1} - 1$ is the growth rate of employment, e_{dt} is the share of new workers entering the dth-decile of the period t income distribution, and s_{dt} is the share of workers in the dth-decile of the period $t-1$ income distribution who lose their job in period t. The result is that

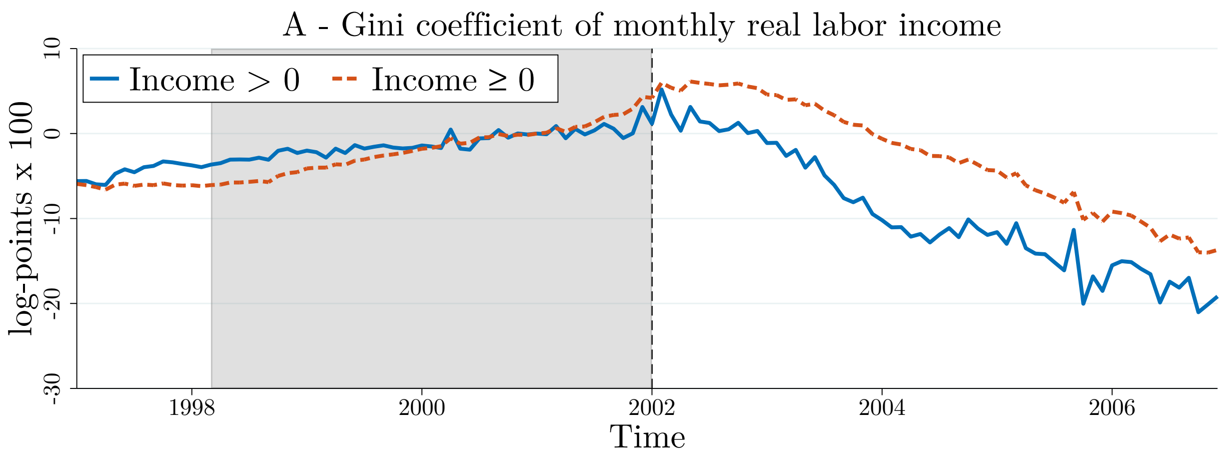
$$
e_t = (1+g_t^N) \sum_{d=1}^{10} \frac{e_{dt}}{10} \quad \text{and } s_t = \sum_{d=1}^{10} \frac{s_{dt}}{10}. \tag{E.11}
$$

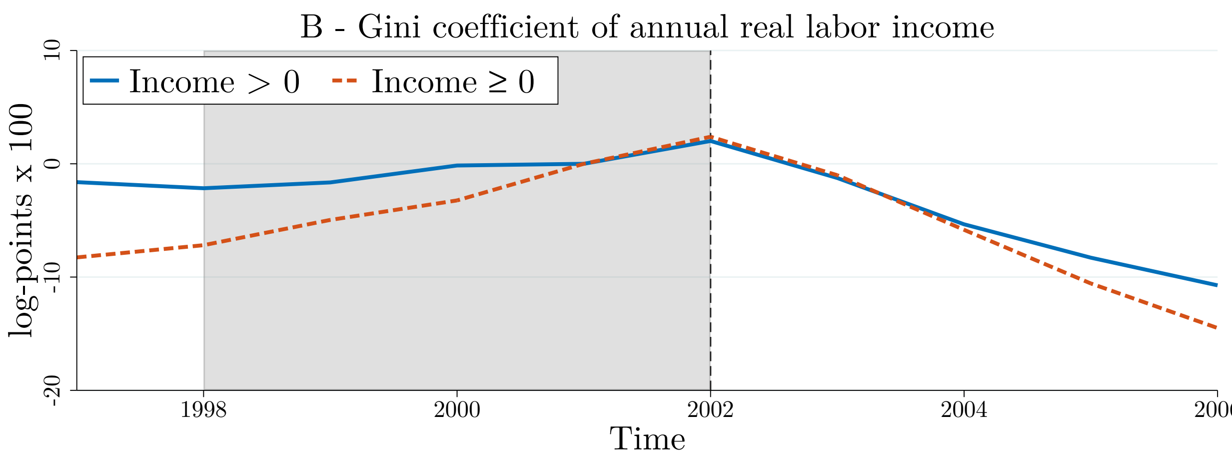
Figure E.2 shows the separation rates s_{dt} and entry rates e_{dt} for the 1st, 3rd, 6th, and 10th deciles of the income distribution. As Figure E.2 clearly shows, the post-devaluation sharp drop in the separation rate and the increase of the entry rate are concentrated among low-income workers. Thus, after the devaluation, low-income workers are much less likely to lose their job and more likely to find a job in the formal sector—the entry and separation rates of high-income workers exhibit much smaller variation. Note that, ceteris paribus, these heterogeneous inflows and outflows work against the documented drop in inequality; as more low-income workers keep their job and more unemployed workers find a new low-paying job, the income distribution among the employed should become *more* unequal; instead, we find that the distribution becomes *less* unequal. To understand the effects of these facts on income inequality, we next analyze the Gini coefficient while taking into account the extensive margin of employment.

Gini Coefficients with and without the Extensive Margin. Figure 5 in the main text shows the Gini coefficient of real labor income from the population of employed workers with positive labor income. Thus, by construction, it excludes workers who are not present in our main dataset, and therefore have zero labor income in the formal sector. Next, we show the effect of incorporating this extensive margin in the calculation of the Gini coefficient.

Figure E.3 shows the Gini coefficient computed using different measures of labor income and at different frequencies. Figure E.3-Panel A shows the Gini coefficient as in the baseline analysis—i.e., including only observations with positive labor income—and with the "zeros." We identify workers with zero labor income in the formal sector in the following way: If a worker is not employed in the formal sector in a given month, but was present at any other point in the sample (within the age limits imposed in the sample selection), we set the monthly income to zero. Since the levels of the Gini coefficients for real monthly income with and without zeros are different, we normalize both measures with their values in 2001 (as Figure 2 in the main text). As the figure shows, the pre-devaluation increase in the Gini coefficient is larger when we include observations with zero incomes, and the post-devaluation decline is parallel to the one without the zeros. Figure E.3-Panel B shows the normalized (log) Gini coefficient of total annual real income with and without observations with zero annual income (relative to Panel A, the latter also includes the extensive margin by including months with zero income in the annual sum). Here, we can see a more pronounced rise and decline in the Gini coefficient when we incorporate the extensive margin. Both exercises highlight an important result: The increase and decline in the Gini coefficient are, at least, more considerable whenever we take into account the extensive margin of labor supply. This is explained by the facts documented above that show a strong post-devaluation recovery of the labor market, which reduces the incidence of workers with zero labor income and overall inequality.

Figure E.3 – Gini coefficient with and without extensive margin of labor supply



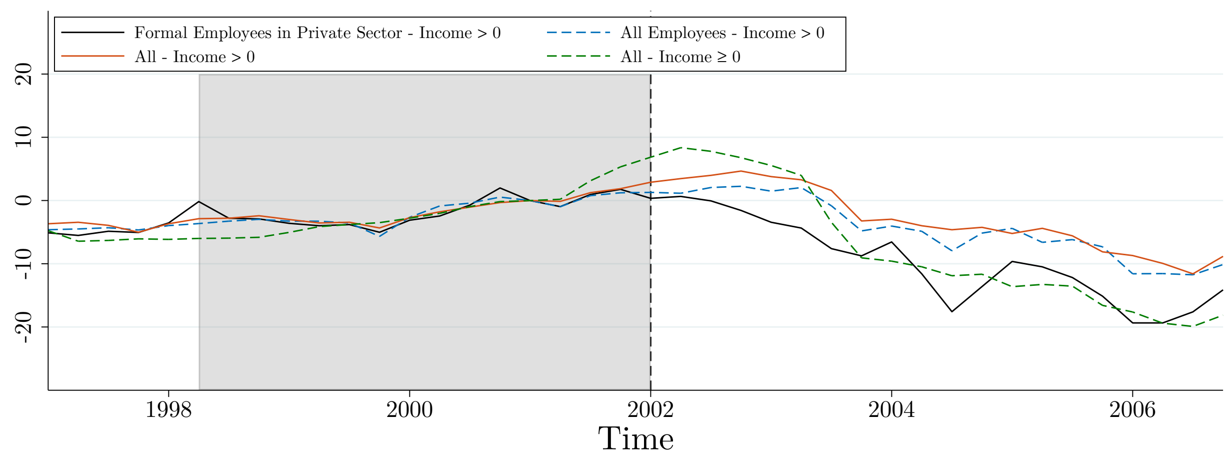


Notes: Panels A and B plot the Gini coefficients at different frequencies and for different measures of labor income from 1997 to 2006. All series are expressed in log-points × 100 and normalized to zero in the year 2001. Panel A plots the monthly series of the Gini coefficient using observations with monthly positive real labor income (blue solid line) and nonnegative real labor income (red dashed line). The Gini coefficient based on observations with monthly positive real labor income reproduces the analysis in the main text in Figure 5. Panel B plots the annual series of the Gini coefficients using observations with total annual positive labor income (blue solid line) and nonnegative labor income (red dashed line). Recession periods are in gray, and monthly devaluations larger than 30% are marked with dotted black lines.

In the previous analysis, we incorporated the extensive margin by analyzing inequality among workers who were ever present in the administrative dataset and by assuming that they earned zero income when not employed in the formal sector. Since these workers might be earning positive income elsewhere, here we dispense with this assumption and study the entire population of reference by conducting a similar analysis using data from the national household survey. These data allow us to include (i) workers with positive income outside the formal sector and (ii) all non-employed workers with zero income.

We compute the Gini coefficient of monthly individual income from all sources for different subpopulations within the sample of all male individuals aged 25-65, as in the baseline analysis. Figure E.4 reports the results for four groups of workers: (i) workers employed in the formal sector with positive monthly income (as in our baseline analysis), (ii) all employees (including public sector and informal workers) with positive monthly income, (iii) all workers with positive monthly income, and (iv) all workers (i.e., those with positive and zero monthly income). All series exhibit a continuous increase in inequality since the beginning of the recession in 1998, followed by a decline following the 2002 devaluation. More importantly, the series that shows the largest decline is the one that includes *all individuals*, highlighting once again the fact that the employment recovery further contributed to the decline in inequality in the overall population.

Figure E.4 – Gini coefficients in the population

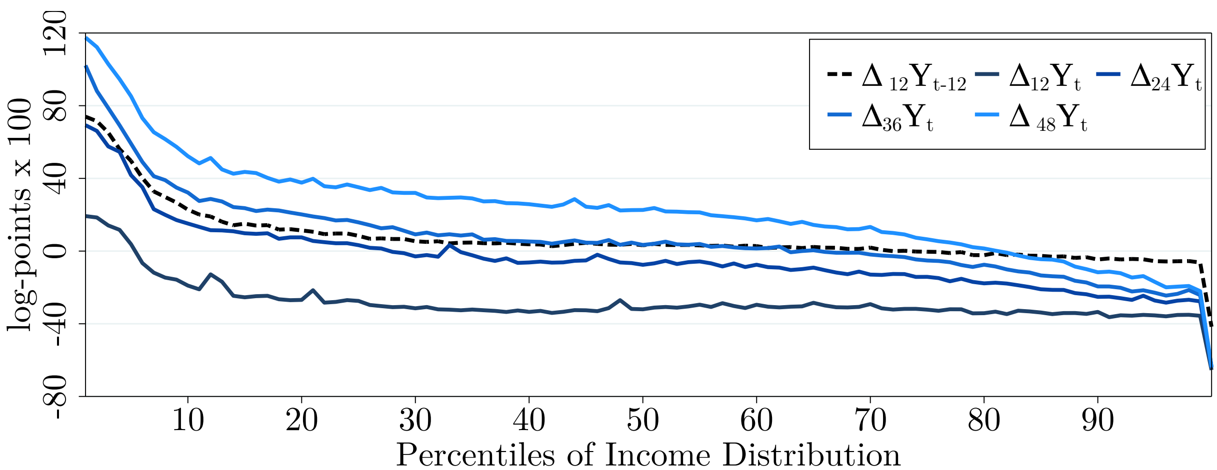


Notes: The figure plots the Gini coefficients for different subpopulations from the first quarter of 1997 to the last quarter of 2006. The broadest sample includes all male individuals aged 25-65. Income is measured as total monthly individual income. The solid black line reports the Gini coefficient for workers employed in the formal private sector (as in our baseline analysis) with positive monthly income. The dashed blue line includes all employees (including public sector and informal workers) with positive monthly income. The solid orange line includes all workers with positive monthly income. The dashed green line includes all workers (i.e., those with positive and zero monthly income). All series are expressed in log-points × 100 and normalized to zero in the year 2001. Recession periods are in gray, and monthly devaluations larger than 30% are marked with dotted black lines.

Workers' Income Growth Conditional on Income Level and the Extensive Margin. To conclude the analysis, we extend Figure 7 to include the extensive margin of employment. One concern regarding our original analysis in Figure 7 is that the documented heterogeneous labor flows across the income distribution could introduce selection and affect the results in three ways. First, for a worker to be included in Figure 7, two conditions must be satisfied: (i) the worker must have been employed in December of 2001 and (ii) the worker must have been employed for at least 6 months during 2000-2001. As previously shown, the separation rate increased before the devaluation, particularly among low-income workers. If these separations are not random, selection could affect the estimates of future income growth. Second, in the baseline figure, we rank workers according to their average monthly income conditional on being employed; omission of the extensive margin could affect the ranking of workers based on proxies of "permanent income." Third, to compute a worker's annual income growth, the worker must be employed in both periods. Again, the heterogeneous separation rates across the distribution can affect the results. Next, we conduct several analyses to address each concern.

In Figure E.5 we incorporate the extensive margin by computing the growth rate of average monthly income (including zeros), while keeping the same sample and ranking of workers from our baseline Figure 7. To do so, we construct a balanced panel: If a worker is not employed in the formal sector in a given month, we replace his income with zero. This generates a balanced panel for each worker employed in December 2001. Figure E.5 shows that the main finding is robust to variations in workers' employment status.[44]

Figure E.5 – Avg. income growth conditional on the average income in 2000-2001: Including zero-income workers



Notes: The figure plots the change in log average income conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period.

In Figure E.6, we instead rank workers taking the extensive margin of employment into account, while computing average income growth rates as in our baseline Figure 7. To do so, we rank workers according to their average annual income (net of the life-cycle profile) during the 2000-2001 period. To report the effects of the extensive margin in a sequential manner, we exclude workers with zero annual income in 2000 or 2001.[45] As the figure shows, ranking workers according to their annual income—instead of their monthly income—barely affects the results. We still find the same "parallel drop and pivoting" pattern, with small differences between the 1st and 10th percentiles relative to Figure 7.

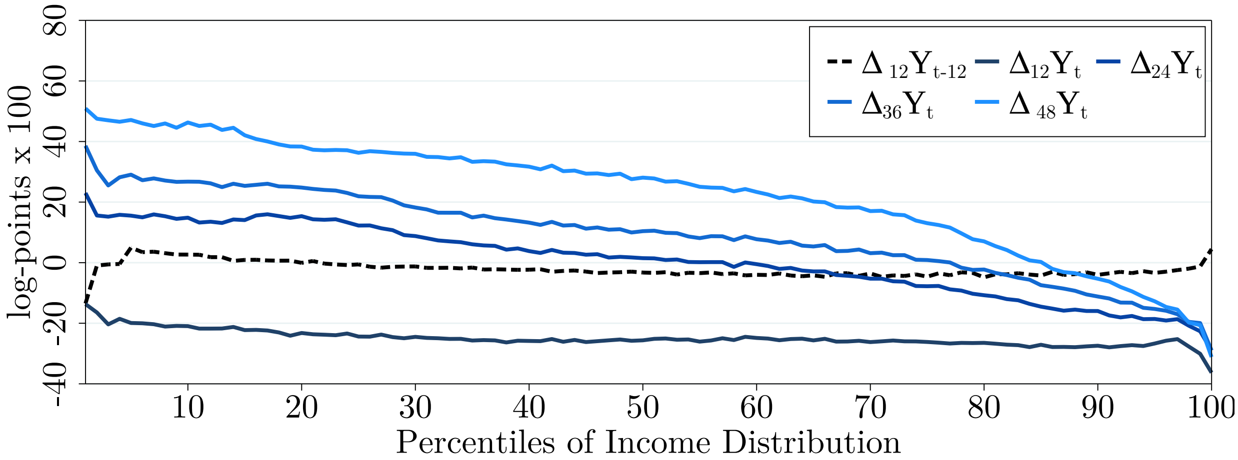
Until now, we have only partially incorporated the extensive margin of labor supply. The following analysis fully incorporates this margin and reveals even more pronounced differences between positive growth rates at the bottom of the distribution and negative growth rates at the top.

Figure E.7 presents the main result in this section. The figure ranks workers according to their total annual income (net of life-cycle profile) *and* reports the average growth rate of annual income. This figure is based on the same sample and ranking of workers as Figure E.6, but reports on the y-axis the average growth

[44]To deal with the log and the zeros, we follow the literature (see, for example, Guvenen *et al.*, 2014) and replace $\mathbb{E}_i(\Delta \log y_{it})$ with $\Delta \log \mathbb{E}_i(y_{it})$, where y_{it} is the real income of worker i in period t. By computing the same statistic in our original sample without the zeros, we conclude that the differences at the bottom of the distribution between Figure 7 and Figure E.5 are mostly due to Jensen-inequality effects.

[45]Once we focus on annual income, this sample selection filter becomes much less restrictive than the filters used in our baseline analysis.

Figure E.6 – Avg. income growth conditional on average annual income in 2000-2001



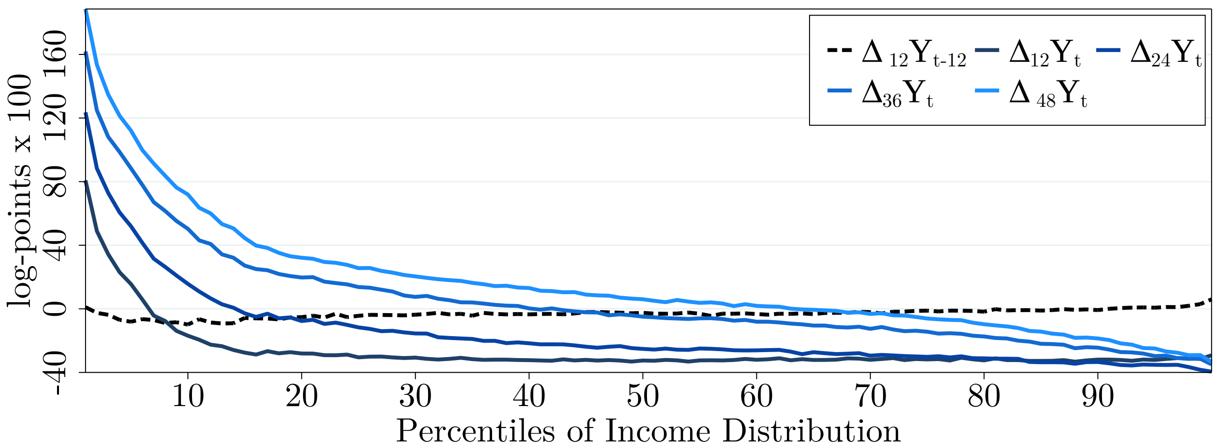
Notes: The figure plots average income growth in December 2000, 2002, 2003, and 2004 relative to December 2001, conditional on the percentile of the distribution of average annual real income during 2000-2001. The sample excludes workers with zero annual income in 2000 or 2001.

in the log annual real labor income. The figure shows similar qualitative patterns, but large quantitative differences relative to Figure E.6. The difference in the average growth rate of annual real income between the 10th and 90th percentiles is 89%. In comparison, the corresponding number in our baseline analysis is 49%. Therefore, inclusion of the extensive margin exacerbates the positive income growth experienced by low-income workers after the devaluation.[46]

To understand the differences between Figures E.6 and E.7 originating from inclusion of the extensive margin, Figure E.8 shows the average number of months of employment as a function of the ranking based on average annual income. As the above analysis suggests—and we have now confirmed—the significant drop in separation rates led to a large increase in months of employment, particularly for workers at the bottom of the income distribution. Therefore, once we consider periods of non-employment, we find an even more impressive recovery of total annual labor income of low-income workers.

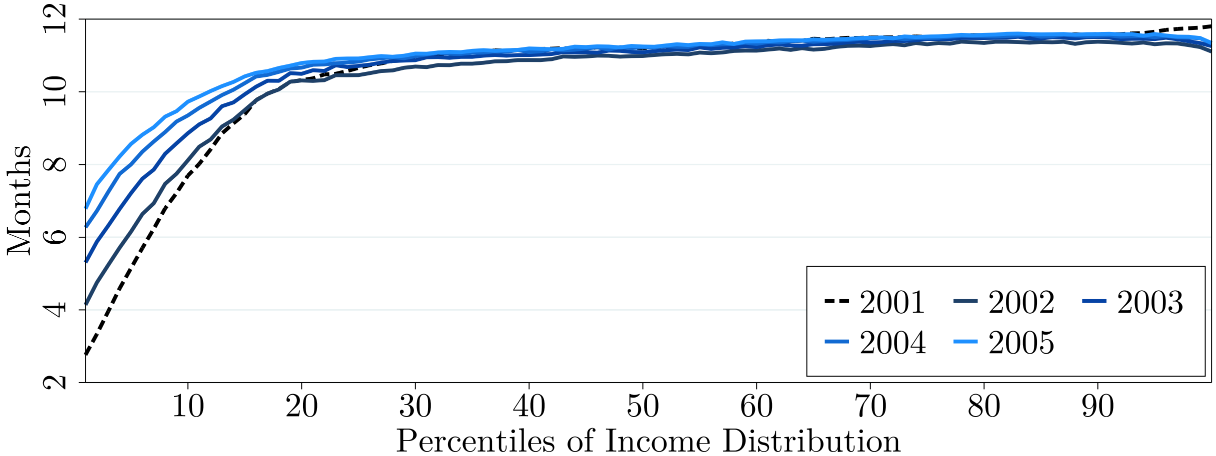
[46]We have reproduced the analysis based on changes in the log average annual income, which allows us to also include observations with zero annual income, and found similar results.

Figure E.7 – Avg. Annual income growth conditional on average annual income in 2000-2001



Notes: The figure plots average growth in log annual income conditional on the percentile of the distribution of average annual real income during 2000-2001. The sample excludes workers with zero annual income in 2000 or 2001.

Figure E.8 – Months worked conditional on average annual income in 2000-2001



Notes: The figure plots the average number of months of employment within each year from 2001 to 2005 conditional on the percentile of the distribution of average annual real income during 2000-2001. The sample excludes workers with zero annual income in 2000 or 2001.

E.1.2 The Hours of Work Margin

One key question surrounding our main facts is whether they are driven by changes in hourly wages or changes in hours of work. For example, if high-income earners work less after devaluations, then the cyclicality of the first moment of the distribution of labor income could be driven by the cyclicality of hours. Here, we show that this is not the case. To do so, we need data on hours of work for each worker. Since our main dataset does not include this information, we rely on hours of work data from the national labor force survey and information on the worker's type of contract (full-time vs. part-time) from our main dataset. Across the different exercises we perform, we do not find a significant variation in hours that explains the main facts in Section 4.

Total hours and distribution of hours by income. Total monthly income in a job can be divided into hours of work and wage per hour. If y_{ti} denotes the log-real income, then

$$y_{it} = \log(4) + \log(h_{it}) + \log(w_{it}), \tag{E.12}$$

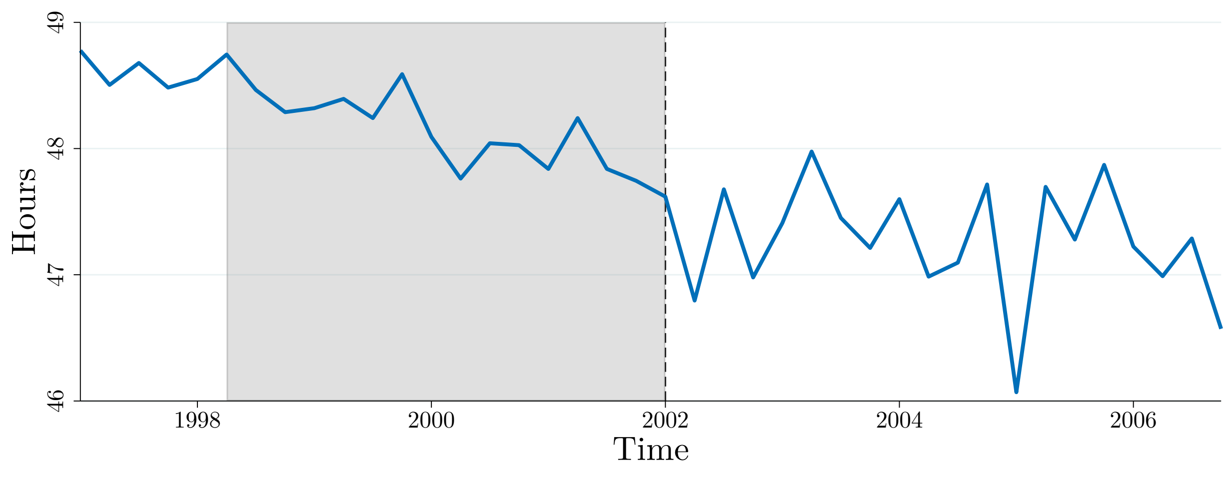
where h_{it} denotes hours per week and w_{it} denotes wage per hour. Figures E.9 and E.10 show average hours per week across workers and by quintiles of the distribution of income in the private formal sector. Total hours drop by at most 2% after the 2002 devaluation. Given that real labor income drops by 28%, we conclude that changes in hours cannot quantitatively explain the facts reported in Section 4. Additionally, we do not find statistically significant differences in average hours worked above the 1st quintile of the income distribution, nor do we find differences in the average hours of work across quintiles. For the 1st quintile, there is a temporary decrease, which reverts in one quarter. Therefore, we conclude that changes in hours cannot explain the decrease in inequality.

The distribution of hourly wages. Figure E.11 plots the evolution of percentiles of the distribution of (log) real hourly wages constructed from the national labor force survey based on equation (E.12). Overall, the dynamics of the distribution of hourly wages resemble the dynamics of the distribution of monthly income (see Figure A.2-Panel B). Before the devaluation, all percentiles are almost constant. After the devaluation, there is a homogeneous drop in real hourly wages followed by a heterogeneous recovery, in which higher percentiles recover at a slower speed.

Facts across types of contract. We use data from SIPA on the worker's type of contract as an additional control for differences in hours of work. We divide workers into two groups: full time and part time. The full-time group includes workers with and without a termination date specified in their contracts. The part-time group includes seasonal workers, trainees, and temporary workers. In order to be sufficiently cautious, we also include in this group all workers in the agriculture, mining, fishing, and construction sectors due to the sectors' intermittent working periods. Figure E.12 plots the evolution of average income for full- and part-time workers. As we can see in this figure, the levels across groups differ, but their cyclical components are similar. Figure E.13 plots the normalized percentiles and two measures of dispersion of the income distribution by type of contract. As we can see, there are no systematic differences across the two groups of workers (perhaps with the exception of the 10th percentile of part-time workers, which recovers at a slower pace). We conclude that our facts are mainly driven by changes in hourly wages and not hours.

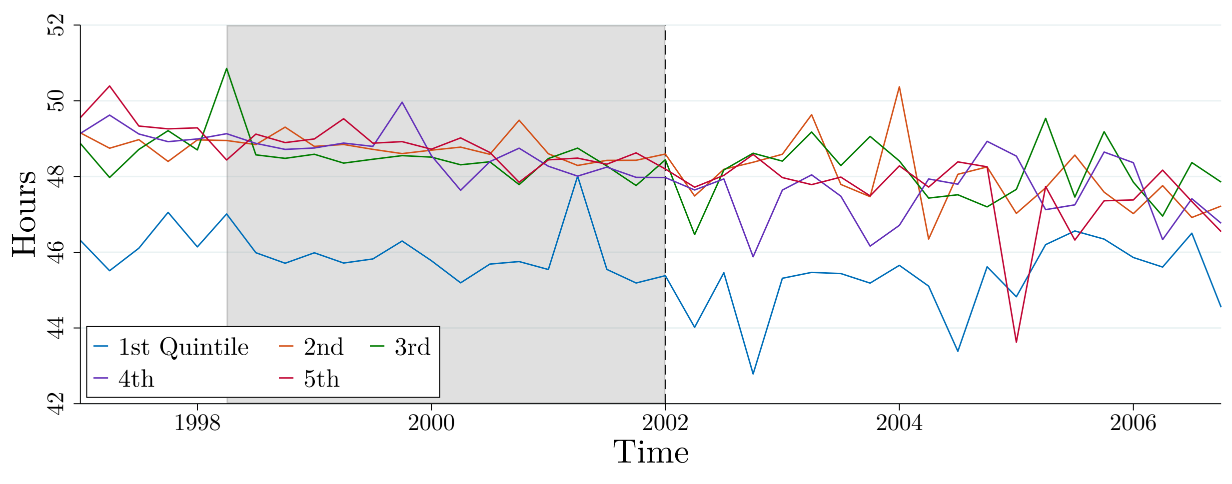
Workers' Income Growth Conditional on Income Level and the Intensive Margin. To show that the results in Figure 7 are not driven by changes in the intensive margin, we exploit information on the full-time/part-time status of the worker's job in our main dataset. Figure E.14 reproduces the main fact, restricting the sample to full-time jobs, and shows a pattern similar to that in the baseline analysis.

Figure E.9 – Average Hours in the Private Formal Sector



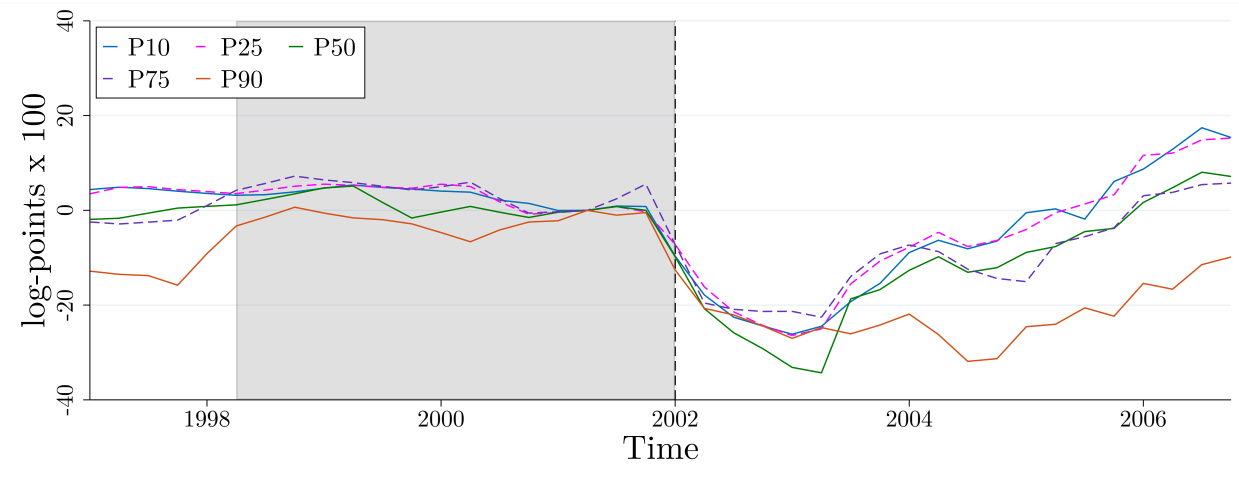
Notes: The figure plots the average hours of work in the primary occupation from the first quarter of 1997 to the last quarter of 2006 for male workers aged 25-65 employed in the private formal sector.

Figure E.10 – Average Hours in the Private Formal Sector by Income Quintiles



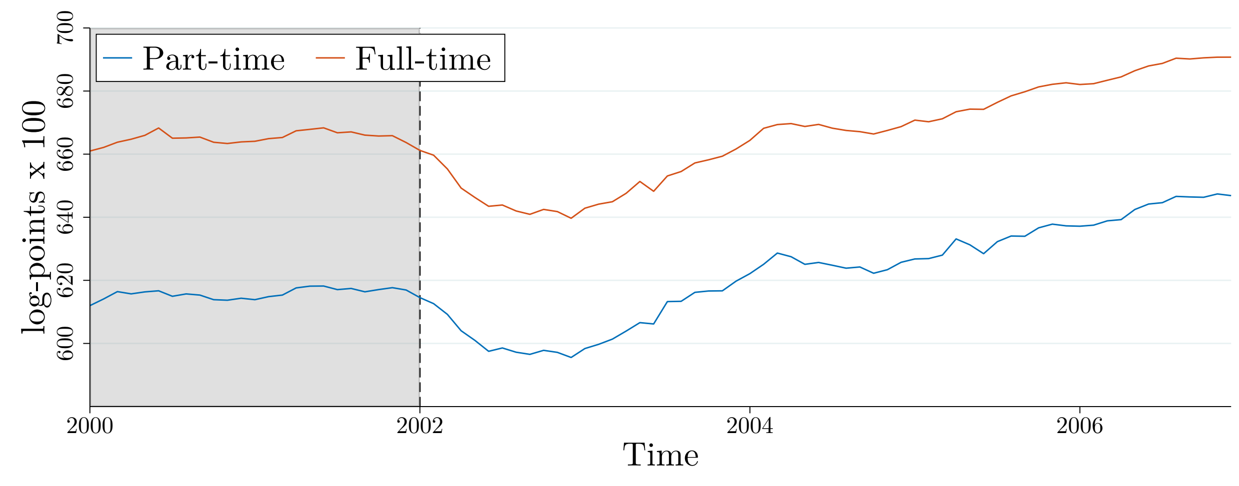
Notes: The figure plots the average hours of work from the first quarter of 1997 to the last quarter of 2006 by income quintile in the primary occupation for male workers aged 25-65 employed in the private formal sector.

Figure E.11 – Percentiles of the Distribution of Hourly Wages



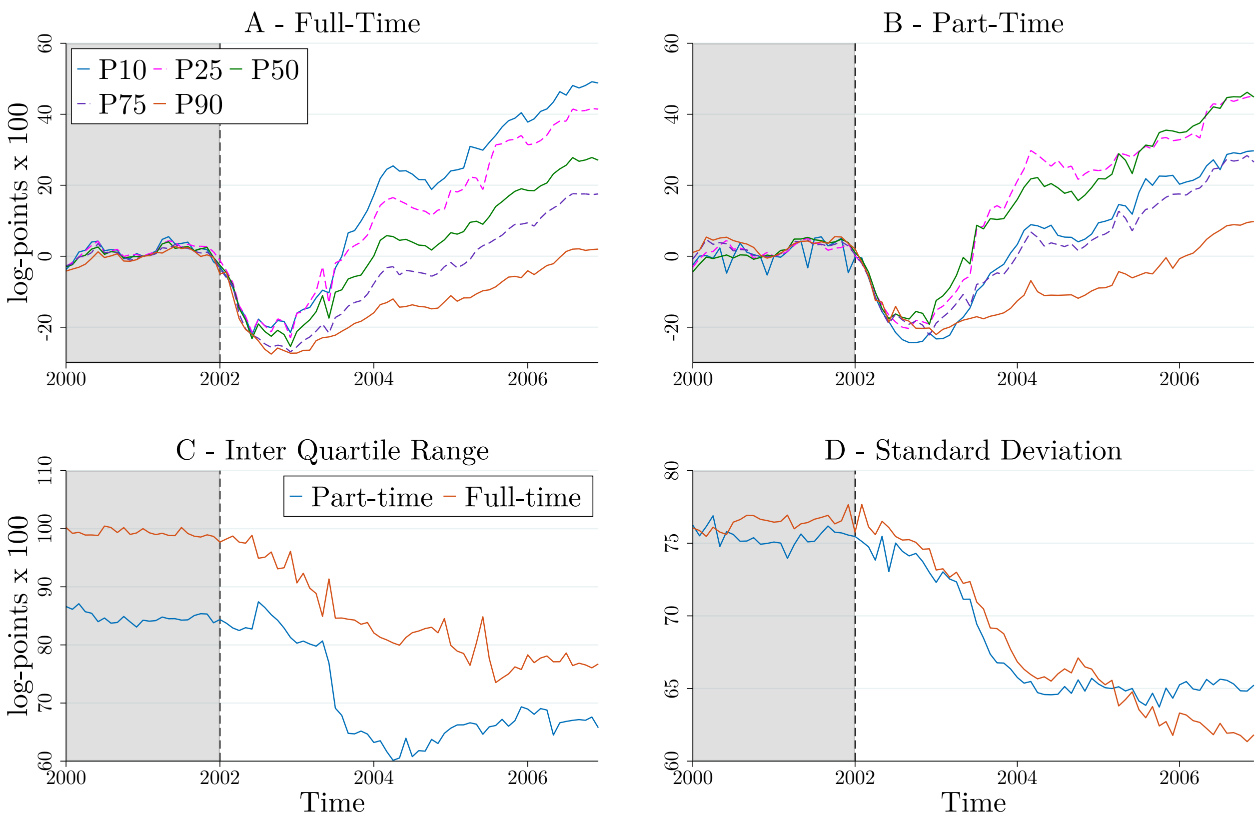
Notes: The figure plots the percentiles of the (log) real hourly wage distribution ($\times$ 100) from the first quarter of 1997 to the last quarter of 2006 normalized by their average value during the second quarter of 2001. The sample includes male workers aged 25-65 employed in the private formal sector. We use Px to denote the x-th percentile of the distribution.

Figure E.12 – Average Real Labor Income: Full-Time vs Part-Time



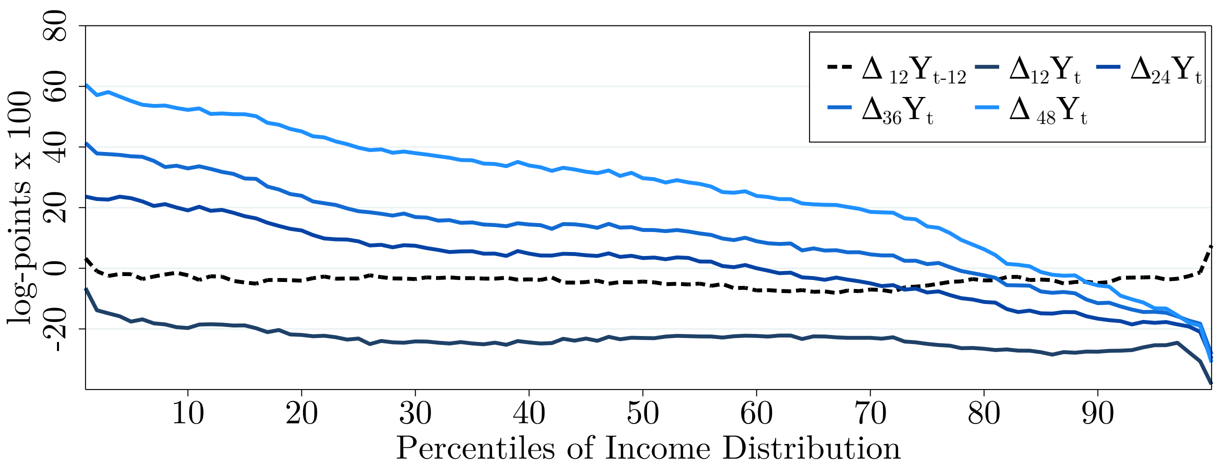
Notes: The figure shows the monthly average (log) real income from January 2000 to December 2006 of part-time and full-time workers by type of contract. The variable is seasonally adjusted. Recession periods are in gray, and monthly devaluations larger than 30% are marked with dotted black lines.

Figure E.13 – Moments of the Distribution of Labor Income: Full-Time vs Part-Time



Notes: The figure shows statistics for the monthly real income from January 2000 to December 2006. Panel A (resp. B) plots the percentiles of the log income distribution ($\times$ 100) normalized by their value in January 2001 for full-time workers (resp. part-time workers). We use Px to the x-th percentile of the distribution. Panels C and D plot the interquartile range ($P75 - P25$) and the standard deviation for the same time period.

Figure E.14 – Avg. income growth conditional on average income in 2000-2001: Full-time workers



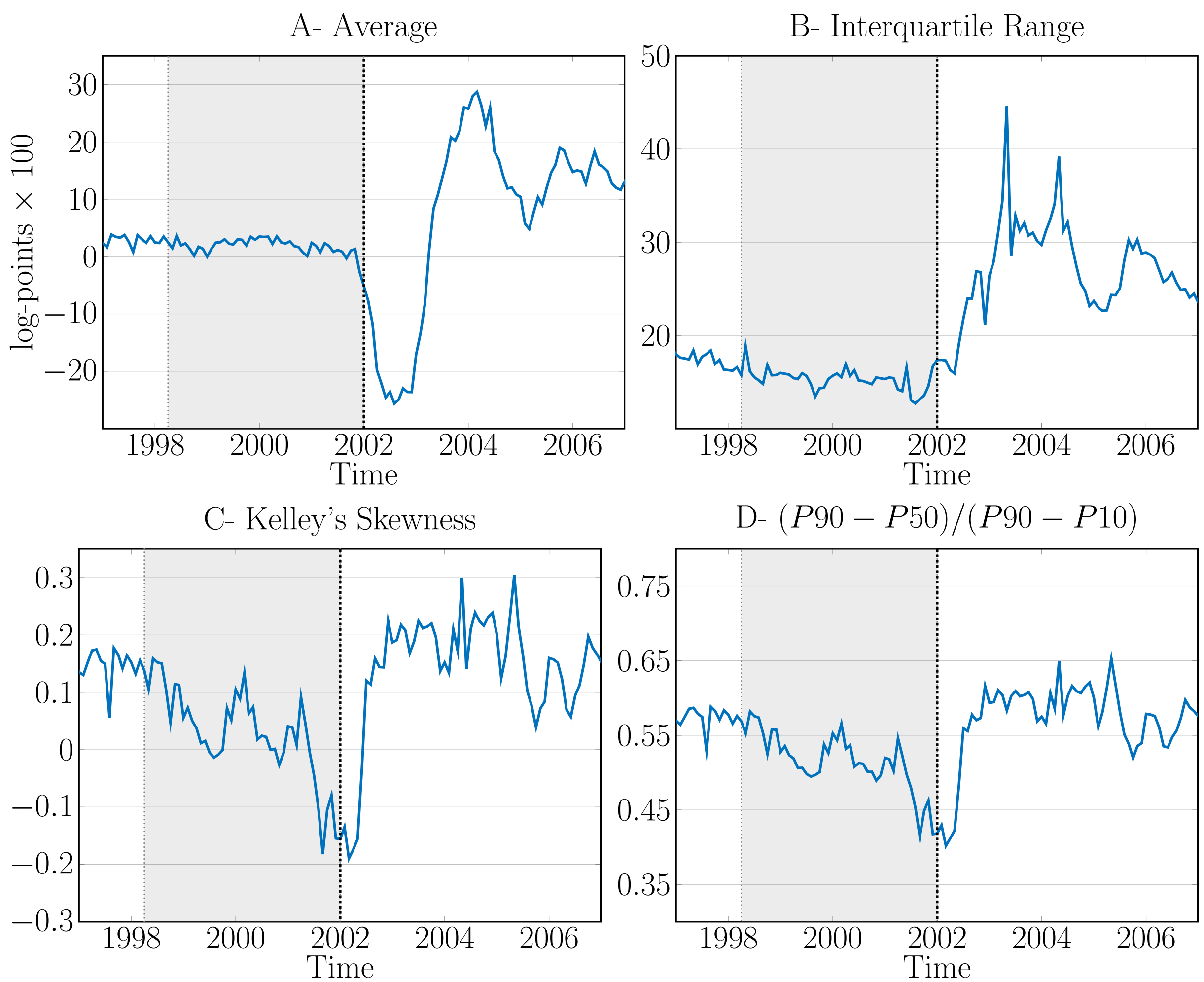
Notes: The figure plots average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to female workers who had at least 6 months of employment during the 2000-2001 period and to full-time jobs only.

E.2 Changes in Labor Income Risk

Can a lower labor income risk explain the decrease in inequality? Again, the answer is no. To illustrate the logic, suppose that the income process follows a standard AR(1) process. Then a decrease in the standard deviation of the innovation would translate into a compression of the stationary distribution, which could explain a lower level of inequality.

One potential source of a decline in labor income risk is the observed sharp decrease in the separation rate after the 2002 devaluation (results available upon request). Previous work in the literature has documented that job displacements are typically associated with large cumulative earnings losses (see, for example, Davis and Wachter, 2011). Thus, if the incidence of such large negative events decreases, the distribution after the devaluation could become more equal.

Figure E.15 – Moments of the Distribution of Labor Income Growth



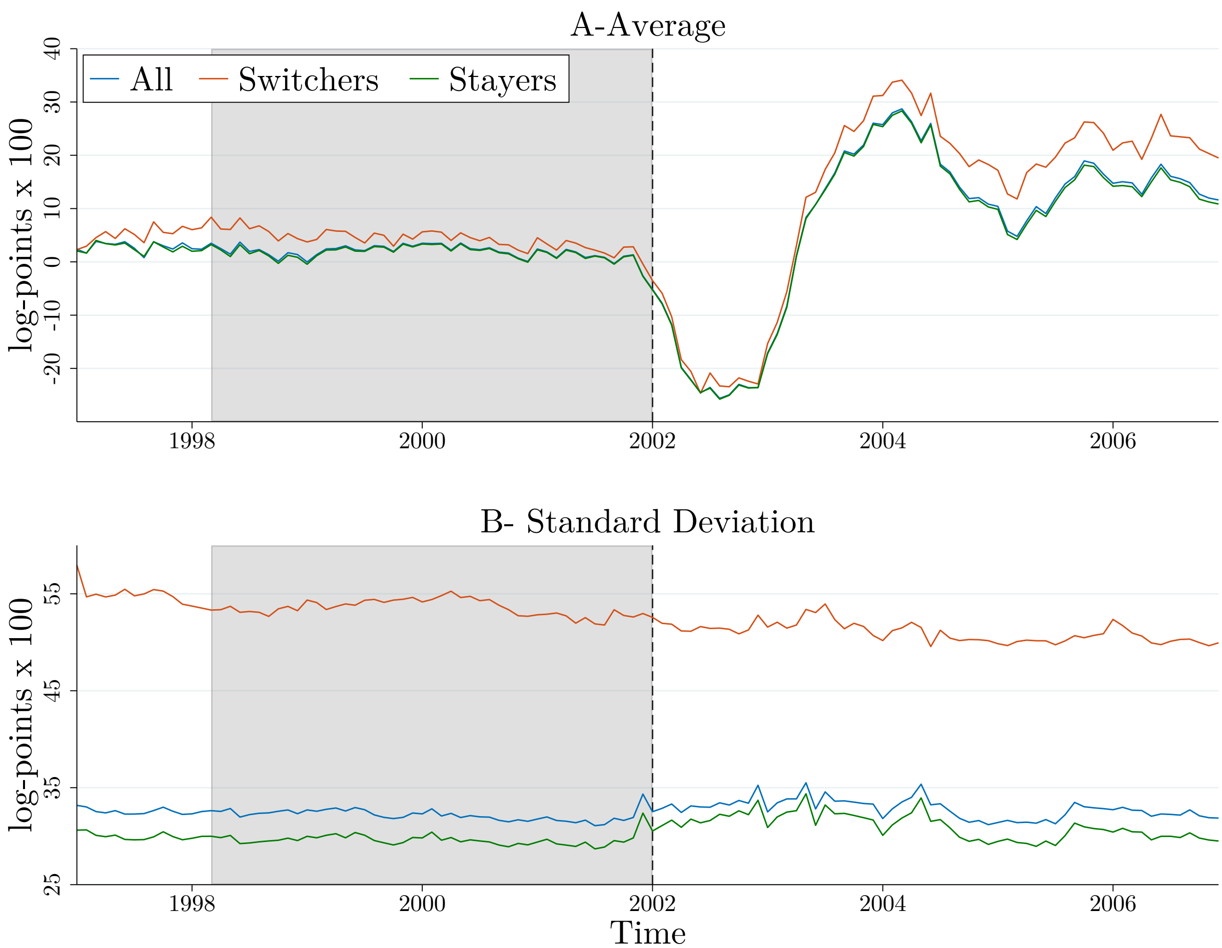
Notes: Panels A to D plot (in the following order) the average, the interquartile range, Kelley's skewness ($\frac{(P90-P50)-(P50-P10)}{P90-P10}$), and the decomposition of the Kelley's skewness ($\frac{P90-P50}{P90-P10}$) of year-over-year income growth from 1997 to 2006. Recession periods are in gray and monthly devaluations larger than 30% are marked with dotted black lines.

Nevertheless, the requirements for this mechanism to work are not observed in the data: Inequality decreased *despite* an increase in the standard deviation of income growth. Figure E.15 shows selected moments of the labor income growth distribution. During the recession and before the devaluation, the interquartile range of the distribution of labor income growth was almost constant, and Kelley's skewness continuously decreased (similar patterns have been documented for the U.S. by Guvenen *et al.*, 2014).[47] After the devaluation, there was a significant increase in the dispersion of year-over-year income growth. Figure E.15-Panel B shows a sharp and persistent increase in the interquartile range of year-over-year income growth from below 20% up to 40%. Moreover, the increase in dispersion was not symmetric. After the devaluation, there was a reversal in the negative trend in the skewness, which changes from -0.2 to an average of 0.15. In other words, the right tail of the distribution of income growth expanded. As Panel D shows, most of the movements in skewness came from changes in the distribution above the median: 60% of Kelley's skewness can be attributed to the upper tail after the devaluation.

Two mechanisms could explain the increase in labor income risk. First, a larger reallocation of labor, since the reallocation of workers across employment states, firms, and sectors is associated with large income variations, as previously shown. The fact that the standard deviation of income growth of job stayers also increases (see Figure E.16) points to an additional mechanism: the heterogeneous arrival rates of adjustment times of nominal income in the short run after a devaluation and heterogeneous growth in real income conditional on adjustment in the medium run.

[47]Kelley's measure of skewness is defined as $\frac{(P90-P50)-(P50-P10)}{P90-P10}$. Since it is based on percentiles, it is more robust to outliers.

Figure E.16 – Moments of Labor Annual Income Growth



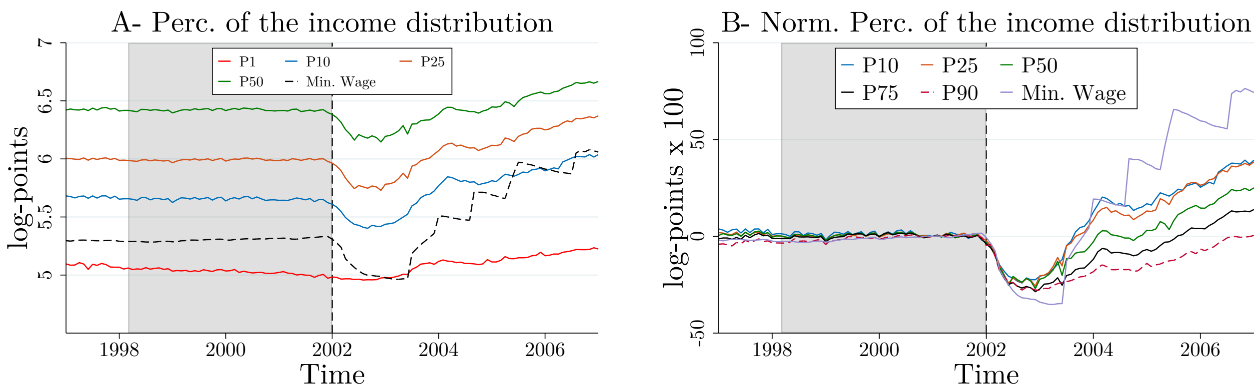
Notes: Panels A and B plot the average and standard deviation of year-over-year income growth from January 1997 to December 2006 for all workers, switchers and stayers. Recession periods are in gray, and monthly devaluations larger than 30% are marked with dotted black lines.

E.3 Changes in the Minimum Wage

Like most countries, Argentina has a minimum wage policy. Given the instability of prices, the length of the period of analysis, and changes in the nominal minimum wage, the real value of the minimum wage may not have been constant over time. The objective of this subsection is to track this real value and show how binding it is at each point in time.

Panel A of Figure E.17 plots different percentiles of the income distribution over time. In all cases, income is measured in real terms and in log points. We also compute the real value of the monthly minimum wage and, as we can see—excluding the last part of 2005—it is always lower than the 10th percentile of the income distribution. Thus, the minimum wage does not seem to be binding for most of the actual income distribution. Panel B of Figure E.17 normalizes percentiles and the minimum wage in order to track their evolution more easily.

Figure E.17 – The role of the minimum wage: 2002 percentiles



Notes: The figure shows percentiles of the monthly real income and the real minimum wage. Panel A shows the level and Panel B the normalized levels. Percentiles 1, 10, 25, 50, 75 and 90 are included to facilitate comparison with the real wage distribution in each period.

E.4 The Informal Labor Market

The purpose of this section is to provide a broad picture of the informal sector. As in many other developing economies, the Argentine informal sector is qualitatively and quantitatively important, but the SIPA database only includes information on the formal sector. Therefore, for the following analysis we rely on the labor force survey.

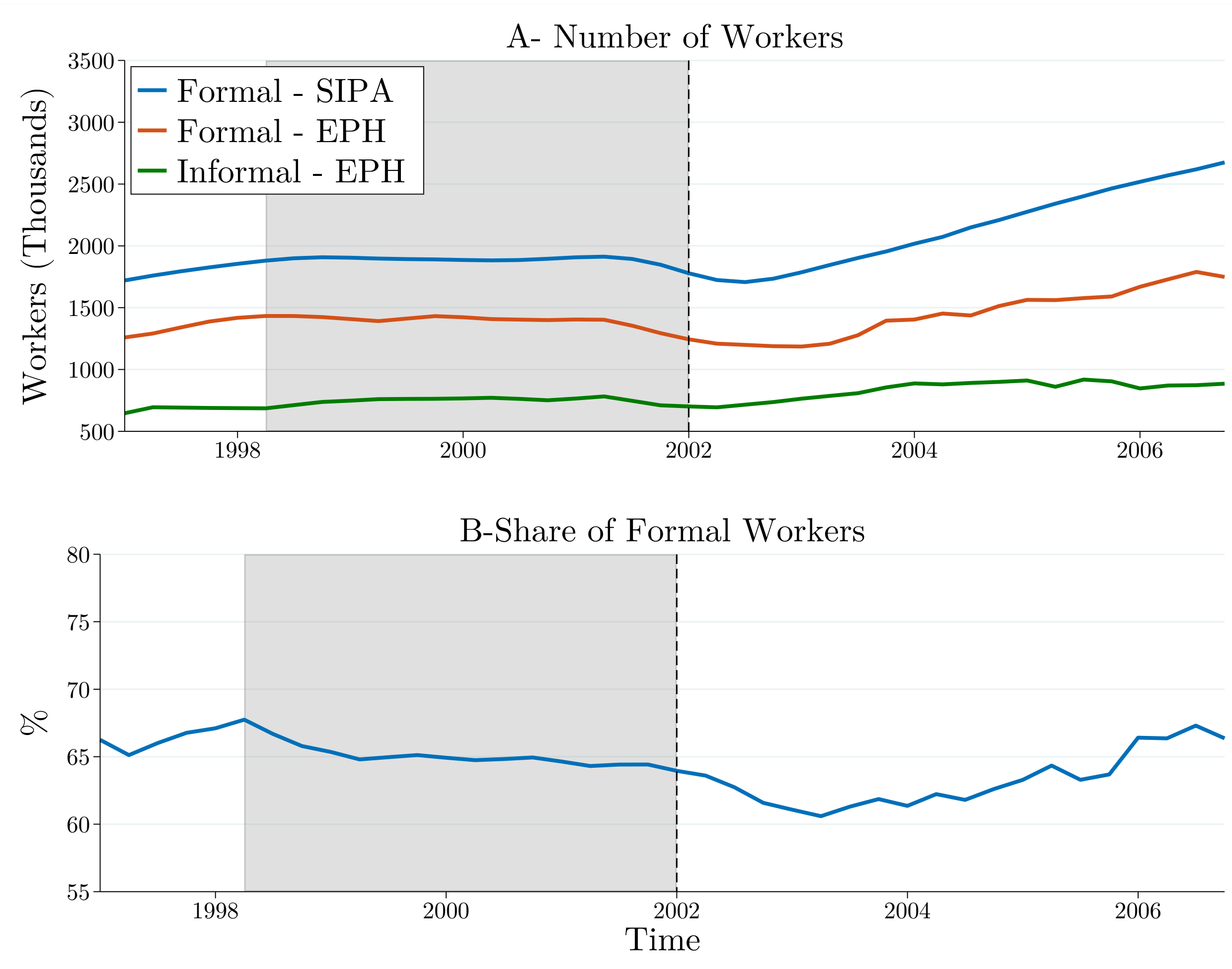
Panel A of Figure E.18 presents the number of formal and informal workers obtained from the labor force survey (EPH) and also the number of formal workers registered in the SIPA database. The number of formal workers we obtain from the EPH is systematically lower than SIPA's counterpart. This is because the EPH only covers urban areas. Despite this difference in levels, we see that their evolution is similar. In contrast, the number of informal workers has remained approximately constant over the period under analysis. In turn, Panel B of Figure E.18 plots the share of formal workers from the EPH. As we would expect, this share increases after 2003, since the number of formal workers increased then, but the number of informal workers remained about the same. After 2009, this share remains more or less stable over time at a level of 75%.

The evolution of real income in both sectors is presented in Figure E.19. As one might expect, the direction of changes in real income in a given period is more closely associated with aggregate conditions and less with formal/informal status. As we can see in the figure, the evolution of real income over time is quite similar across groups of workers, and trajectories differ mostly in levels. Big drops in real income, regardless of the formality status, are preceded by an episode of a devaluation.

Finally, Figure E.20 compares the evolution of percentiles of the income distribution for the two sectors. Panel A plots the percentiles for the formal sector and shows the previously discussed fall after the 2002 devaluation, with the associated slower recovery of the right tail of the distribution. The general pattern is similar in the informal sector, as can be seen in Panel B of Figure E.20, with one exception: When analyzing the speed of recovery, there is no difference across percentiles.

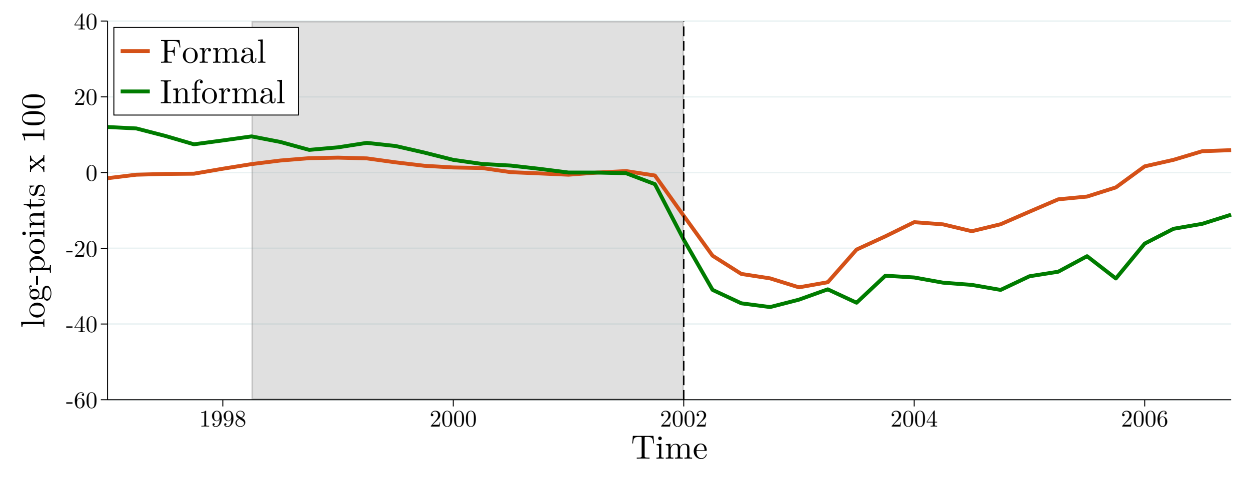
These patterns are consistent with the fact that unions, which are present only in the formal sector and do not cover the right tail of the distribution, explain the faster recovery of real incomes. In addition, if the decline in the informality rate is associated with transitions from the informal to the formal sector (which on average pays higher wages), labor mobility plays an additional role in compressing the overall income distribution.

Figure E.18 – Number of Formal and Informal Workers in Argentina: SIPA and EPH



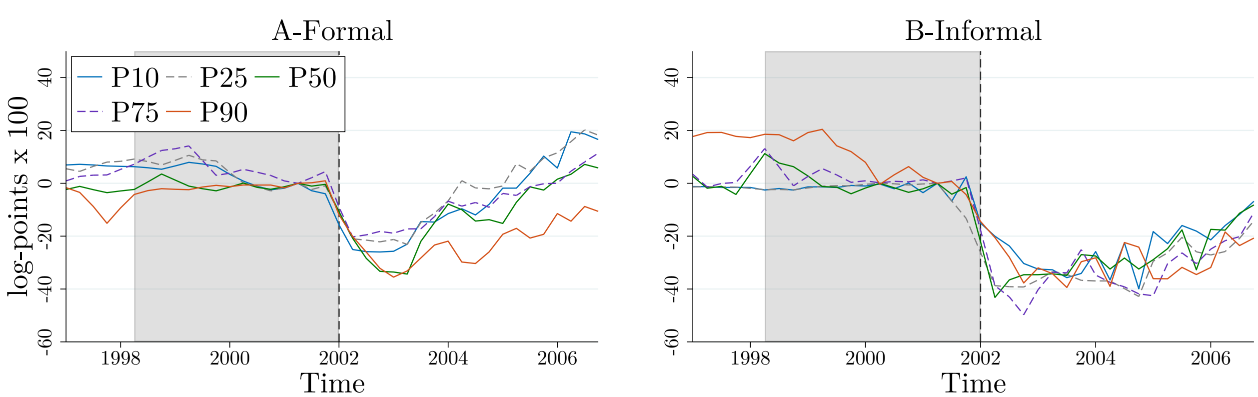
Notes: The figure compares the populations in SIPA and EPH. Panel A plots the number of private male workers aged 25-65 from the first quarter of 1997 to the last quarter of 2006 in SIPA and EPH, where EPH population estimates were obtained using the survey's expansion factors. Panel B plots the share of formal workers in EPH. Recession periods are in gray, and monthly devaluations larger than 10% are marked with dotted black lines.

Figure E.19 – Average Log Real Earnings in Argentina: Formal vs. Informal



Notes: The figure plots the mean (log) real wages in EPH from the first quarter of 1997 to the last quarter of 2006 for male workers aged 25-65 employed in the formal and informal sectors. EPH population estimates are obtained using the survey's expansion factors. Wages are normalized to their values in the second quarter of 2001.

Figure E.20 – Percentiles of Labor Income: Formal vs Informal Sectors



Notes: The figure plots moments of the monthly real income distribution from January 2000 to December 2006 in the national labor force survey. Panel A (resp. B) plots the percentiles of the log income distribution (× 100) in the formal (resp. informal) sector normalized by the value in the second quarter of 2001. EPH population estimates are obtained using the survey's expansion factors.

E.5 The Cyclicality of Labor Income

This section provides business cycle statistics for Argentina to complement the analysis in the main text.

Business cycle properties of labor income. We document the business cycle properties of labor income shown in Section 4 by reporting a strong (resp. weak) correlation between average labor income and the NER (resp. output) in Table E.1. The first two columns present quarterly correlations of labor income with output and the NER after applying an HP filter (we converted monthly variables by taking within-quarter averages). As we can see, mean labor income is procyclical and negatively correlated with the NER. In the next two columns, we report the residual correlation between one of the aggregate variables and labor income. We define the residual correlation as the correlation of an aggregate with the residuals resulting from a regression of labor income on the other aggregate variable. For instance, the residual correlation of labor income and GDP is the correlation of GDP with the residuals resulting from a regression of labor income on the NER. The procyclicality of average labor income with GDP decreases from 0.56 to 0.18 once we correlate it with the residuals of the projection between labor income and the NER. However, the (negative) residual correlation with the NER continues to be quantitatively significant. Similar results hold for the analysis based on growth rates. The residual correlation between mean labor income and GDP is close to 0, and the residual correlation with the NER remains large. In conclusion, average real income is mildly procyclical, as documented for real wages in advanced economies (see Blanco, 2021), but highly negatively correlated with the NER, which reflects the fact that labor income does not fall in recessions without large devaluations.

This finding is robust to analyzing deciles rather than the mean of the real labor income distribution. Rows 2 to 10 reproduce the analysis for each of the deciles. When analyzing the HP-filtered levels of the variables, we find a strong negative correlation between each percentile and the NER, even after controlling for fluctuations in GDP. Instead, the residual correlation of each percentile with GDP is weak, especially for the highest deciles. Importantly, the magnitudes of these correlations are a function of the position in the income distribution: Top incomes exhibit a lower comovement with GDP, but a higher comovement with the NER (in absolute value). The correlation analysis based on growth rates shows similar results across the distribution, with all deciles showing correlation coefficients much closer to that of the mean real labor income.

More importantly, we do not consistently find particularly large differences in the cyclicality of labor income across the distribution that could account for the decline in inequality after the 2002 devaluation. To illustrate, the residual correlations of P10 and P50 with GDP are quite similar (i.e., 0.26 and 0.15, respectively). However, in Figure 7 we report large differences in the income growth of workers in the 10th and 50th percentiles in the income distribution (a differential of almost 20 pp).

Table E.1 – Quarterly Correlations

	Levels				Growth Rates			
Moment	Correlation		Residual Correlation		Correlation		Residual Correlation	
	NER	GDP	NER	GDP	NER	GDP	NER	GDP
Mean	-0.86	0.56	-0.66	0.18	-0.65	0.21	-0.60	0.02
P10	-0.76	0.59	-0.53	0.26	-0.57	0.27	-0.50	0.11
P20	-0.78	0.60	-0.57	0.27	-0.62	0.27	-0.56	0.09
P30	-0.81	0.57	-0.61	0.21	-0.63	0.20	-0.58	0.01
P40	-0.81	0.54	-0.61	0.16	-0.60	0.14	-0.56	-0.04
P50	-0.84	0.54	-0.64	0.15	-0.62	0.19	-0.57	0.00
P60	-0.85	0.53	-0.66	0.12	-0.63	0.19	-0.58	0.00
P70	-0.86	0.52	-0.67	0.10	-0.63	0.19	-0.58	-0.00
P80	-0.86	0.51	-0.67	0.07	-0.63	0.19	-0.58	-0.00
P90	-0.87	0.46	-0.69	-0.03	-0.66	0.19	-0.61	-0.01

Notes: The table presents quarterly business cycles moments of the mean and selected percentiles of labor income with output and the RER and their respective growth rates. Column 2 shows data correlations, and column 4 the correlation between the residual of labor income with respect to a linear projection of the RER (resp. GDP) and (resp. RER) GDP. Columns 4 to 8 repeat the exercise for the growth rates of the moments. All series were deseasoned using ARIMA-X13. Series in levels were also detrended using the HP filter. The estimation is ran for the period 1996Q1 - 2018Q2.

E.6 Worker-specific Inflation Rates

Households across the income distribution consume different mixes of goods. Cravino and Levchenko (2017) document this fact for Mexico after the 1994 devaluation. They distinguish between *across* and *within* effects. The first is due to poorer households consuming a higher share of tradable products, which experience a rise in relative price after devaluations. The second comes from richer households consuming more expensive goods within categories, whose prices do not increase as much. They find that 2 years after the devaluation, the poorest households experienced an inflation rate that was between 34 and 41 percentage points higher than the richest ones. If these findings also apply in Argentina, this differential in inflation rates could explain income in the bottom of the distribution rising more to compensate for this gap in worker-specific inflation rates. Next, we provide evidence that this is highly unlikely.

To construct worker-specific price indexes, we use Argentina's National Survey of Household Expenditures (Encuesta Nacional de Gasto de los Hogares–ENGH) to compute expenditure shares of households with heads who were employed, male, and between 25 and 65 years old. We use microdata from the survey conducted in 1996, which is the closest to the 2002 devaluation. Although the survey allows us to compute shares for fairly specific categories, price data for such categories are not available at the same level of disaggregation. Hence, we focus on nine broad categories: Food and Beverages, Clothing, Housing, Housing Upkeep, Health, Transportation, Education, Leisure, and Other.[48] We then build worker-specific price indices using the weights that correspond to household h according to

$$p_t^h = \sum_g \omega_g^h p_{gt}, \tag{E.13}$$

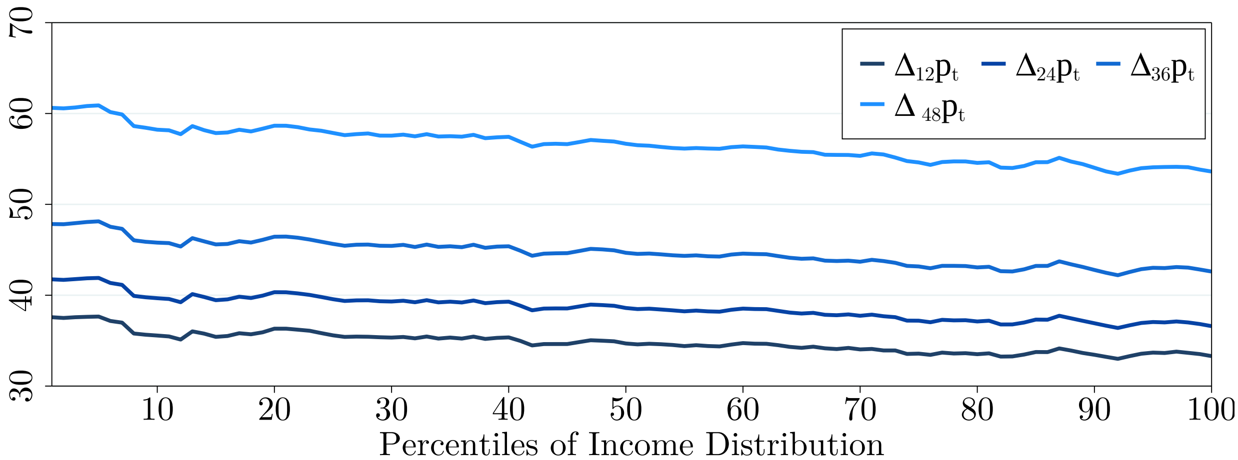
where g denotes the good category, ω_g^h is the share of household's h expenditure in good category g (computed from the expenditure survey in 1996), and p_{gt} is the price index of good g in month t (obtained from national statistics). These price indices allow us to compute an upper bound for the inflation rates experienced by different types of households since households can substitute their demand toward goods that experience a lower price increase after a devaluation.

Figure E.21 plots the average change in prices relative to December 2001, conditional on the position in the income distribution. While the curves are not constant, the negative slope is not significant in magnitude, showing that this differential in inflation rates was not as big in this episode. Figure E.22 plots the equivalent of Figure 7 using income-bin-specific inflation rates from Figure E.21 to compute real income growth. It is easy to see that the main results are unchanged when taking differences in inflation rates across workers into account: Four years after the devaluation, the difference in growth rates between the 10th and 90th percentiles of the pre-devaluation distribution is 40%. In our baseline analysis (see Figure 7), the corresponding number is 49%.[49]

[48] Cravino and Levchenko (2017) report the *across* results for 1-digit and 9-digit classifications of expenditures. While the magnitudes differ according to the level of disaggregation, they show that the 1-digit effect (the same as we compute) remains a good approximation of the 9-digit effect.

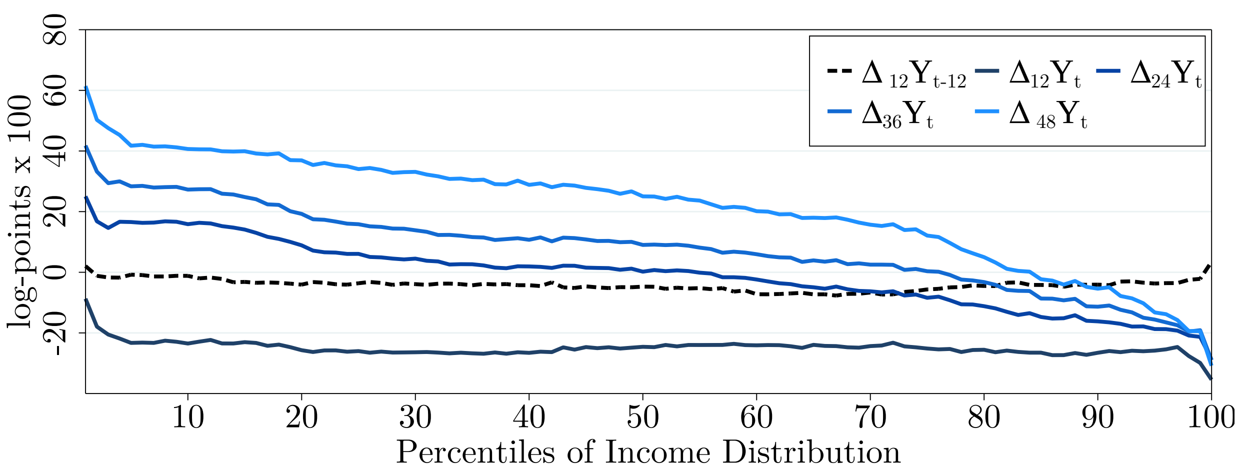
[49] While the broad definition of expenditure categories does not allow us to estimate the *within* effect, as in Cravino and Levchenko (2017), the difference in growth rates of income across workers is so significant that it should be robust to the expected magnitude of this effect. Cravino and Levchenko (2017) report that as a result of the 1994 Mexican devaluation, absent any changes in nominal income, real income fell about 50% in poor households as opposed to a 40% decline in richer households. Under this scenario, our main results would still hold.

Figure E.21 – Inflation with respect to 2001 across the income distribution



Notes: The figure plots the log change in prices faced by households conditional on their position in the income distribution.

Figure E.22 – Average income growth conditional on average income in 2000-2001: Income-specific inflation rates



Notes: The figure plots average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. Income-specific inflation was subtracted from nominal wage growth to construct real wage growth.

F Two Models of Labor Mobility

In Section 5, we document the heterogeneous dynamics of labor mobility and income growth across the income distribution during a large devaluation. This section shows how two canonical parsimonious search and matching models can micro-found the labor mobility patterns observed in our data. For simplicity, we focus on the steady-state predictions of these models. More specifically, we analyze the random search model of Burdett and Mortensen (1998) and the directed search model of Menzio and Shi (2010). Both models share the following core predictions. First, the probability of making a job-to-job transition is decreasing in the current wage. Second, conditional on experiencing a job-to-job transition or a separation, the wage difference between the new and the previous job is also a decreasing function of the wage received in the previous job. While a quantitative analysis of a model of labor market dynamics during large devaluations is outside the scope of this paper, the following analysis shows how both models incorporate a crucial mechanism that deserves further exploration in future work: Low-income workers have a lower opportunity cost of labor mobility than high-income workers. Thus, the prevalence and gains from labor mobility are more significant for low-income workers.

In what follows, we examine the model predictions regarding three statistics of interest. Let $p^{jj}(w)$, $\mathbb{E}^{jj}[\Delta w|w]$, and $\mathbb{E}^{sep}[\Delta w|w]$ be the job-to-job transition rate, the average (log) wage change across job spells, and the average wage change following a separation for a given wage level w, respectively. We now present two micro-foundations for these labor market variables and show the model-based counterparts of Figures 7 and 9.

F.1 The Burdett and Mortensen (1998) Model

Below, we describe a simplified version of the Burdett and Mortensen (1998) model. We focus on the main ingredients of the model and refer the reader who is interested in the technical details to the original paper.

Environment and equilibrium definition. Time is continuous. The economy is populated by a measure one of ex ante homogeneous workers and firms. Workers search for a job that pays a higher wage while employed and for an acceptable wage while unemployed. Each firm attracts workers by posting a wage conditional on the search behavior of workers and the wages offered by other firms. At each point in time, a worker is either unemployed or employed. Workers receive job offers at a rate λ, which is independent of their employment status. Workers search randomly among firms and receive wage offers drawn from the distribution of wages posted by firms, whose cumulative distribution is denoted by $F(w)$. The match between a worker and a firm is subject to an exogenous separation shock, which occurs at a rate δ. The worker's flow income during unemployment is 0, and the revenue generated per employed worker is 1. All agents discount the future at rate r. In what follows, we characterize the steady state of the economy.

Let U and $E(w)$ denote the present discounted value of a worker's lifetime income. For a given distribution of wage offers $F(w)$, U and $E(w)$ satisfy

$$rU = \lambda \left[\int \max\{U, E(w')\} dF(w') - U \right], \tag{F.14}$$

$$rE(w) = w + \lambda \left[\int \max\{E(w), E(w')\} dF(w') - E(w) \right] + \delta \left[U - E(w) \right]. \tag{F.15}$$

The main choice made by an unemployed worker is the reservation wage denoted by R (i.e., the minimum wage the worker is willing to accept rather than remaining unemployed). Since $E(w)$ increases in w, employed workers accept all job offers that pay a higher wage $w' > w$. From now on, we assume that $F(w)$ is differentiable with support $[R, \bar{w}]$ (these assumptions are satisfied in equilibrium, as shown by Burdett and

Mortensen, 1998).

For a given reservation wage R and a wage distribution $F(w)$, in the steady state the flow of workers from unemployment to employment (given by $\lambda\,[1-F(R)]\,u$) is equal to the flow of workers from employment to unemployment (given by $\delta[1-u]$); in this way, steady-state unemployment remains constant. Thus, the unemployment and employment rates are given by

$$u = \frac{1}{1+\kappa[1-F(R)]} \text{ and } e = \frac{\kappa[1-F(R)]}{1+\kappa[1-F(R)]}, \tag{F.16}$$

where $\kappa \equiv \lambda/\delta$. Let $G(w)$ denote the share of employed workers receiving a wage less than or equal to w. To obtain $G(w)$, note that the entry rate to employment with a wage lower than w is given by $\lambda[F(w)-F(R)]u$, i.e., the flow from unemployment to employment with an offer lower than w. Similarly, the mass of workers that exit employment at a wage lower than w is given by $[\delta+\lambda[1-F(w)]]\,G(w)(1-u)$, i.e., the mass of workers employed at a wage lower than w who either get a wage offer higher than w or get exogenously separated. Since in the steady state the masses of workers exiting and entering employment with a wage lower than w must be equal, we have that

$$\lambda[F(w)-F(R)]u = [\delta+\lambda[1-F(w)]]\,G(w)e \iff G(w) = \frac{(F(w)-F(R))/(1-F(R))}{1+\kappa(1-F(w))} \tag{F.17}$$

for all $w \geq R$. To obtain this expression, we use the steady-state unemployment and employment rates in (F.16). Given R and $F(w)$, the measure of workers per firm earning a wage between w and $w+dw$ (with $dw \to 0$), which is denoted by $l(w|R,F)$, is equal to the mass of employed workers with a wage in the interval $(w, w+dw)$ (i.e., $dG(w)e$), divided by the mass of firms offering wages in the same interval $(w, w+dw)$ (i.e., $dF(w)$). Thus, using equations (F.16) and (F.17), we have that for $w \geq R$,

$$\begin{aligned}
l(w|R,F) &= \frac{dG(w)e}{dF(w)}, \\
&= \frac{\frac{dG(w)}{dw}\frac{\kappa[1-F(R)]}{1+\kappa[1-F(R)]}}{\frac{dF(w)}{dw}}, \\
&= \frac{\kappa[1-F(R)]}{f(w)(1+\kappa[1-F(R)])}\frac{d\left[\frac{(F(w)-F(R))/(1-F(R))}{1+\kappa(1-F(w))}\right]}{dw}, \\
&= \frac{\kappa}{f(w)(1+\kappa[1-F(R)])}\frac{f(w)[1+\kappa(1-F(w))]+f(w)\kappa(F(w)-F(R))}{(1+\kappa(1-F(w)))^2}, \\
&= \frac{\kappa}{(1+\kappa(1-F(w)))^2}.
\end{aligned} \tag{F.18}$$

Let π denote the profits of a firm. Given R and $F(w)$, each firm posts wages to maximize the flow profits

$$\pi = \max_w (1-w)l(w|R,F). \tag{F.19}$$

Intuitively, by choosing a higher wage, the firm trades off lower profits per worker with larger firm size. By offering a higher wage, the firm is more likely to poach workers employed at firms that pay lower wages and less likely to lose workers to other firms offering higher wages.

The equilibrium is defined by a reservation wage R, a wage distribution $F(w)$, and profits π such that (1) given $F(w)$, $E(R)=U$; (2) given R and $F(w)$, π satisfies (F.19); and (3) and $(1-w)l(w|R,F) \leq \pi$ for any wage (with strict equality if w is in the support $[R, \bar{w}]$)[50].

[50]The situation in which two firms offer different wages, but earn different profits, violates profit maximization. To generate a dispersed-wage equilibrium, firms must be indifferent between all wages in the

Equilibrium characterization. Next, we characterize the equilibrium triple $(R, \pi, F(w))$. To find R, define

$$S(w) := E(w) - U. \tag{F.20}$$

Subtracting (F.14) from (F.15), $S(w)$ satisfies

$$(\delta + r)S(w) = w + \lambda \left[\int [\max\{0, S(w') - S(w)\} - \max\{0, S(w')\}]\, dF(w') \right]. \tag{F.21}$$

By definition, the reservation wage satisfies $E(R) = U$ if and only if $S(R) = 0$. Thus,

$$\begin{aligned} 0 &= (\delta + r)S(R) \\ &= R + \lambda \left[\int \left[\max\{0, S(w') - \underbrace{S(R)}_{=0}\} - \max\{0, S(w')\} \right] dF(w') \right] \\ &= R + \lambda \left[\int \underbrace{[\max\{0, S(w')\} - \max\{0, S(w')\}]}_{=0} dF(w') \right] \\ &= R. \end{aligned} \tag{F.22}$$

Thus, the reservation wage satisfies $R = 0$. Intuitively, since the flow income of an unemployed worker is zero, an unemployed worker accepts any job offer paying a nonnegative wage.

To find π, we use the fact that by definition, all firms must be indifferent between offering any wage in the support. Thus, $\pi = (1 - w)l(w|R, F)$ for all $w \in [0, \bar{w}]$. Evaluating profits at $w = 0$, we obtain

$$\pi = (1 - 0)l(0|0, F) = \frac{\kappa}{(1 + \kappa(1 - F(0)))^2} = \frac{\kappa}{(1 + \kappa)^2}. \tag{F.23}$$

Here, we use that $F(0) = 0$, since the distribution $F(w)$ has no probability atoms (see Burdett and Mortensen, 1998, for a formal proof of this result).

Finally, by firm's indifference, $(1 - w)l(w|R, F) = \pi = \frac{\kappa}{(1+\kappa)^2}$ for all w in the support $[R, \bar{w}]$. We use the fact that $l(w|R, F) = \frac{\kappa}{(1+\kappa(1-F(w)))^2}$ to solve for the equilibrium distribution of wage offers F:

$$(1 - w)l(w|R, F) = \frac{\kappa}{(1 + \kappa)^2} \iff \frac{\kappa(1 - w)}{(1 + \kappa(1 - F(w)))^2} = \frac{\kappa}{(1 + \kappa)^2} \iff F(w) = \frac{1 + \kappa}{\kappa} \left(1 - (1 - w)^{1/2}\right). \tag{F.24}$$

To find the upper bound in the support $\bar{w}$, we use the fact that $F(\bar{w}) = 1$. Solving for $\bar{w}$, we have that $\bar{w} = 1 - (1 + \kappa)^{-2}$.

Heterogeneous labor mobility and income growth. Before characterizing the statistics of interest $p^{jj}(w)$, $\mathbb{E}^{jj}[\Delta w|w]$, and $\mathbb{E}^{sep}[\Delta w|w]$, we highlight a key property of the model: The worker's value of employment at wage w, $E(w)$, is increasing in w. Thus, the opportunity cost of labor mobility is lower for workers with lower wages.

In the model, the job-to-job transition rate is given by the probability of receiving an offer that pays a wage higher than the current wage w:

$$p^{jj}(w) = \lambda[1 - F(w)] = \lambda \left[1 - \frac{1 + \kappa}{\kappa} \left(1 - (1 - w)^{1/2}\right) \right]. \tag{F.25}$$

As can be seen from this expression, the job-to-job transition rate is decreasing in w. Intuitively, the higher

support of the distribution.

the current wage, the less likely it becomes for a worker to receive an offer that pays an even higher wage. Conditional on a job-to-job transition, the expected wage change across job spells for a given wage w is given by

$$\mathbb{E}^{jj}[\Delta w|w] = \int_{w}^{1-(1+\kappa)^{-2}} (\log(w') - \log(w)) f(w')dw. \tag{F.26}$$

The derivative of $\mathbb{E}^{jj}[\Delta w|w]$ with respect to w is given by

$$\frac{d\mathbb{E}^{jj}[\Delta w|w]}{dw} = -\frac{\int_{w}^{1-(1+\kappa)^{-2}} f(w')dw}{w} = -\frac{1-F(w)}{w} < 0, \tag{F.27}$$

i.e., the expected wage change across job spells is decreasing in current wages. Following an intuition similar to the above, the higher the current wage, the lower the expected wage gains conditional on a job-to-job transition. The reason the model delivers both facts related to job-to-job transitions is that the model features a job ladder (see Moscarini and Postel-Vinay, 2018). As workers climb the ladder, it gets harder to find even better jobs and, conditional on finding one, the average wage gain becomes smaller.

Finally, the expected wage change conditional on going through a separation event, $\mathbb{E}^{sep}[\Delta w|w]$, can be computed as

$$\mathbb{E}^{sep}[\Delta w|w] = \int_{R}^{1-(1+\kappa)^{-2}} \log(w') f(w')dw - \log(w), \tag{F.28}$$

which is decreasing in the current wage w. This is because the entering wage following an unemployment spell is independent of the current wage. Intuitively, since search is random, the model exhibits mean reversion: Workers at the top of the job ladder will, on expectation, "fall down" the ladder after a separation.

Heterogeneous dynamics of labor mobility and income growth. In the main text, we document that heterogeneous labor mobility patterns across the income distribution can partially account for the observed decline in inequality after the devaluation. While the previous model does not incorporate business cycle fluctuations, as in our data, we can still explore the model's steady-state predictions regarding labor income dynamics and labor mobility patterns across the income distribution. Before, we performed comparative statics analysis to understand how $p^{jj}(w)$, $\mathbb{E}^{jj}[\Delta w|w]$, and $\mathbb{E}^{sep}[\Delta w|w]$ depend on the current wage w. Here, we provide a simple quantitative illustration of the mechanisms. With this objective in mind, we extend the model described above to its original version in Burdett and Mortensen (1998). First, the arrival rate of job offers depends on the employment status (i.e., λ_0 is the arrival rate of job offers when unemployed, and λ_1 is the arrival rate when employed). Second, the worker's flow income during unemployment b is different from zero. Given the uncertainty around most of the parameters of the Argentinian economy, and to make this exercise as transparent as possible, we calibrate this model using standard targets in the literature. Table F.1 describes the set of parameters and the targets computed at a monthly frequency.

Figure F.1 reproduces Figures 7 and 9 using model-simulated data. We omit the figure of the cumulative separation rate, since it is exogenous and constant in the model.[51] In all figures, the x-axis plots the percentiles of the income distribution based on the model's ergodic distribution, i.e., $G^{-1}(x)$ with $x \in \{0.01, 0.02, \ldots, 0.99\}$.

Figure F.1-Panel (a) shows the average monthly income growth in period $t = 1$ and $t = 12$ as a function of a worker's position in the income distribution in period $t = 0$. The figure shows a "pivoting" pattern similar to the one we document in the Argentinean data. The intuition is that labor mobility leads to a future income loss on average for workers currently at the top of the income distribution.

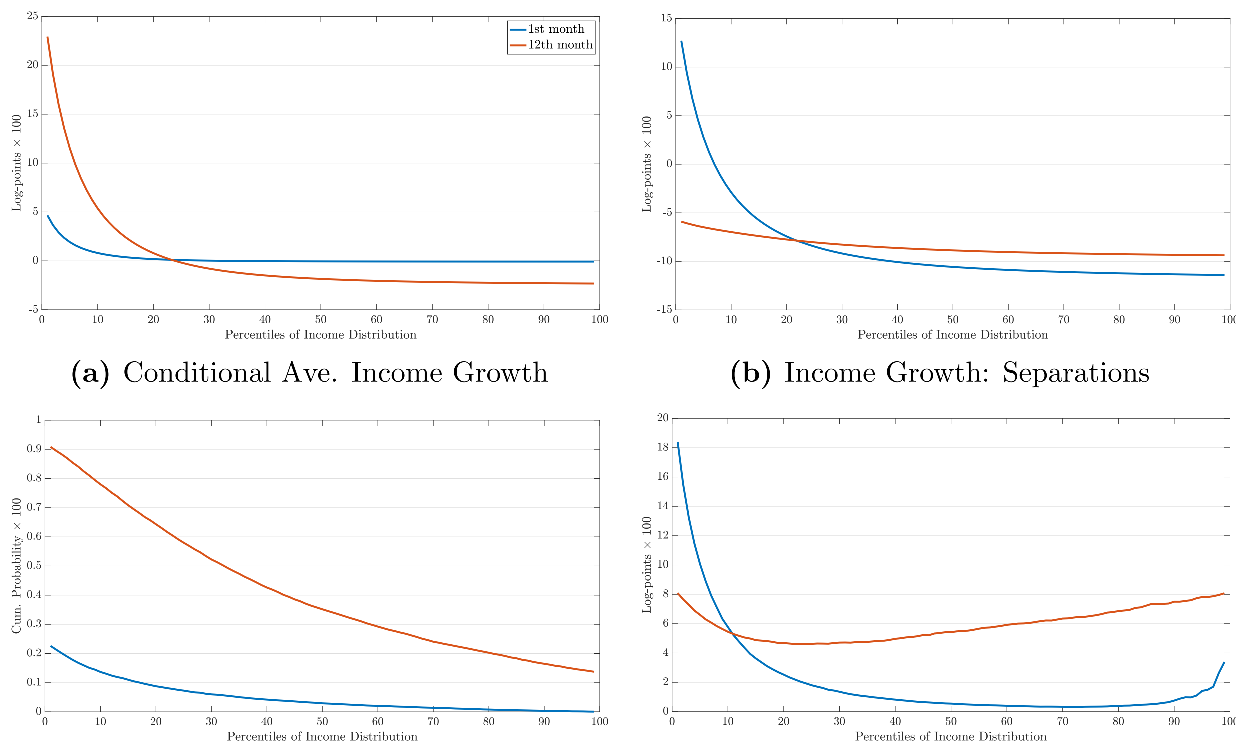
[51] Note that the observed heterogeneous pattern in separation rates across the income distribution could be generated in a model with endogenous separation rates, such as Mortensen and Pissarides (1994).

Table F.1 – Burdett and Mortensen (1998) Model Parameters and Targets

Parameters: Description	Value	Target
λ_0 : Job-finding arrival rate	0.6	Job-finding probability of 0.45, (see Shimer, 2005a)
λ_1 : Job-to-job offer arrival rate	0.27	Job-to-job probability of 0.05 (see Shimer, 2005b)
b : Unemployment income	0.46	US replacement ratio (see Shimer, 2005a)
δ : Separation arrival rate	0.036	Separation probability of 0.035 (see Shimer, 2005a)
p : Output per worker	1	Normalization

Notes: The table presents the parameter values assigned in the Burdett and Mortensen (1998) model. In the model, we compute the monthly job-finding probability as $1 - e^{-\lambda_0(1-F(R))}$ and the monthly job-to-job probability as $1 - e^{-\int \lambda_1(1-F(w))g(w)dw}$. Similarly, the monthly separation rate is $1 - e^{-\delta}$. The replacement ratio is computed as $\frac{b}{\int wg(w)dw}$.

Figure F.1 – Average Income Growth and Labor Mobility Across the Income Distribution



(a) Conditional Ave. Income Growth

(b) Income Growth: Separations

(c) Cum. Prob. Job-to-Job Trans.

(d) Income Growth: Job-To-Job Trans.

Notes: Panel (a) plots the average income growth. Panel (b) plots the average difference between the (log) income in the new job found after a separation and the (log) income in the previous job. Panel (c) plots the cumulative probability of experiencing a job-to-job transition over time. Panel (d) plots the average difference between the (log) income in the new job found after a job-to-job transition and the (log) income in the previous job. Each panel plots the variables in periods $t = 1$ (blue line) and $t = 12$ (red line) as a function of the percentiles of the distribution of labor income in period $t = 0$.

Figure F.1-Panel (b) shows the average (log) income growth conditional on a separation shock. In the short run, workers at the bottom (resp. top) of the income distribution experience a positive (resp. negative) average income growth after a separation, as in the data. Intuitively, for workers at the bottom of the income distribution, the separation shock gives them a new random draw from the wage offer distribution, which on average should be higher than their (low) income in the previous job. Since the model is stationary, as time goes to infinity, the income growth conditional on a separation shock converges to -11%.[52]

Figure F.1-Panel (c) and Figure F.1-Panel (d) plot the cumulative probability of experiencing a job-to-job transition and the average income growth conditional on making such a transition, respectively. The cumulative job-to-job transition probability decreases in the percentile of the income distribution for the same reason the job-to-job rate decreases in the current wage: Workers employed at a lower wage have a higher probability of receiving and accepting a wage offer that is larger than their current wage. Finally, notice that the average income growth conditional on a job-to-job transition is (mostly) decreasing in the percentile of the income distribution in the "short run".[53]

In summary, despite the stylized nature of the quantitative analysis, this section shows how the job-ladder mechanism behind the Burdett and Mortensen (1998) model can micro-found the patterns observed in the data.

F.2 The Menzio and Shi (2010) Model

We now present the Menzio and Shi (2010) model with wage posting and on-the-job search.

Environment. Time is continuous. The economy is populated by a measure one of ex ante homogeneous workers and an endogenous measure of homogeneous firms. The labor market is divided into a continuum of submarkets indexed by the wage w offered to workers. As in the original model, we assume that wages remain constant within the job spell. At each point in time, a worker is either unemployed or employed, and can search for a job by choosing which submarket to visit (i.e., search is directed). We assume that the search efficiency of employed workers is lower relative to the efficiency of the unemployed by a factor of $\lambda < 1$.[54] Similarly, firms can search for workers by paying a per-period cost κ to post a vacancy and choosing in which submarket to locate it. In each submarket, matches between workers and firms are produced according to the matching function $m(u(w), v(w)) = \sqrt{u(w)v(w)}$, where $u(w)$ and $v(w)$ denote the mass of unemployed workers searching for a job and the mass of vacancies posted in submarket w. Let $f(\theta(w))$ and $\lambda f(\theta(w))$ denote the job-finding rates for the unemployed and employed workers, respectively, as a function of market

[52] In the steady state, the average income growth conditional on separation is approximately equal to

$$\left(\int_R^{\bar{w}} \log(w) dF(x) / \int_R^{\bar{w}} \log(w) dG(x)\right) \times 100 = -11\%. \tag{F.29}$$

[53] In the "medium run", this relationship becomes U-shaped. The intuition for this is the following. Job-to-job transitions can occur before or after the first separation shock since period $t = 0$ (i.e., when a worker's position in the income distribution is measured). If a worker is at the very top of the income distribution, the probability of experiencing a job-to-job transition is close to zero; see Figure F.1-Panel (c). Therefore, those workers are more likely to first experience a separation shock that brings them closer to the middle of the income distribution before experiencing a job-to-job transition. When such a transition occurs, they experience a larger income gain. On the other hand, workers at the bottom of the income distribution experience job-to-job transitions at a higher rate (see Figure F.1-Panel (c)) and will likely occur before the separation shock. Therefore, these workers also experience a larger income gain conditional on a job-to-job transition. More broadly, separation shocks and job-to-job transitions move workers around the income distribution. As time goes by, their original position in the income distribution becomes a worse predictor of their future income dynamics.

[54] The discrete-time interpretation of this assumption is that employed workers can only search for a job with probability $\lambda < 1$.

tightness $\theta \equiv v/u$. Similarly, let $q(\theta(w))$ denote the vacancy-filling rate of a firm. At each point in time, matches get exogenously separated at the rate δ. The worker's flow income during unemployment is b, and the revenue generated by a match is equal to 1. All agents discount the future at the rate r. We characterize the steady state of the economy.

Let $H(w)$ and U denote the present discounted value of the lifetime income of the employed and unemployed worker, respectively. For a given market tightness in each submarket $\theta(w)$, the values $H(w)$ and U satisfy

$$rU = b + \max_{w'} f(\theta(w'))[H(w') - U], \tag{F.30}$$

$$rH(w) = w + \max_{w'} \lambda f(\theta(w'))[H(w') - H(w)] + \delta[U - H(w)]. \tag{F.31}$$

Equations (F.30) and (F.31) are the standard arbitrage equations. The annuity value of unemployment has to be equal to the flow income during unemployment plus the expected capital gain of finding a job. Similarly, the annuity value of employment has to be equal to the flow income during employment plus the expected capital gain of a job-to-job transition or the capital loss of a transition to unemployment. The worker chooses in which submarket to search for jobs when unemployed, w_U, and when employed, $w_H(w)$, by trading off the probability of finding a job in a given submarket $f(\theta(w'))$ with the net value of being employed at the wage w'.

Similarly, let $J(w)$ denote the firm's value of offering a wage w. Given the free-entry condition, $\theta(w)$ and $J(w)$ satisfy

$$\frac{\kappa}{q(\theta(w))} = J(w), \quad \forall \theta(w) > 0 \tag{F.32}$$

$$rJ(w) = 1 - w - (\delta + \lambda f(\theta(w_H(w))))J(w). \tag{F.33}$$

Equation (F.32) equalizes the expected cost and benefit of posting a vacancy. The cost of posting a vacancy in a period of time dt is given by κdt. The benefit of posting a vacancy is given by the probability of finding a worker $q(\theta(w))dt$ times the value of having a worker $J(w)$. Equation (F.33) shows the counterpart of the worker's Bellman equation for the firm, in which the worker's strategy is taken as given.

A block recursive equilibrium consists of the value of unemployment U, the value of employment $H(w)$, the value of the matched firm $J(w)$, and a market tightness function such that equations (F.30) to (F.33) are satisfied.

Equilibrium characterization. Next, we characterize the equilibrium triple $(\theta(w), w_H(w), w_U)$. Using the functional form assumption regarding the matching function, we have that $f(\theta(w)) = \frac{\sqrt{uv}}{u} = \theta^{1/2}$ and $q(\theta(w)) = \frac{\sqrt{uv}}{v} = \theta^{-1/2}$. Thus, from the entry condition we obtain an expression for the vacancy-filling rate of the firm

$$\frac{\kappa}{q(\theta(w))} = J(w) \iff \kappa\theta(w)^{1/2} = J(w) \iff f(\theta(w)) = \frac{J(w)}{\kappa}. \tag{F.34}$$

Replacing this expression in the value of the firm (F.33), we obtain

$$(\delta + r)J(w) = 1 - w - \frac{\lambda}{\kappa} J\left(w_H(w)\right) J(w). \tag{F.35}$$

Define $W(w) := H(w) - U$. Taking the difference between (F.31) and (F.30), we have that

$$(\delta + r)W(w) = w - b + \max_{w_H} \frac{\lambda}{\kappa} J(w_H)[W(w_H) - W(w)] - \max_{w_U} \frac{J(w_U)W(w_U)}{\kappa}. \tag{F.36}$$

Next, we can define the sequence of submarkets that workers visit over time. Define w_i for $i = 1, 2, \ldots, \infty$ recursively, as follows:

$$w_i = w_H(w_{i-1}) \quad for\ i = 2, 3, \ldots, \infty\ with\ w_1 = w_U. \tag{F.37}$$

Thus, unemployed workers search for jobs in the submarket that offers a fixed wage $w_1 = w_U$. Similarly, a worker currently employed at the wage w_{i-1} searches for a better-paying job in submarket $w_i = w_H(w_{i-1})$. The discrete distribution of wages offered in equilibrium is given by the unemployment rate u and the mass of firms offering each wage $\{P(i)\}_{i=1}^{\infty}$. The steady-state distribution is determined by the fact that inflows into employment at a given wage must equal outflows from employment at that wage into unemployment:

$$(\delta + \frac{\lambda}{\kappa} J(w_1))P(1) = \frac{J(w_1)}{\kappa} u, \tag{F.38}$$

$$(\delta + \frac{\lambda}{\kappa} J(w_i))P(i) = \frac{\lambda}{\kappa} J(w_{i-1})P(i-1) \quad for\ i = 2, 3, \ldots, \infty. \tag{F.39}$$

Since $P(\cdot)$ is a probability distribution, it must also satisfy $u + \sum_{i=1}^{\infty} P(i) = 1$. It is easy to show that the steady-state distribution of wages satisfies

$$P(i) = \frac{\delta}{\delta + \frac{J(w_1)}{\kappa}} \frac{1}{\delta + \frac{\lambda J(w_i)}{\kappa}} \prod_{j=1}^{i-1} \frac{\frac{\lambda J(w_{j-1})}{\kappa}}{\delta + \frac{\lambda J(w_{j-1})}{\kappa}} \tag{F.40}$$

with the unemployment and employment rates given by

$$u = \frac{\delta}{\delta + \frac{J(w_1)}{\kappa}} \quad \text{and} \quad e = 1 - u. \tag{F.41}$$

In what follows, we provide a quantitative exploration of the model predictions. To do so, we numerically solve the system of functional equations (F.35) and (F.36). Again, in the spirit of keeping this exercise as transparent as possible, we calibrate the model using standard targets in the literature. Table F.2 describes the parameter values and targets computed at a monthly frequency.

Table F.2 – Menzio and Shi (2010) Model Parameters and Targets

Parameters: Description	**Value**	**Target**
κ : Job-finding arrival rate	3.2	Job-finding probability of 0.45 (see Shimer, 2005a)
λ : Job-to-job search efficiency	0.17	Job-to-job probability of 0.05 (see Shimer, 2005b)
b : Unemployment income	0.42	US replacement ratio (see Shimer, 2005a)
δ : Separation arrival rate	0.036	Separation probability of 0.035 (see Shimer, 2005a)
r : Discount factor	0.04/12	4% annualized real interest rate
p : Output per worker	1	Normalization

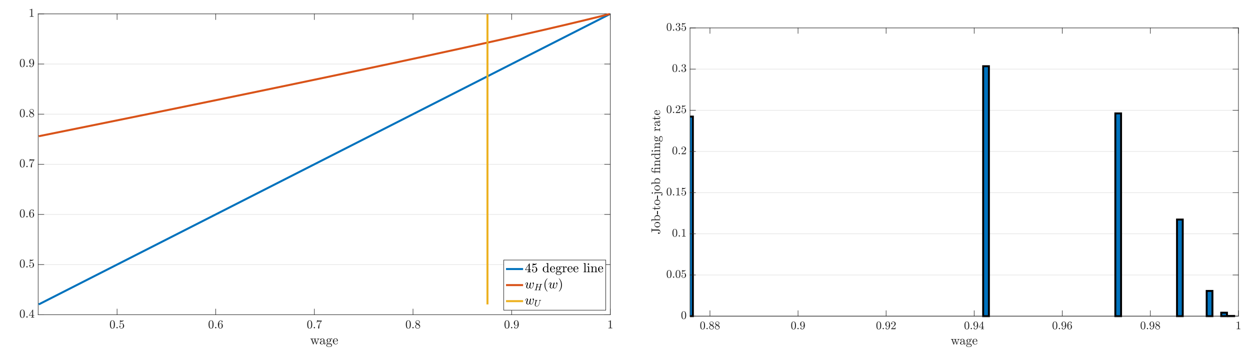
Notes: The table presents the parameter values assigned in the Menzio and Shi (2010) model. In the model, we compute the monthly job-finding probability as $1 - e^{-\frac{\lambda J(w_1)}{\kappa}})$ and the monthly job-to-job probability as $1 - e^{-\frac{\lambda}{\kappa} \frac{\sum_{i=1}^{\infty} J(w_i)P(i)}{\sum_{i=1}^{\infty} P(i)}}$. Similarly, the monthly separation rate is $1 - e^{-\delta}$. The replacement ratio is computed as $\frac{b}{\frac{\sum_{i=1}^{\infty} w_i P(i)}{\sum_{i=1}^{\infty} P(i)}}$.

Policy functions and steady-state wage distribution. Figure F.2-Panel (a) shows the policy function of the unemployed worker. The target wage for an unemployed worker w_U follows from the standard trade-off between the wage offered in a submarket and the probability of finding a job. To see this trade-off, from the first-order condition of equation (F.36), we have that

$$\underbrace{J'(w_U)W(w_U)}_{\text{Job finding effect }(-)} + \underbrace{J(w_U)W'(w_U)}_{\text{Wage effect }(+)} = 0, \tag{F.42}$$

where the first term represents the marginal cost and the second term represents the marginal benefit of a marginal increase in w_U. The marginal cost of increasing the target wage is given by the reduction in the firm's value and the job-finding rate, which is necessary to satisfy the firm's free-entry condition. The marginal benefit is given by the marginal increase in wages conditional on finding a job.

Figure F.2 – Policy functions and the steady-state wage distribution in Menzio and Shi (2010) model with on-the-job search



(a) Worker's policy function **(b)** Steady-state distribution of wages

Notes: Panel (a) plots the target wage of an unemployed worker w_U and the target wage of an employed worker $w_H(w)$. Panel (b) plots the steady-state distribution of wages.
Source: Author's calculations.

The same two mechanisms that determine the wage of a newly employed worker also determine the size of the wage increase following a job-to-job transition. The critical difference between the search behavior of an unemployed and employed worker is that the opportunity cost of on-the-job search increases in the current wage. To see this, from the first-order conditions of equation (F.36), we have that

$$\underbrace{J'(w_H(w))(W(w_H(w)) - W(w))}_{\text{Job finding effect }(-)} + \underbrace{J(w_H(w))W'(w_H(w))}_{\text{Wage effect }(+)} = 0. \tag{F.43}$$

Since the marginal cost is lower (which is represented by the additional term $W(w)$), the target wage of workers searching on the job satisfies $W_H(w_U) > w_U$ with $w_H(1) = 1$.

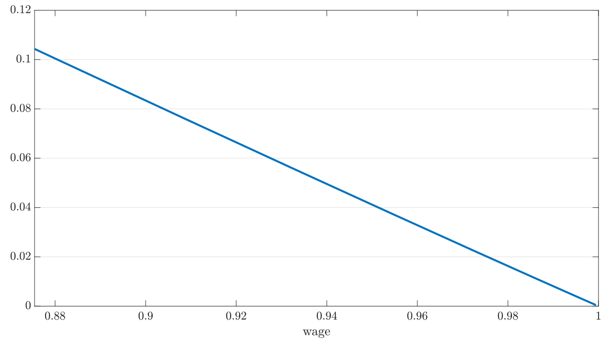
Heterogeneous labor mobility and income growth. Having described the policy functions, we can now focus on the statistics of interest $p^{jj}(w)$, $\mathbb{E}^{jj}[\Delta w|w]$, and $\mathbb{E}^{sep}[\Delta w|w]$. Figure F.3 shows these three variables for all $w \in [w_U, 1]$. As expected, $p^{jj}(w)$ is decreasing in w: Higher wages decrease the value of the firm and discourage vacancy creation, which decreases the workers' job-finding probabilities.[55]

[55]It is easy to show theoretically that $p^{jj}(w)$ is decreasing for w close to 1. Using a Taylor approximation of equation (F.35) around this point, we have that

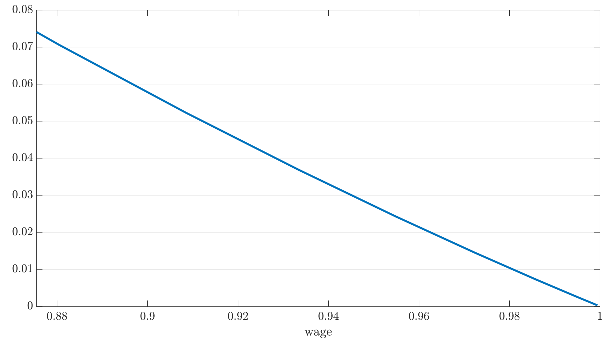
$$p^{jj}(w) = \frac{\lambda}{\kappa}J(w) = \frac{\lambda}{\kappa}\left(J(1) + J'(1)(w-1) + o((w-1)^2)\right) = \frac{\lambda}{\kappa}\left(0 - \frac{1}{r+\delta}(w-1) + o((w-1)^2)\right),$$

which is a decreasing function of w.

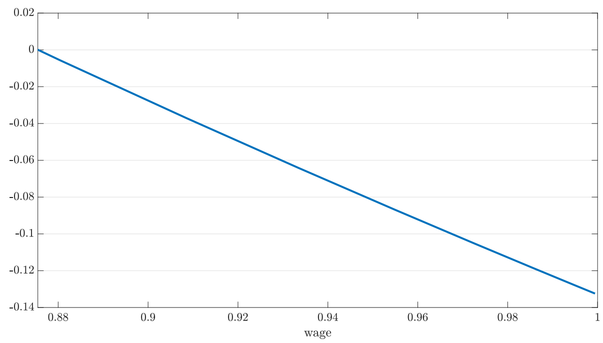
Figure F.3 – Policy functions with on-the-job search



(a) $p^{jj}(w)$



(b) $\mathbb{E}^{jj}[\Delta w|w]$



(c) $\mathbb{E}^{sep}[\Delta w|w]$

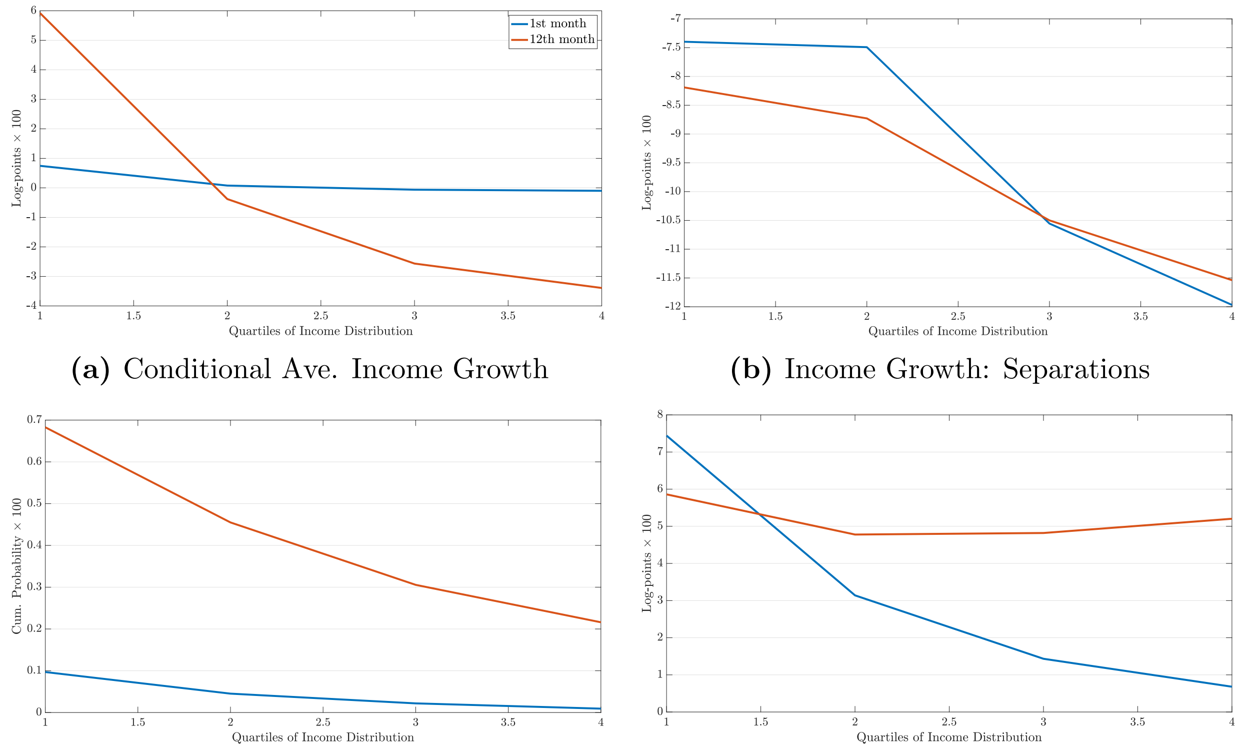
Notes: Panel (a) plots the job-to-job finding rate for a worker employed at the wage w. Panel (b) plots the expected income growth conditional of a job-to-job transition for a worker currently employed at the wage w. Panel (c) plots the expected income growth for a worker that experiences a separation shock as a function of the wage paid in the previous job.
Source: Author's calculations.

Figure F.3 also shows that the expected income growth following a job-to-job transition $\mathbb{E}^{jj}[\Delta w|w]$ is also decreasing in the current wage w. Again, as workers climb the job ladder and earn higher wages, the potential income growth becomes smaller. Indeed, at the top of the job ladder (i.e., when $w = 1$), the expected income growth becomes zero. Finally, as in the Burdett and Mortensen (1998) model, the new wage a worker receives following a separation shock is independent of the wage earned in the previous job—i.e., $\mathbb{E}^{sep}[\Delta w|w] = log(w_U/w)$. Thus, the expected change in wages after a separation shock $\mathbb{E}^{sep}[\Delta w|w]$ is decreasing in w.

Heterogeneous dynamics of labor mobility and income growth. Figure F.4 reproduces Figures 7 and 9 using model-simulated data. Once again, we omit the figure of the cumulative separation rate, since it is exogenous and constant in the model. The x-axis in all figures plots w_i for $i = 1, 2, 3,$ and 4, where each w_i is close to the quartiles of the model's ergodic income distribution, i.e., $G^{-1}(x)$ with $x \in \{0.25, 0.58, 0.83, 1\}$.

Figure F.4-Panels (a), (c), and (d) show qualitative patterns similar to those in Figure F.1: Average income growth, the probability of job-to-job transitions, and the corresponding expected income growth are all decreasing functions of a worker's position in the income distribution. The key difference between the models of Burdett and Mortensen (1998) and Menzio and Shi (2010) resides in the predictions regarding the expected income growth of newly hired workers from unemployment. While in the Menzio and Shi (2010)

Figure F.4 – Average Income Growth and Labor Mobility Across the Income Distribution



(a) Conditional Ave. Income Growth

(b) Income Growth: Separations

(c) Cum. Prob. Job-to-Job Trans.

(d) Income Growth: Job-To-Job Trans.

Notes: Panel (a) plots the average income growth. Panel (b) plots the average difference between the (log) income in the new job found after a separation and the (log) income in the previous job. Panel (c) plots the cumulative probability of experiencing a job-to-job transition over time. Panel (d) plots the average difference between the (log) income in the new job found after a job-to-job transition and the (log) income in the previous job. Each panel plots the variables in periods $t = 1$ (blue line) and $t = 12$ (red line) as a function of the percentiles of the distribution of labor income in period $t = 0$.

model with directed search, newly hired workers always start from the bottom of the job ladder, in the Burdett and Mortensen (1998) model with random search, these workers get employed at a random position in the steady-state distribution of wages. Despite these differences, both models predict that the expected income growth after a separation shock is decreasing in the wage earned in the previous job.

F.3 Discussion

The dynamic analysis of these models during large devaluations is outside the scope of this paper. However, we finish this section with a discussion of how these models would behave during these episodes. To fix ideas, this discussion focuses on the Menzio and Shi (2010) model.

In the models discussed above, we normalized the marginal revenue product of a worker to one. This normalization is without loss of generality, since the relevant variables for agents' decisions are the cost of posting vacancies (κ), the flow income during unemployment (b), and wages (w) *relative to* the marginal revenue product of a worker. Abstracting from the cost of posting vacancies and the flow income during unemployment, any unexpected change in the marginal revenue product in the economy will shift the current distribution of wages relative to the marginal revenue product. While this shift can change the level of the probability of transitions and the income growth conditional on making those transitions, it does not change the heterogeneous pattern across the wage distribution. Thus, there would be a heterogeneous recovery in the short run with the direct effect of a decline in the dispersion of labor income.

How should we interpret large devaluations in light of the previous discussion? Large devaluations lead to a sudden and significant increase in a worker's nominal marginal revenue product. As shown in Section 3, large devaluations are followed by a rapid increase in inflation. Thus, as long as the real marginal product of labor does not fall and overturn the rise in inflation, a worker's nominal marginal revenue product will increase during large devaluations.

G Inequality Dynamics during Large NER Devaluations in Brazil

This section extends the main analysis to the 1990 and 1994 devaluations in Brazil. The objective is to document the external validity of some of the mechanisms that drive income inequality during large devaluations for another country.

G.1 Data Description

We use administrative employer-employee matched data compiled by the Ministry of Labor and Employment in Brazil. The dataset starts in January 1985 and ends in December 2017. Our data source is *Relação Anual de Informações Sociais* (RAIS). As these data have been extensively used in the literature (see Krishna, Poole and Senses, 2014, Dix-Carneiro and Kovak, 2017, Engbom and Moser, 2018, Alvarez, Benguria, Engbom and Moser, 2018, among many others), we will keep the description short. The dataset contains data on the labor income of the universe of formal workers, together with demographic information, and some firm characteristics, such as industry defined at the four-digit sectoral classifications (*Classificação Nacional de Atividades Económicas, or CNAE*).[56]

As with SIPA, RAIS provides time-invariant firm and worker identifiers throughout the period. However, unlike SIPA, RAIS contains the following information for each match between a worker and a firm: (1) the start and end date of the employment relationship, (2) the total labor income within the job spell during the year, and (3) the labor income received in the month of December.[57] As our main income measure, we use the labor income received in December for two reasons: (1) to render our analysis comparable with SIPA and (2) to avoid seasonal fluctuations in income (the results do not change much when we use average labor income within the job spell).

We apply the same sample restriction we imposed in the SIPA dataset to render our analysis comparable across countries. We analyze the total labor compensation of male workers aged between 25 and 64.[58] We eliminate job spells in public sectors and outliers defined as workers with income below half of the minimum wage.

Table G.1 describes the sample selection process used in the analysis, following the same format in Table A.6. The sample size after applying the filters is similar to that in Argentina. For example, around 15% of workers are younger than 25 or older than 65 (8% in Argentina). The final sample includes 34% of the initial sample in Brazil, as in Argentina.

[56]The formality rate is similar across countries during the sample period 1990-2003. The share of formal employment for male salaried workers aged between 25 and 65 in Argentina and Brazil was 74% and 71%, respectively (see Gasparini and Tornarolli, 2009).

[57]Labor income is gross and includes regular salary payments, holiday bonuses, performance-based and commission bonuses, etc.

[58]We cannot compute a worker's exact age across the entire sample period. Age is only reported in bins prior to 1994, so we code all subsequent years into the same age bins: 25-29, 30-39, 40-49, 50-64, and more than 65 years old.

Table G.1 – Data Description: Cleaning Statistics

Description	RAIS	
Start date	Jan-1985	
End date	Dec-1998	
Total number of date-worker observations	4,021,153,839	
Average annual number of workers	28,300,234	
Average annual number of firms	1,105,746	
Cleaning	Number of Removed Observations	
	Total	%
Age <25 or >65	625,967,473	15.57%
Female	1,415,099,862	35.19%
Worker-date duplicate observations (second job)	86,394,749	2.15%
Public sector worker	339,207,702	8.44%
Wage below half of the minimum wage	939,390	0.02%
First or last observation in an employment spell	174,315,757	4.33%
Remaining observations	1,379,228,906	34.30%

G.2 Macroeconomic Context and Wage-setting in Brazil

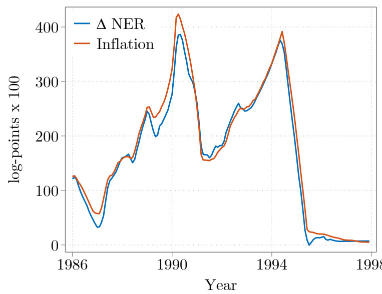
To contextualize our measurement exercise during these large devaluations, we first describe the macroeconomic context and the wage-setting context during these episodes.

The sample period covers four large nominal devaluations: 1990, 1994, 1999, and 2015. We focus on the 1990 and 1994 devaluations because of the following data limitations and confounding factors. Since our dataset ends in 2017, we cannot analyze inequality dynamics during the 3 and 4 years after the 2015 devaluations, as in our main analysis. While there was a substantial decrease in inequality during 1999, we do not study the 1999 devaluation due to concerns about the effects of the significant increase in the real minimum wage. During the 1996-2004 period, there was a 30% increase in the real minimum wage (see Engbom and Moser, 2018, Figure 2). Similar changes in the minimum wage did not coincide during the 2002 devaluation in Argentina or the 1990 and 1994 devaluations in Brazil. Indeed, the real minimum wage decreased in the aftermath of those devaluations.

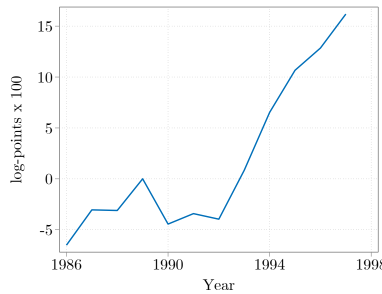
Brazil is characterized by significant variation in the macroeconomic context. Figure G.1 reproduces Figure 4 in the main text, and adds the series of the real minimum wage and the Gini coefficient. Given the proximity of both devaluations, we plot the time series from 4 years before the first devaluation to 3 years after the second devaluation. Figure G.1-Panel A shows annual growth rates of inflation and nominal exchange rates. As we can see in the figure, both devaluations occur during a period of high and volatile inflation. Nonetheless, the two devaluations coincide with two sharp increases in inflation. During this period, GDP and employment fall and start to recover following the second devaluation and introduction of the Plano Real. This ambitious stabilization program introduced a gradual float of the local currency, tightened monetary and fiscal policy, and lowered inflation below two digits.

Key for our analysis, during this period there is a drop of 30% in real labor income followed by a strong recovery. Importantly, the Gini coefficient drops around each devaluation and surge in inflation. One potential concern during this period is the possibility of wage indexation to the minimum wage, which could lead to labor mobility playing a smaller role in determining workers' incomes. However, the real minimum wage dropped by 60% following the first devaluation and only recovered to its 1989 level in 1996. Since the drop in average real labor income is close to half of the decline in the real minimum wage, there is room for labor market forces to determine workers' income. Finally, if the Gini coefficient was fully determined by changes in the minimum wage, then we should see a temporary increase in the Gini coefficient during the 1990-1994 period. Nevertheless, the Gini coefficient dropped following the 1990 devaluation despite the substantial decrease In the real minimum wage.

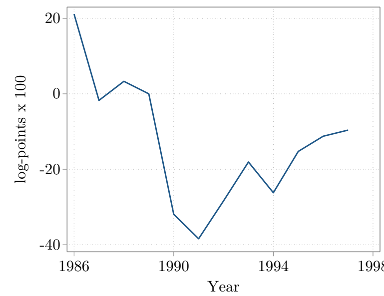
Figure G.1 – Labor Market Facts over the 1986-1997 period



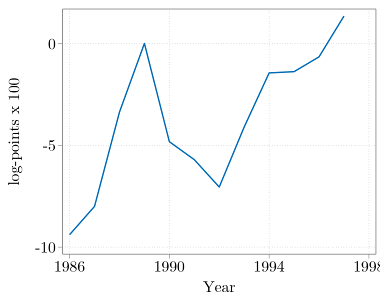
(a) NER and Inflation



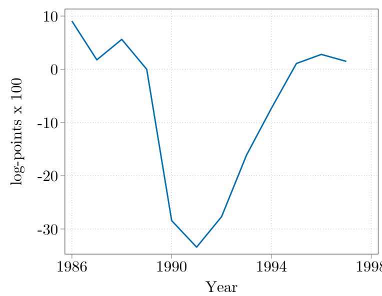
(b) GDP



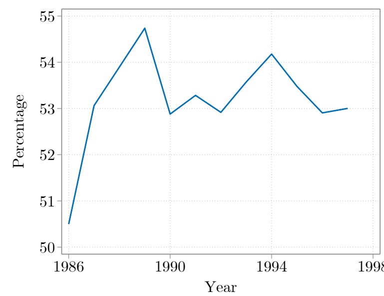
(c) Real Minimum Wage



(d) Employment



(e) Average Real Labor Income



(f) Gini coefficient

Notes: The figure plots macroeconomic and labor market time series in Brazil between January 1987 and December 1996. Panel (a) plots the annual growth rate of CPI and NER. Panels (b) and (c) plot real GDP and the real minimum wage. Panel (d) shows total employment. Panels (e) and (f) plot the average labor income and the Gini coefficient, respectively. Variables in Panels (b), (c), (d), and (e) are normalized to zero in the year 1989. Panel (a) is at a monthly frequency, and Panels (b) to (f) are at an annual frequency. Annual average real labor income and the Gini coefficient are computed using December labor income.

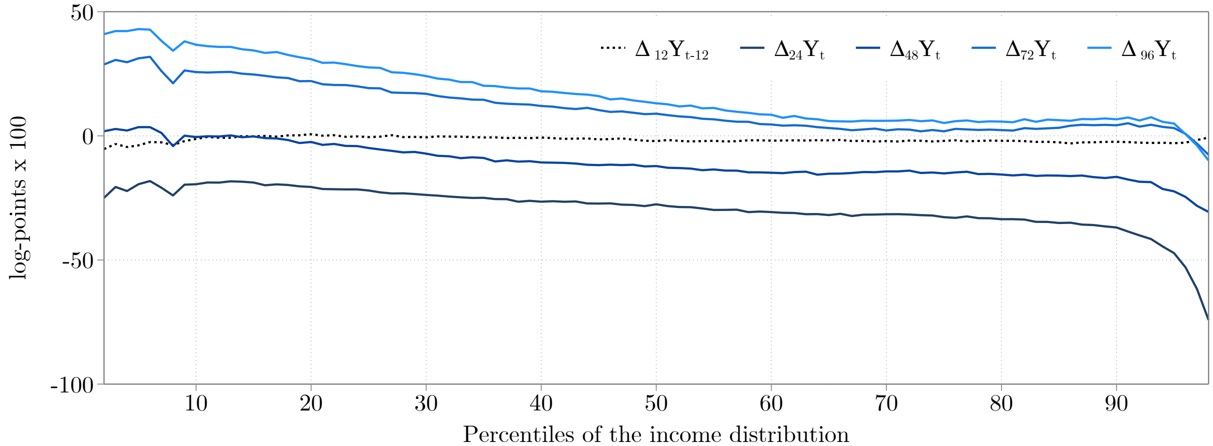
Next, we document inequality dynamics and investigate the mechanisms of adjustment during the episode analyzed above by replicating Section 5 in the main text.

G.3 Mechanisms behind Inequality Dynamics

Below we reproduce the analysis in Section 5 using data from Brazil.

Worker' income growth conditional on income level. We analyze workers' income growth conditional on their pre-devaluation level of income. Figure G.2 replicates Figure 7, with two small differences. First, to construct the ranking of workers on the x-axis, we first run a pooled regression with the complete sample of log labor income in December of each year on a set of age and year dummies. Then, we rank workers according to their average log monthly income net of the life-cycle profile during the 1988-1989 period. Second, on the y-axis, we show the average growth of real monthly income (net of the life-cycle profile) over 2-year periods from December 1989 to capture the drop and the full recovery of real labor income.

Figure G.2 – Average Income Growth Conditional on Average Income in 1988-1989

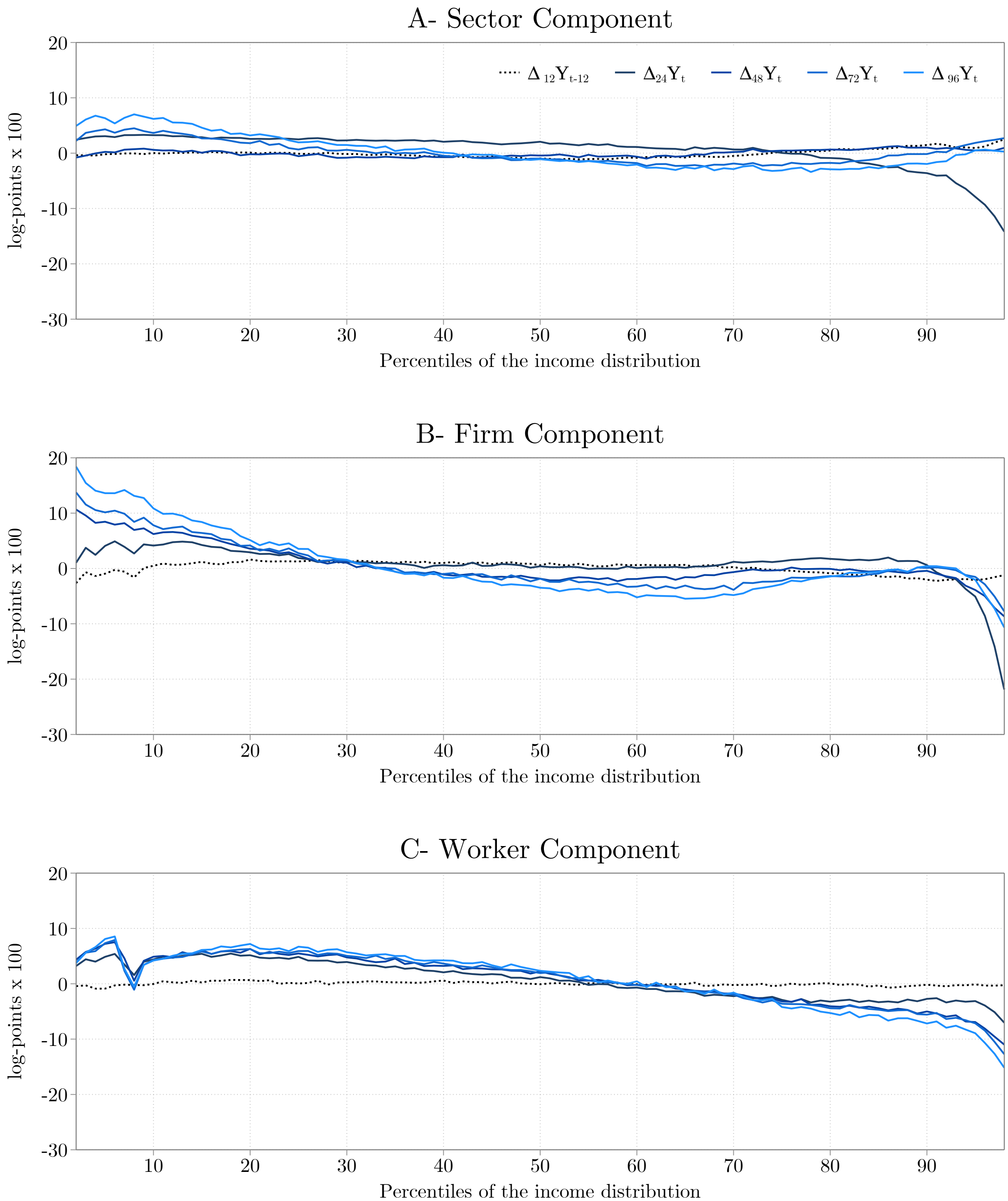


Notes: The figure plots average income growth conditional on the percentile of the distribution of average monthly real income during 1988-1989. The sample is restricted to workers who had at least 6 months of employment during the 1988-1989.

We reach three conclusions from this analysis. First, as in Argentina, real labor income growth in Brazil is close to zero in the year before the 1990 devaluation; see also Figure G.1. This occurs despite the high levels of inflation in Brazil. Second, while the timing of the drop and the recovery is longer than in Argentina, average income dynamics monotonically depend on the worker's position in the pre-devaluation income distribution, as in Argentina. Finally, we quantify the asymmetric recovery by computing the difference in average cumulative growth between workers at the 10th and 90th percentiles of the distribution. The differences 2, 4, 6, and 8 years following the first devaluation are 17%, 16%, 21%, and 30%, respectively.

The role of sectors, firms, and workers for the pivoting effect. We next analyze the between-sector, -firm, and -worker components of income by replicating Figure 8. We quantify each component with the difference in the average cumulative growth 8 years after the devaluation between workers at the 10th and 90th percentiles. The differences in the sector-, firm-, and worker-components are 8%, 10%, and 11%, respectively.

Figure G.3 – Decomposition of Average Income Growth Conditional on Average Income in 1988-1989

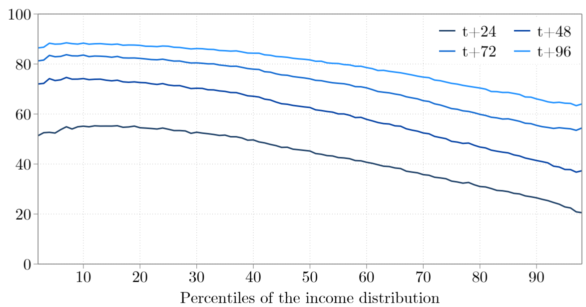


Notes: The figure plots average income growth conditional on the percentile of the distribution of average monthly real income during 1988-1989. The sample is restricted to workers who had at least 6 months of employment during the 1988-1989 period. Panel A replaces a worker's labor income with the average labor income in the sector of employment net of the overall average labor income for a given year. Panel B replaces a worker's labor income with the average labor income in the firm of employment net of the sectoral average labor income. Panel C replaces a worker's labor income with the worker's labor income net of the firm's average labor income.

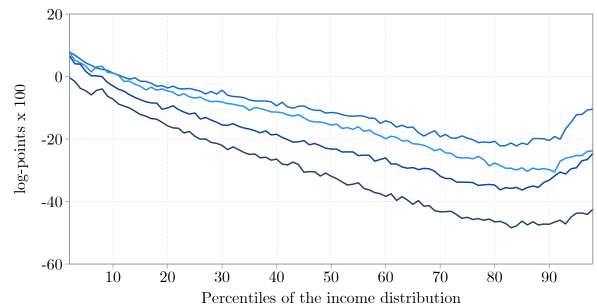
Labor mobility. In the main analysis, we found that labor mobility is the most important mechanism for the heterogeneous income recovery across workers. Therefore, we replicate the Argentinean analysis around the devaluations in Brazil. Figures G.4 and G.5 replicate Figures 9 and 10 in the main text.

Figure G.4 shows patterns that are quite similar to those found in Argentina, with some caveats. Job-to-job transition probabilities are increasing (resp.decreasing) for very low-income workers in Brazil (resp. Argentina). Also, the average income growth conditional on a job separation is lower, in levels, than in Argentina. This empirical result is not surprising given the larger drop in average real labor income in Brazil. More importantly, the counterfactual exercises also show similar results. As Figure G.5 shows, labor mobility generates substantial heterogeneity in income growth across the income distribution, as also found in Argentina. Panels on the left clearly show that average income growth would have been much more homogeneous across workers in the absence of job mobility. The only difference with Argentina is at the top of the distribution. In Brazil, the average income growth after a separation exhibits a small U-shaped pattern at the top of the distribution and, in consequence, the counterfactual income growth is closer to zero at the top.

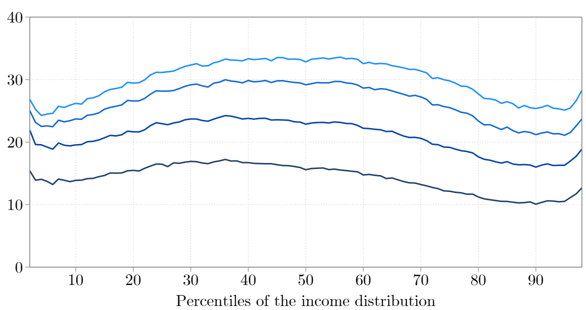
Figure G.4 – Income Mobility across the Income Distribution



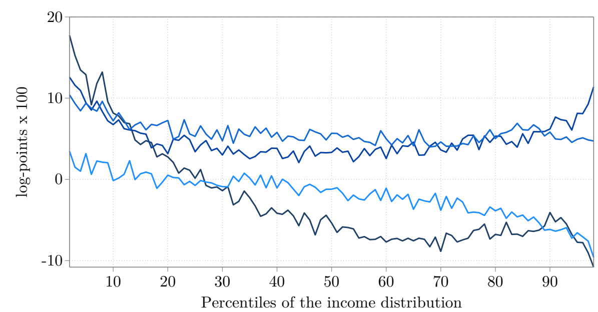
(a) Cum. Prob. of Separation



(b) Income Growth: Separations



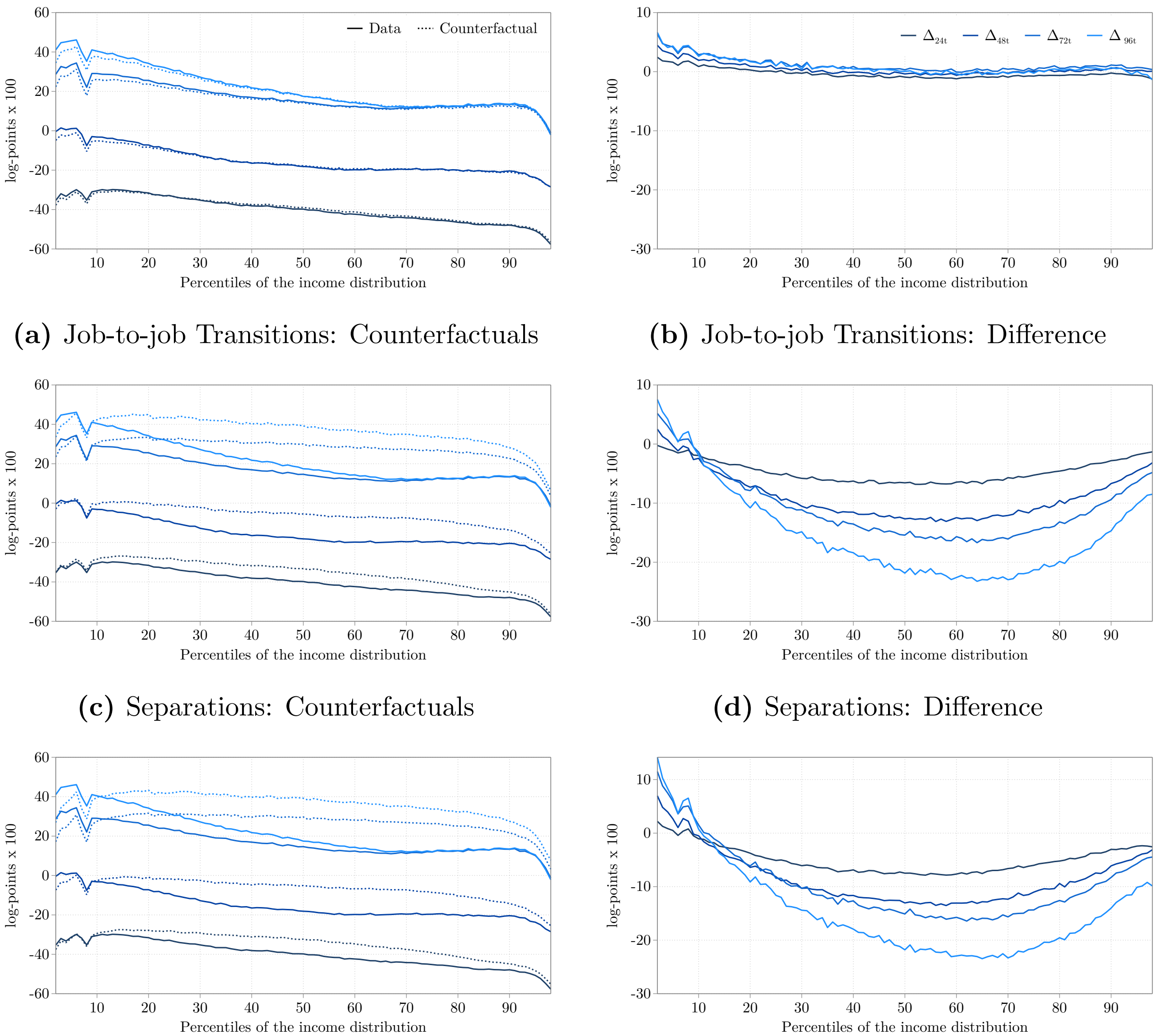
(c) Cum. Prob. of Job-to-job Transition



(d) Income Growth: Job-to-job Transitions

Notes: Panel A plots the cumulative probability of experiencing a separation between the month of the episode and that same month in the next 8 years. Panel B plots the average difference between the (log) income in the new job found after a separation during each year after the devaluation and the (log) income in the previous job. Panel C plots the cumulative probability of experiencing a job-to-job transition between the month of the episode and that same month in the next 8 years. Panel D plots the average difference between the (log) income in the new job found after a job-to-job transition during each year after the devaluation and the (log) income in the previous job. All figures are conditional on the percentile of the distribution of average monthly real income during 1988-1989. The sample is restricted to workers who had at least 6 months of employment during that period. We truncate the distribution of income changes at the 1% and 99% percentiles to construct Panels B and D.

Figure G.5 – Counterfactual Income Growth across the Distribution



(a) Job-to-job Transitions: Counterfactuals

(b) Job-to-job Transitions: Difference

(c) Separations: Counterfactuals

(d) Separations: Difference

(e) Both: Counterfactuals

(f) Both: Difference

Notes: Panel A describes both the actual average income growth and the counterfactual income growth, which omits income changes experienced during job-to-job transitions. Panel B plots the difference between the actual and the counterfactual dynamics to ease the comparison. Panel C describes both the actual average income growth and the counterfactual income growth, which omits income changes experienced after separations. Panel D plots the difference between the actual and the counterfactual dynamics to ease the comparison. Panels E and F present similar results for the combined effects of job-to-job transitions and separations. All figures are conditional on the percentile of the distribution of average monthly real income during 1988-1989. The sample is restricted to workers who had at least 6 months of employment during that period.

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