

Devaluations, Inflation, and Labor Income Dynamics

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Online Appendix: Not for Publication

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A Data: Additional Information

A.1 Cross-country Data: Sample Construction

Description and sources. Our aggregate analysis requires combining data on output, exchange rate, prices, inequality, and wages for several countries. To measure output, we use constant GDP in local currency from the World Bank. We use GDP per capita in PPP from the World Bank to classify countries. Prices and nominal exchange rates come from the IMF International Financial Statistics Dataset. We use the consumer price index as our measure of the price level. We measure inequality using the Gini coefficient, which can be obtained from PovcalNet via a direct query from STATA. We complement this dataset with data from Korea Statistics to get Gini’s time series for South Korea. We use [Laeven and Valencia \(2012\)](#) (updated in [Laeven and Valencia \(2018\)](#)) to identify currency crisis, banking crisis, and sovereign defaults . Lastly, we combine data from a variety of sources to build our database on wages. Table [A.1](#) describes the different sources for wage data.

Table A.1 – Sources of Wages Time Series

Source	Countries
ECLAC	El Salvador
ILO	Armenia, Colombia, Georgia, Hungary Indonesia, Moldova, Montenegro, Russia Slovak Republic, Ukraine.
OECD	Austria, Belgium, Czech Republic, Cyprus Denmark , France, Finland, Germany, Greece Italy, Korea, Lithuania, Luxembourg, Mexico Netherlands, Portugal, Spain, Sweden, Slovenia United Kingdom, Ireland.
SEDLAC	Brazil, Costa Rica, Honduras, Argentina
Dominican Republic Central Bank	Dominican Republic
National Statistical Institute (Bulgaria)	Bulgaria
Statistics Estonia	Estonia
Statistics Iceland	Iceland
Central Statistics Bureau (Latvia)	Latvia
DGEEC (Paraguay)	Paraguay
National Institute of Statistics (Romania)	Romania
Instituto Nacional de Estadística (Uruguay)	Uruguay

Sample selection. We consider two kinds of episodes: Devaluations and recessions. To identify the former, we follow [Laeven and Valencia \(2012\)](#). They consider a currency crisis a nominal devaluation of more than 30%, which is at least 10% higher than the depreciation rate of the previous year. We classify an episode as a recession if there’s a cumulative output loss of at least 2% in consecutive years.²² We focus on the four years before and after the episode, where we use the trough to date the recession.

To build our sample, we proceed as follows. First, we identify both kinds of episodes separately focusing only on emerging and rich economies in 1990-2015.²³ The total initial sample size is yields 109 devaluations and 227 recessions; of the latter, 51 overlaps with a devaluation. That is, there’s a big devaluation during

²²The threshold resembles [Calvo, Izquierdo and Talvi \(2006\)](#), who establish a cutoff of 4%. Our lower threshold allows us to increase the sample size given the scarcity of Gini data.

²³We follow [Uribe and Schmitt-Grohé \(2017\)](#) for classifying countries as emerging or rich. They consider an economy as emerging if the geometric mean of its GDP per capita in PPP US dollars of 2005 is between 3,000 and 25,000, and rich if its larger than 25,000.

the recession or one year before or after it. We further discard 133 recessions and 83 devaluations for lack of Gini or wage data. From the resulting 43 recessions and 26 devaluations, we discard a few more episodes for different reasons, summarized in Table A.2. We don't consider Belarus, as it is mainly a command economy. The mechanisms we explore in this paper depend on part in the presence of markets, and thus these episodes are not a good illustration. Because our paper focuses on devaluations, we don't consider Cyprus episodes, the Slovak Republic and Slovenia, that occur just as these economies were transitioning into the Eurozone. We prefer not to include them in the nominally stable recessions as they move into a completely different monetary regime. Lastly, we exclude episodes from Syria, Ukraine, and Venezuela during periods of civil war, strife, or military coups.

Table A.2 – Excluded Episodes

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

Our final sample has 40 recessions and 19 devaluations. Table A.3 describes recessions and devaluations episodes. We also consider different subsamples for robustness. Section A.2 details the motivation and the composition of each of them.

Variable normalization. We normalize the data so that NER, GDP, inflation, wages, and Gini have a value of 0 one year before the episode. Gini data is sometimes not available in an annual frequency, being released biannually. To avoid having gaps in our panel, we linearly interpolated Gini data. We also normalize the devaluation and inflation rate so that the plots can be read as percentage points deviations from their value one year before the episode.

Because some episodes in the sample feature very high inflation and devaluation rates, we Winsorize the

Table A.3 – Episodes where we measure Income Inequality

Devaluations	Recessions
Argentina-2002, Argentina-2014, Brazil-1990	Argentina-1995, Argentina-2009
Brazil-1993, Brazil-1999, Brazil-2015	Austria-2009, Belgium-2009, Bulgaria-2009
Colombia-2015, Costa Rica-1991	Colombia-1999, Cyprus-2014, Czech Republic-2009
Dominican Republic-2003	Denmark-2009, El Salvador-2009, Estonia-2009
Iceland-2008, Korea-1998	Finland-2009, Finland-2014, France-2009
Mexico-1995	Germany-2009, Greece-2013, Honduras-2009
Paraguay-2002 Uruguay-2002	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
	United Kingdom-2009

Table A.4 – Samples of Episodes

Sample	Recessions	Devaluations
Full sample	40	19
No banking crisis	20	8
Banking crisis	20	11
No defaults	39	14
Recessions: all devaluations are also recessions	40	11
Income Inequality	35	14
Short recessions: only recessions up to a year	24	19
Recent sample: Episodes from 2000 onwards	38	10
No Hyperinflation	39	16

top and bottom 2.5% of their distribution. We do this to increase the readability of the plots, and it has no impact on the interpretation of our results.

A.2 Cross-Country Data: Robustness

This section explains the subsamples we consider to control for special kinds of recessions or devaluations.

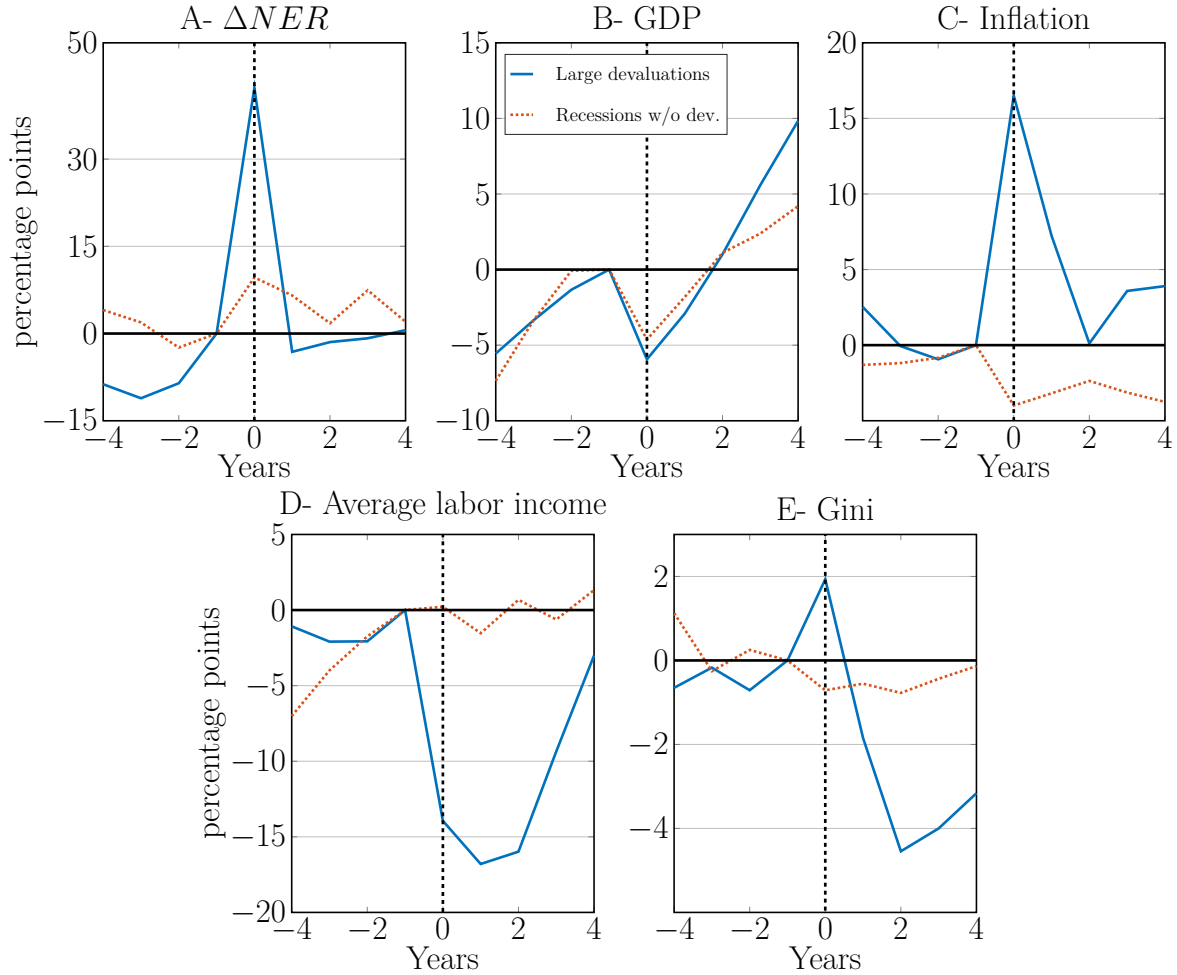
Table A.4 lists the different subsamples we consider. We consider the first four samples to isolate the effect of devaluations from the sovereign or banking crisis. Half of the recession episodes also feature a banking crisis, while approximately 40% of devaluations coincided with a banking crisis. Almost none of the recessions feature a default, with Greece’s 2009-2013 recession being the only exception. For this reason, we don’t consider the subsample of defaults, focusing only on episodes without a default. In the case of devaluations, almost 3/4 of the episodes don’t have a default. It might also be the case that some devaluations do not lead to contractions in output. Thus, the comparison with recessions is not appropriate. We consider a subsample in which we keep only those devaluations with recessions. We keep almost 60% of our recessions in this sample.

Inequality can be measured consumption or income data. Because we are ultimately interested in the labor market implications of inequality, we consider a subsample in which we only include episodes for which the Gini is estimated using household’s income. PovCal includes a variable indicating whether income or consumption was used for estimation, which allows us to find the subsample. 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, there might be long episodes, reducing the recessions sample’s comparability. We consider a subsample in which the only recessions included are those that last a year or less. In this subsample, the total number of recession episodes is 24.

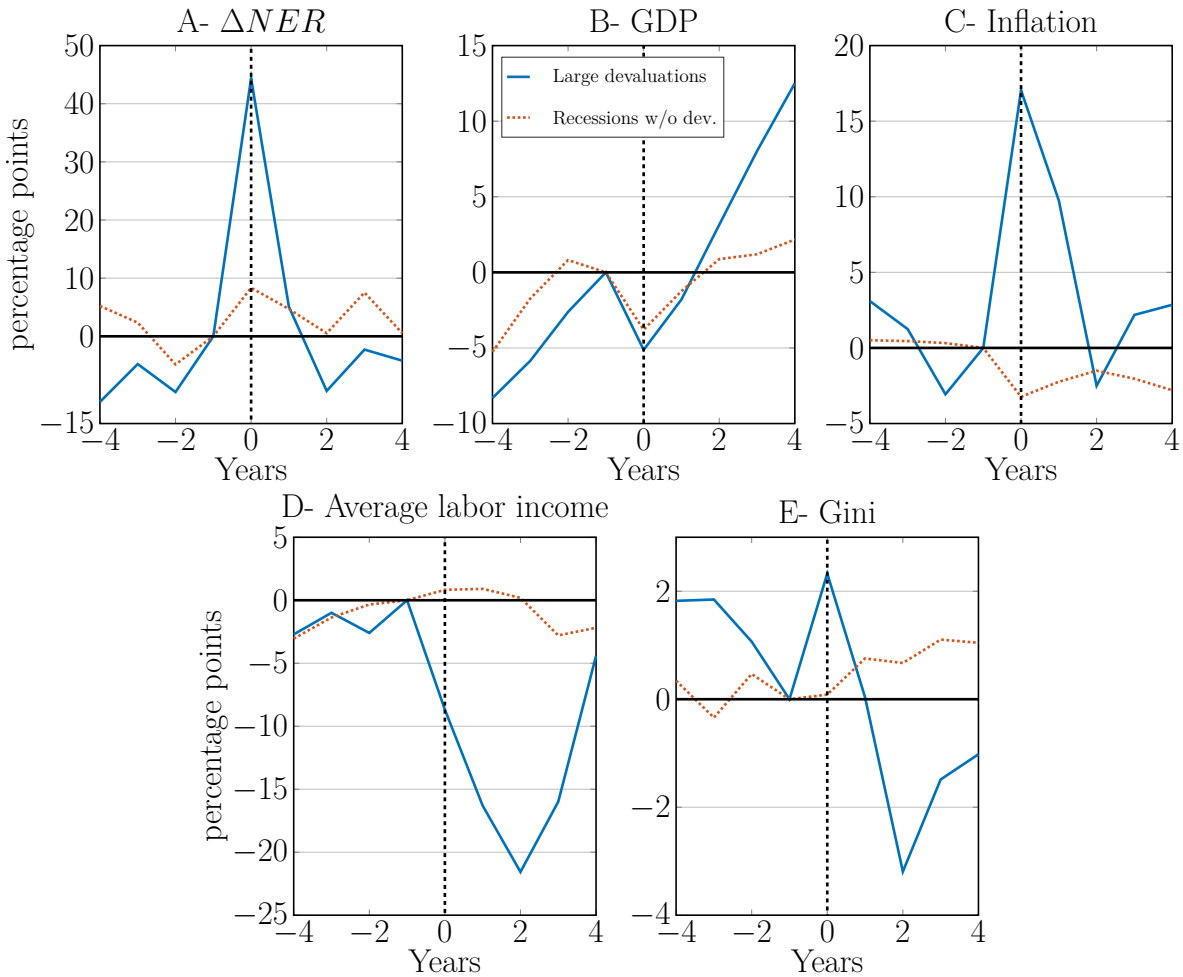
Our sample of recessions has almost no episodes from before 2000, while our devaluations sample includes several episodes from the late ’90s. To remedy this, we consider a subsample of recent episodes, where we only keep those that occurred after 2000. This sample yields 38 recessions and 10 devaluations, just over half the original number of devaluations. Lastly, 4 of our episodes feature high inflation or hyperinflation. These kinds of events are known to have different dynamics, and they also make our averages much less representative of the whole sample. For that reason, we consider a sample without one recession (Argentina-1995) and three devaluations (Brazil 1990 and 1993 and Georgia 1999).

Figure A.1 – Macroeconomic Facts After Large Devaluations - All Recessions



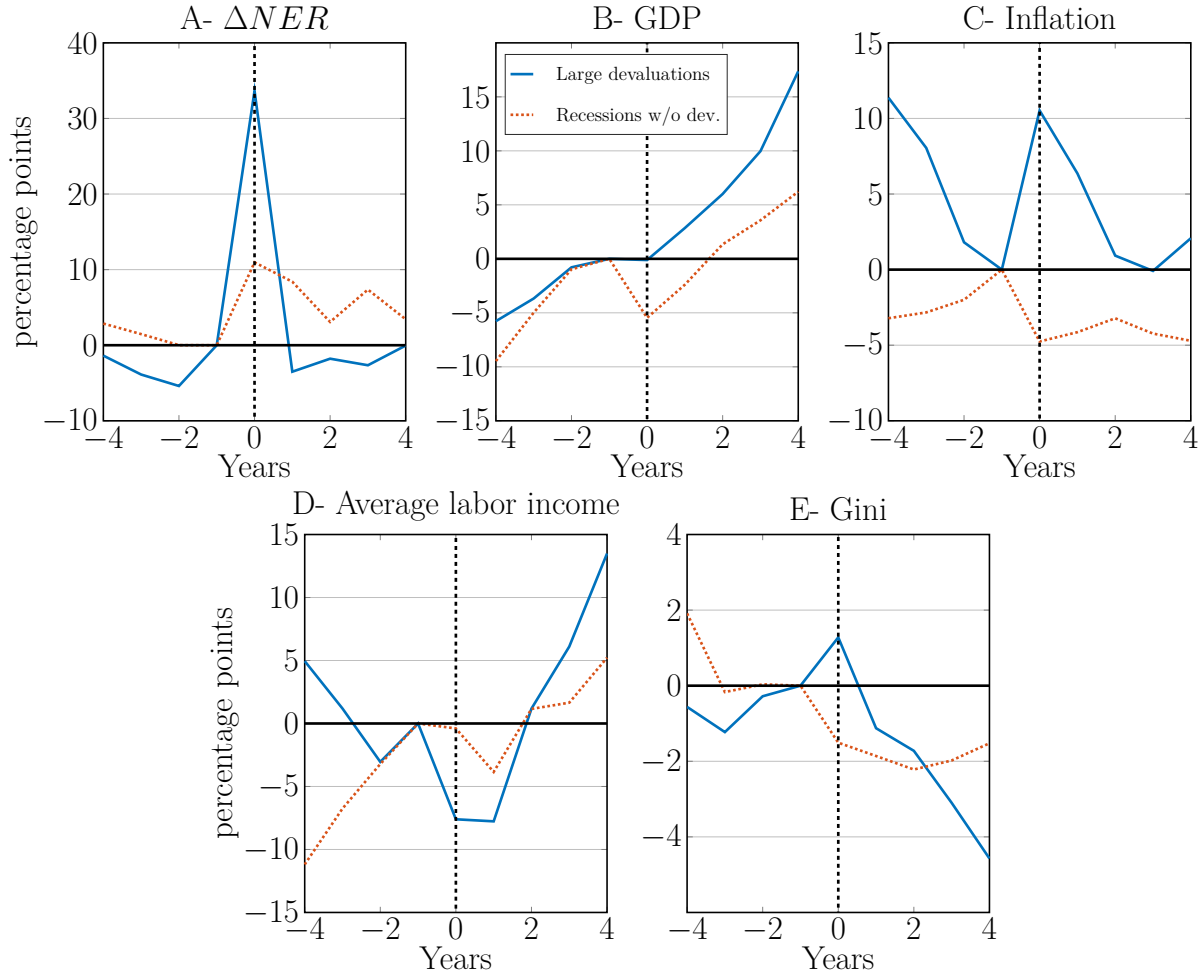
Notes: Panels A to E plot (in the following order) the change in the NER, real GDP, inflation, average real labor income and Gini at an annual frequency. All variables are expressed in percentage points and normalized to zero in year -1. The blue solid line shows the average macroeconomic dynamics in a 8-year window around a large devaluation. The year zero corresponds to the year of the devaluation. The red red dotted line plots the same variables for recessions without devaluations. The year zero corresponds to the year with the first drop in GDP. Large devaluation episodes include Argentina (2002), Argentina (2014), Brazil (1990), Iceland (2008), Indonesia (1998), Korea (1998), Mexico (1995), Moldova (1999), Paraguay (2002), Ukraine (2009) and Uruguay (2002). Nominally stable recessions 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 A.2 – Macroeconomic Facts After Large Devaluations - Only Banking Crisis



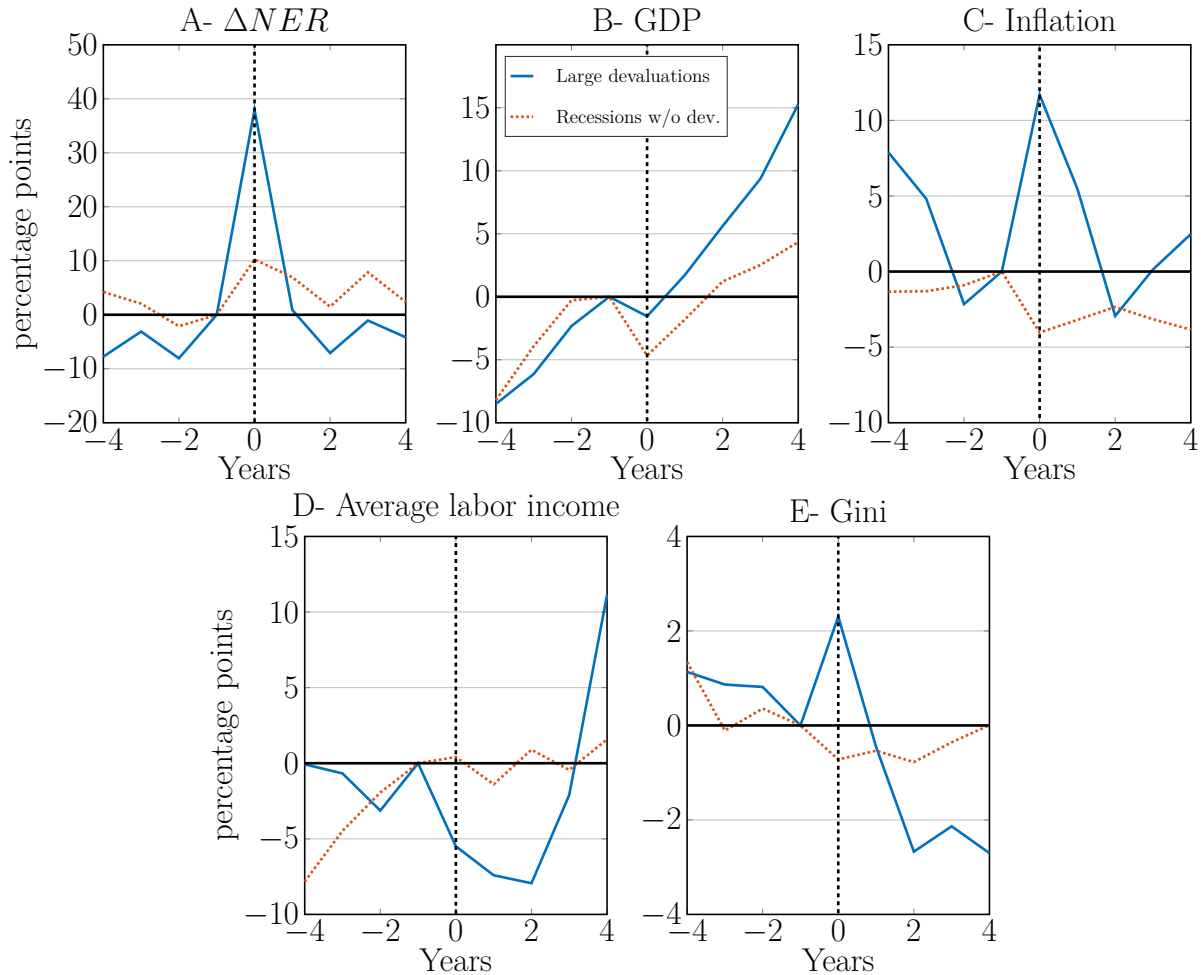
Notes: Panels A to E plot (in the following order) the change in the NER, real GDP, inflation, average real labor income and Gini at an annual frequency. All variables are expressed in percentage points and normalized to zero in year -1. The blue solid line shows the average macroeconomic dynamics in a 8-year window around a large devaluation. The year zero corresponds to the year of the devaluation. The red dotted line plots the same variables for recessions without devaluations. The year zero corresponds to the year with the first drop in GDP. Large devaluation episodes include Argentina (2002), Brazil (1990), Brazil (1993), Dominican Republic (2003), Iceland (2008), Indonesia (1998), Korea (1998), Mexico (1995), Moldova (2015), Ukraine (2009) and Uruguay (2002). Nominally stable recessions 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 A.3 – Macroeconomic Facts After Large Devaluations - No Banking Crisis



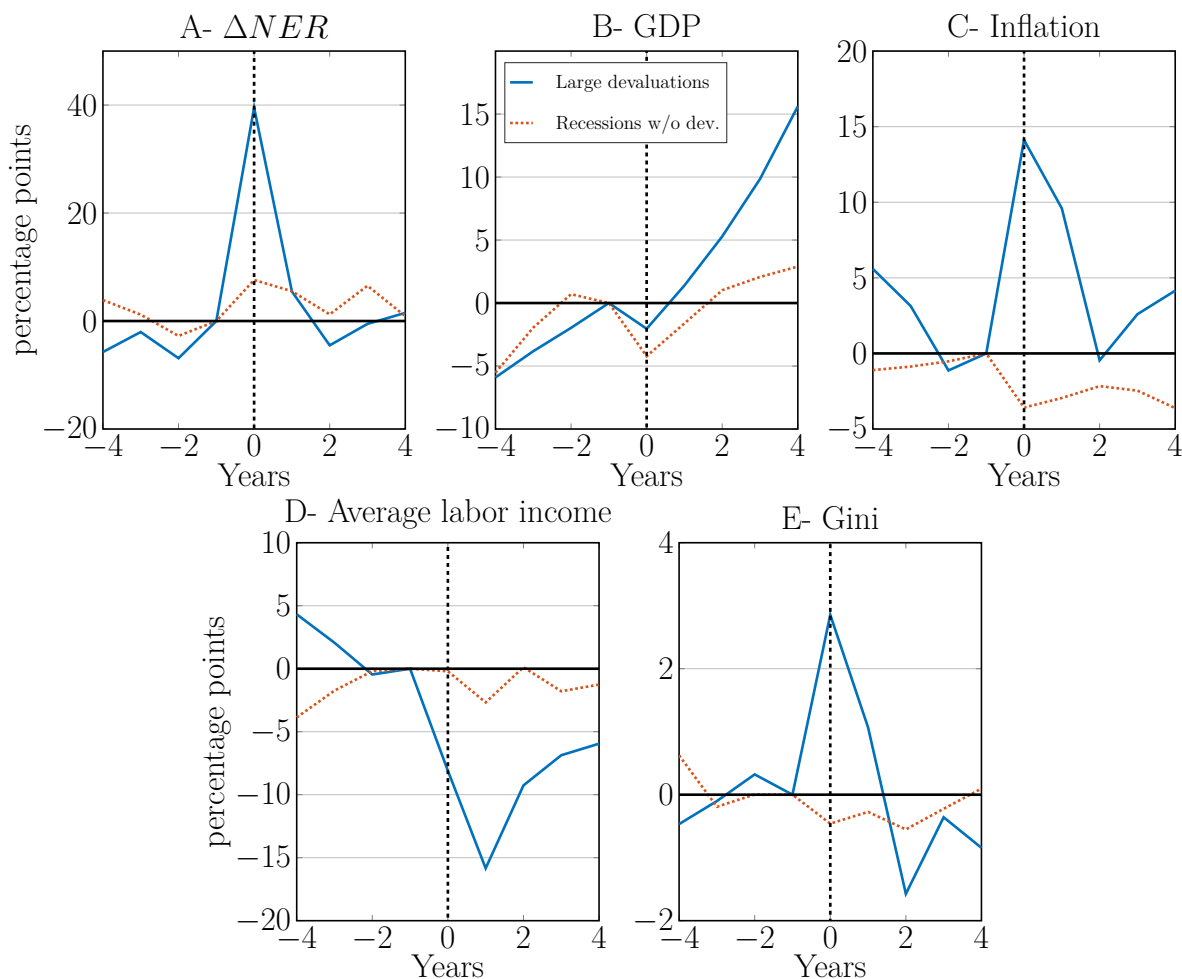
Notes: Panels A to E plot (in the following order) the change in the NER, real GDP, inflation, average real labor income and Gini at an annual frequency. All variables are expressed in percentage points and normalized to zero in year -1. The blue solid line shows the average macroeconomic dynamics in a 8-year window around a large devaluation. The year zero corresponds to the year of the devaluation. The red dotted line plots the same variables for recessions without devaluations. The year zero corresponds to the year with the first drop in GDP. Large devaluation episodes include Argentina (2014), Brazil (1999), Brazil (2015), Colombia (2015), Costa Rica (1991), Georgia (1999), Moldova (1999) and Paraguay (2002). Nominally stable recessions 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 A.4 – Macroeconomic Facts After Large Devaluations - No Defaults



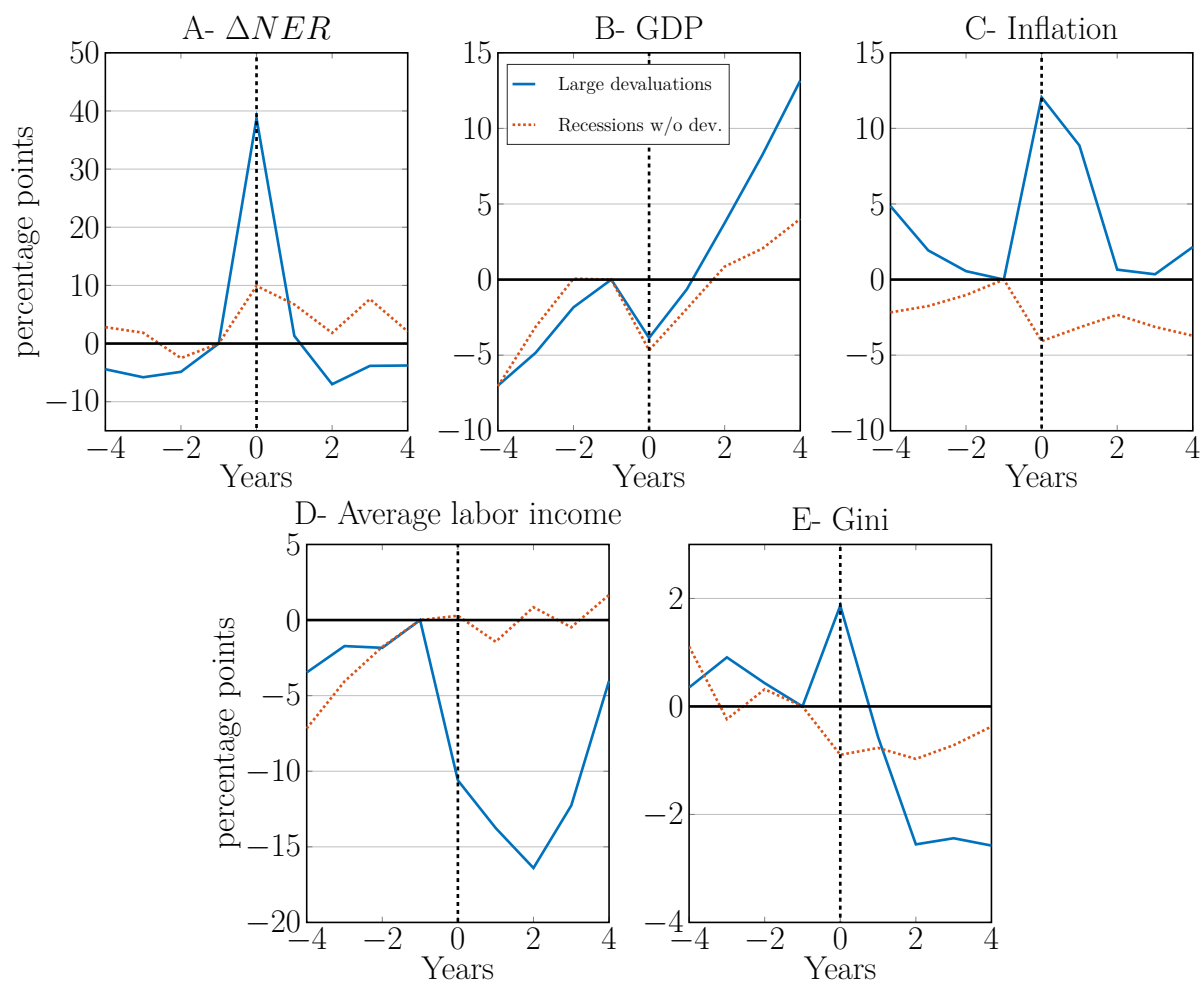
Notes: Panels A to E plot (in the following order) the change in the NER, real GDP, inflation, average real labor income and Gini at an annual frequency. All variables are expressed in percentage points and normalized to zero in year -1. The blue solid line shows the average macroeconomic dynamics in a 8-year window around a large devaluation. The year zero corresponds to the year of the devaluation. The red red dotted line plots the same variables for recessions without devaluations. The year zero corresponds to the year with the first drop in GDP. Large devaluation episodes include Brazil (1990), Brazil (1993), Brazil (1999), Colombia (2015), Costa Rica (1991), Georgia (1999), Iceland (2008), Korea (1998), Mexico (1995), Moldova (1999), Moldova (2015), Paraguay (2002) and Ukraine (2009) . Nominally stable recessions 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 A.5 – Macroeconomic Facts After Large Devaluations - Income Inequality



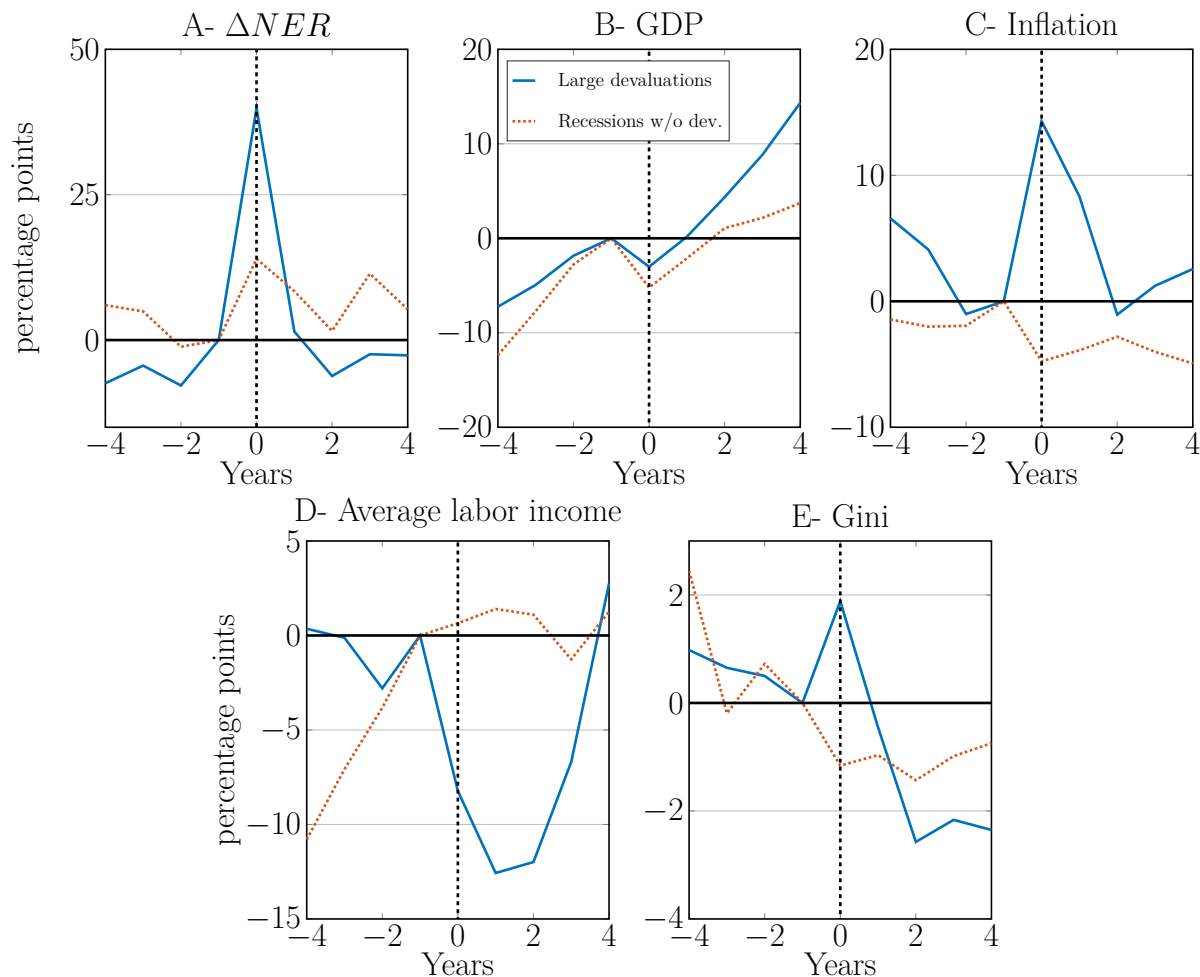
Notes: Panels A to E plot (in the following order) the change in the NER, real GDP, inflation, average real labor income and Gini at an annual frequency. All variables are expressed in percentage points and normalized to zero in year -1. The blue solid line shows the average macroeconomic dynamics in a 8-year window around a large devaluation. The year zero corresponds to the year of the devaluation. The red dotted line plots the same variables for recessions without devaluations. The year zero corresponds to the year with the first drop in GDP. 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), Korea (1998), Mexico (1995), Paraguay (2002) and Uruguay (2002). Nominally stable recessions 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 A.6 – Macroeconomic Facts After Large Devaluations - No Hyperinflations



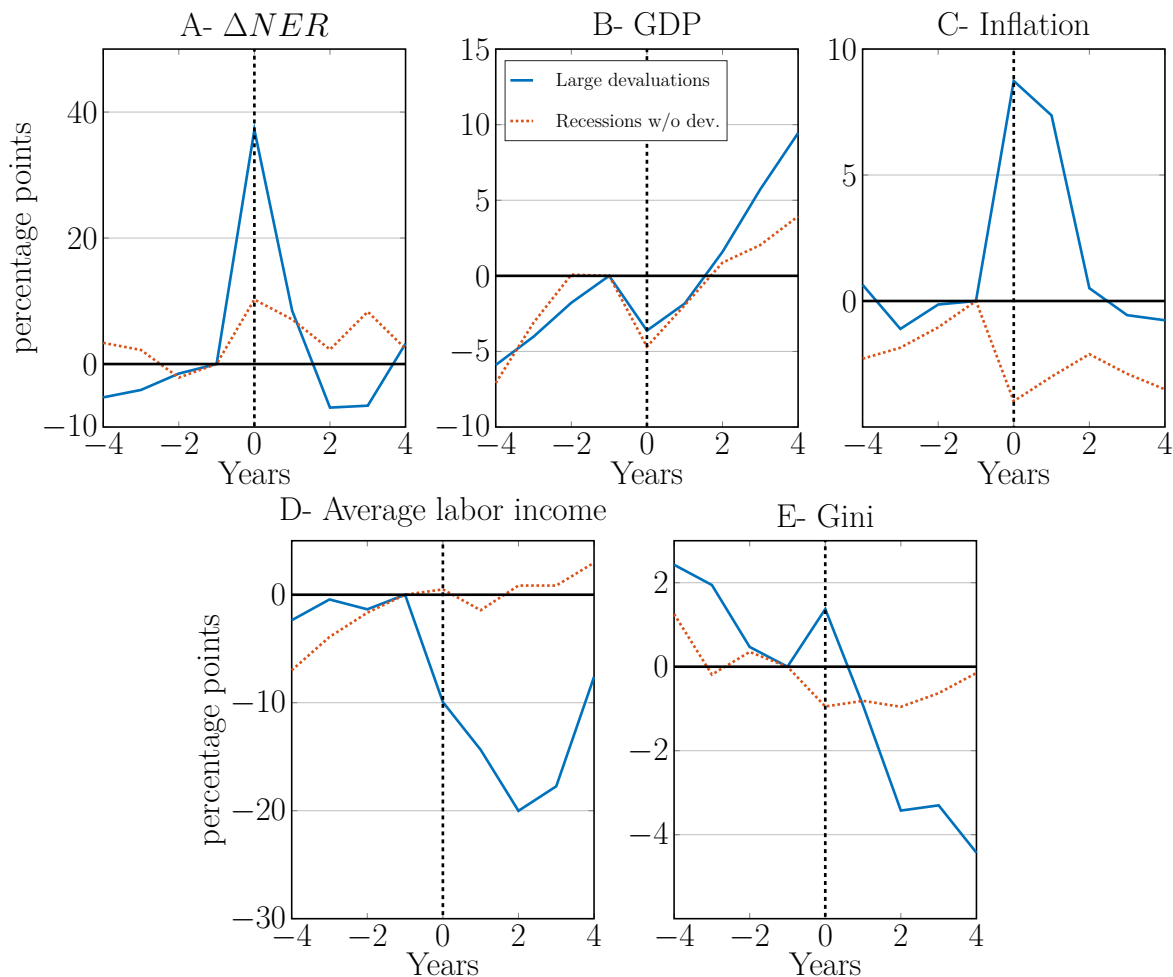
Notes: Panels A to E plot (in the following order) the change in the NER, real GDP, inflation, average real labor income and Gini at an annual frequency. All variables are expressed in percentage points and normalized to zero in year -1. The blue solid line shows the average macroeconomic dynamics in a 8-year window around a large devaluation. The year zero corresponds to the year of the devaluation. The red red dotted line plots the same variables for recessions without devaluations. The year zero corresponds to the year with the first drop in GDP. Large devaluation episodes include Argentina (2002), Argentina (2014), Brazil (1999), Brazil (2015), Colombia (2015), Costa Rica (1991), Dominican Republic (2003), Iceland (2008), Indonesia (1998), Korea (1998), Mexico (1995), Moldova (1999), Moldova (2015), Paraguay (2002), Ukraine (2009) and Uruguay (2002). Nominally stable recessions 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 A.7 – Macroeconomic Facts After Large Devaluations - Short Recessions



Notes: Panels A to E plot (in the following order) the change in the NER, real GDP, inflation, average real labor income and Gini at an annual frequency. All variables are expressed in percentage points and normalized to zero in year -1. The blue solid line shows the average macroeconomic dynamics in a 8-year window around a large devaluation. The year zero corresponds to the year of the devaluation. The red dotted line plots the same variables for recessions without devaluations. The year zero corresponds to the year with the first drop in GDP. 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), Korea (1998), Mexico (1995), Moldova (1999), Moldova (2015), Paraguay (2002), Ukraine (2009) and Uruguay (2002). Nominally stable recessions 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 A.8 – Macroeconomic Facts After Large Devaluations - 2000 Onwards



Notes: Panels A to E plot (in the following order) the change in the NER, real GDP, inflation, average real labor income and Gini at an annual frequency. All variables are expressed in percentage points and normalized to zero in year -1. The blue solid line shows the average macroeconomic dynamics in a 8-year window around a large devaluation. The year zero corresponds to the year of the devaluation. The red dotted line plots the same variables for recessions without devaluations. The year zero corresponds to the year with the first drop in GDP. 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). Nominally stable recessions 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 United Kingdom (2009)

A.3 SIPA: Data Description

Software for sworn statements. By law, all employers in the formal sectors, both private and public, must submit sworn statements providing the information included in workers' paychecks to SIPA every month. This information is used for tax purposes and to calculate contributions to the social security system made by employees. Figures A.9 to A.11 describe the most important entries of the sworn statement. For more information, the reader should refer to the manual for declaring sworn statements, SICOSS (*Aplicativo Sistema de Cálculo de Obligaciones de la Seguridad Social*).

Figure A.9 shows the items included in the SICOSS general information form: worker identification number ("CUIL"), legal name and last name ("Apellido y Nombres"), type of contract ("Modalidad de Contratacion"), and CBA coverage ("Trabajador en convenio colectivo de trabajo"). Figure A.10 shows the items featured in the labor income components form in SICOSS: basic labor income ("Sueldo") and additional compensation ("adicionales"). Additional compensation includes extra income from tenure or night work, among others. Finally, Figure A.11 shows tax liabilities and social security contributions.

Figure A.9 – SICOSS: Sworn Statement for General Information

Notes: The figure shows the electronic form employers fill out to provide their general information to SIPA.

Figure A.10 – SICOSS: Sworn Statement of Labor Income Components

Notes: The figure shows the electronic form employers fill out to report the components of their labor income to SIPA.

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

Figure A.11 – SICOSS: Sworn Statement for Tax and Social Security Contribution

The screenshot shows a software interface titled 'Remuneraciones 30-5466243-4 55 MALBEC SOCIEDAD ANONIMA'. It features a table with the following data:

Component	Description	Value
Remuneración Total		7.831,32
Asign. Familiares Pagadas		0,00
Remuneración 1	Cálculo de Aportes SIPA y RENATEA	7.831,32
Remuneración 2	Cálculo Contribuciones Jubilatorias e INSSJP	7.831,32
Remuneración 3	Cálculo de Contribuciones al FNE, AAFP y RENATEA	7.831,32
Remuneración 4	Cálculo Aportes de Obra Social y ANSSAL	7.831,32
Remuneración 5	Cálculo Aportes INSSJP	7.831,32
Remuneración 8	Cálculo de contribuciones Obra Social y ANSSAL	7.831,32
Remuneración 9	LRT Base de cálculo LRT	7.831,32

Annotations on the left side of the form indicate that 'Remuneración Total' corresponds to 'Total income' and the remaining rows correspond to 'Tax / social security contributions'.

Notes: The figure shows the electronic form that calculates tax and social security contributions.

birth, type of contract, and CBA coverage. 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 classification.

The SIPA dataset also includes variables on total labor income and its components for each worker. 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., 1994 and 2019), while data on the components of labor income are only available after 2008.

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
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-digits CIU
Labor income components		
Total labor income	1994-2019	Nominal in pesos
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.

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

In the original dataset, around 8% of workers are younger than 25 or older than 65 years, and of those workers, 41% are female. Therefore, 51% of the original sample is male 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. Labor legislation mandates that workers employed in 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 2.28% of the original sample.

When we limit 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 35% of the original sample.

Table A.6 – Data Description: Cleaning Statistics

Description	SIPA	
Start date	1994-m7	
End date	2019-m7	
Total number of date-workers observations	2,025,937,636	
Average annual number of workers	7,796,674	
Average annual number of firms	561,538	
Cleaning	Number of Removed Observations	
	Total	%
Age <25 or >65	169,286,588	8.36%
Female	831,627,970	41.05%
Temp. workers duplicate observations	1,069,314	0.05%
Workers date duplicate observations (second job)	45,966,458	2.27%
Public sector worker	199,466,215	9.84%
Wage below half minimum wage	13,529,437	0.67%
First or last observation in an employment spell	64,164,318	3.17%
Remaining observations	700,827,336	34.59%

Notes: The table describes 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.

13th wage. We purge 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 that the law establishes. We use the following equation to impute the *aguinaldo*:

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

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.). For example, according to the formula, a worker employed in the same firm for

the entire semester receives half of the maximum 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 the 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 the workers represented by the union.

Figures A.12 to A.14 show some examples of the original CBA contracts signed by union representatives for some sectors and dates. By law, whenever there is no new negotiation of CBA in a given year, the previous CBA is valid for that year. There are no CBAs between 1996 and 2002 in the sectors that we study. Figure A.12 shows the CBA contracts for the automotive sector in 1994 and 2003. Figure A.13 shows the CBA contracts for freight transport by road sector in 1995 and 2003. Figure A.14 shows the CBA contracts for the retail sector in 2003 and 2005.

Figure A.12 – CBA examples: Automotive sector in 1994 and 2003

CONVENIO COLECTIVO DE TRABAJO N° 27/88 S.M.A.T.A. - F.A.A.T.R.A.						
Artículo 34*		Vigencia				
		sep./03	oct./03	nov./03	dic./03	ene./04
Personal	Oficial Inspector	4.70	4.85	5.01	5.16	5.32
Jornalizado	Oficial de Primera	4.35	4.50	4.66	4.81	4.97
Valores \$/h.	Oficial	4.14	4.29	4.45	4.60	4.76
	Medio Oficial	3.92	4.07	4.23	4.38	4.54
	Peón	3.32	3.47	3.63	3.78	3.94
	Aprendices Ayudantes					
	A los 16 y 17 años	2.85	3.00	3.16	3.31	3.47
	A los 18 y 19 años	3.01	3.16	3.32	3.47	3.63
	Ingrasadores-Operario Ayudante-Lavadores	3.85	4.00	4.16	4.31	4.47
	Limpiaadores Expeditores de Combustible					
Personal	Auxiliar de Primera	871.91	902.16	932.41	962.66	992.91
Mensualizado	Auxiliar de Segunda	786.67	816.92	847.17	877.42	907.67
Valores \$/mes	Auxiliar de Tercera	735.33	765.58	795.83	826.08	856.33
	Auxiliar de Cuarta	649.77	680.02	710.27	740.52	770.77
	Choferes	745.88	774.13	804.38	834.63	864.88
	Maestranta	652.82	683.07	713.32	743.57	773.82
	Colecta					
	Menores de hasta 16 años	512.30	542.55	572.80	603.05	633.30
	Menores de 17 hasta 18 años	540.41	570.66	600.91	631.16	661.41
	Personal a sueldo común y/o bonificación	649.77	680.02	710.27	740.52	770.77

Artículo 50*		COEFICIENTE ZONAL (REGIÓN PATAGÓNICA)	
		2003	1994
Coeficiente Zonal (Región Patagónica) adicional del 20% sobre las remuneraciones establecidas en el presente convenio.		1.20	1.20

SOCIA SALARIAL DE LA FEDERACION ARGENTINA DE ASOCIACIONES DE TALLERES DE REPARACION DE AUTOMOTORES Y AFINES (F.A.A.T.R.A.) Y DEL SINDICATO DE MECANICOS Y AFINES DEL TRANSPORTE AUTOMOTOR DE LA REPUBLICA ARGENTINA (S.M.A.T.A.) - CONVENIO N. 27/88											
ARTICULO 34				JULIO 94 a		NOV. 94 a		FEBRERO 95		MAYO 95 a	
				OCTUBRE 94		FEBRERO 95		JUNIO 95		OCTUBRE 95	
PERSONAL JORNALIZADO				3.98		4.23		4.48		4.73	
OFICIAL INSPECTOR				3.86		3.77		3.88		3.99	
OFICIAL DE PRIMERA				3.46		3.57		3.67		3.78	
OFICIAL MEDIO				3.28		3.35		3.45		3.55	
PEON				2.68		2.78		2.85		2.95	
APRENDICES AYUDANTES											
A LOS 16 Y 17 AÑOS				2.25		2.31		2.38		2.44	
A LOS 18 Y 19 AÑOS				2.39		2.46		2.54		2.61	
ENGRASADORES - OPERARIO AYUDANTE - LAVADORES LIMPIADORES Y EXPEDITORES DE COMBUSTIBLE				3.18		3.28		3.38		3.48	
PERSONAL MENSUALIZADO											
AUXILIAR DE PRIMERA				736.32		758.41		781.16		804.52	
AUXILIAR DE SEGUNDA				655.97		675.55		695.92		716.52	
AUXILIAR DE TERCERA				607.58		625.81		644.58		663.92	
AUXILIAR DE CUARTA				526.93		542.73		559.02		575.92	
CHOFERES				815.84		836.11		857.13		878.92	
MAESTRANTA				529.81		548.70		568.07		587.92	
COLECTA											
MEJORES DE HASTA 16 AÑOS				397.35		409.27		421.55		434.27	
MEJORES DE 17 HASTA 18 AÑOS				423.85		436.57		449.68		463.27	
PERSONAL A SUeldo COMún Y/O BONIFICACION				526.93		542.73		559.02		575.92	

20% MAS SOBRE EL TOTAL DE LA REMUNERACION (ART. 50)

ADICIONAL POR ANTIQUEDAD: VIGENCIA 1/07/88 (ART. 32)

ANOS	%	ANOS	%	ANOS	%	ANOS	%
1	2.0	8	8.0	11	13.0	16	16.5
2	4.0	9	9.0	12	14.0	17	17.0
3	6.0	10	10.0	13	15.0	18	17.5
4	8.0	11	11.0	14	15.5	19	18.0
5	10.0	12	12.0	15	16.0	20	18.5
MAS DE 25 AÑOS 21%							

SUBSIDIOS CONVENIO PATRA. - SMATA. ART. No. 36. POR MES:

b) POR SERVICIO MILITAR 20 HS. = 79.00 = 82.00 = 84.00

e) y f) FALLECIMIENTO DE CONYUGE, HIJOS Y PADRES 50 HS. DE LA CATEGORIA DE OFICIAL INSPECTOR = 199.00 = 205.00 = 211.50

g) FALLECIMIENTO DE HERMANOS Y PADRES POLITICOS 30 HS. DE LA CATEGORIA DE OFICIAL INSPECTOR = 119.40 = 123.00 = 126.90

PERSONAL QUE UTILICE IDIOMAS EXTRANJEROS. 10 HS. DEL JORNAL O SUELDO DE SU CATEGORIA POR MES

PERSONAL CON TITULO DEL COMET O EQUIVALENTE. 10% DEL SALARIO QUE PERCIBE EL TRABAJADOR POR MES

VIATICOS: POR COMIDA PARA REALIZAR TAREAS FUERA DEL ESTABLECIMIENTO: HASTA 5 (CINCO) HS. DE LA CATEGORIA DE OFICIAL INSPECTOR

FUERA DE UN RADIO DE 40 Km.: EL 30 % SOBRE SUS HABERES (ARTICULO 31)

Notes: This figure shows the original CBAs for the automotive sector in 1994 and 2003.

Figure A.13 – CBA examples: Freight transport sector by road sector in 1995 and 2003

Federación Nacional de Trabajadores Camioneros y Obreros del Transporte Automotor de Cargas
PERSONERIA GREMIAL N° 76 - ADHESION A LA C.G.T.
Avda. CASEROS 921/23 Cod. 1152 BUENOS AIRES TEL. 23-1294

Federación Nacional de Trabajadores Camioneros y Obreros del Transporte Automotor de Cargas, Logística y Servicios
PERSONERIA GREMIAL N° 76 - ADHESION A LA C.G.T. - I.S.
Avda. CASEROS 801 Tel/Fax: 430-1294/97501912000 Cod. 1152 - BUENOS AIRES

CONVENIO COLECTIVO DE TRABAJO N° 40/9 PLANILLA 31/95
SALARIOS BASICOS A PARTIR DEL 1° DE MARZO DE 1995 EMERGENTES DEL CONVENIO COLECTIVO DE TRABAJO, ÍTEM 6.1.1. Y 6.2.13.

CONVENIO COLECTIVO DE TRABAJO N° 40/ 98 PLANILLA 30/3
SALARIOS BASICOS A PARTIR DEL 1° DE JULIO DE 2003 EMERGENTES DEL CONVENIO COLECTIVO DE TRABAJO, ÍTEM 6.1.1. Y 6.2.13

PROFESIONALES	POR MES		POR DIA	
	1995	2003	1995	2003
CONDUCTOR DE PRIMERA CATEGORIA	444,25	17,27	487,24	23,79
CONDUCTOR DE SEGUNDA CATEGORIA	398,14	16,59	477,77	19,91
CONDUCTOR DE TERCERA CATEGORIA (FLETES AL INSTANTE)	351,70	15,91	438,28	19,09
CONDUCTORES DE GRUPOS DE MAS DE 10 TONELADAS Y OPERADORES DE AUTOVHICULOS	430,60	19,84	516,72	25,53
CONDUCTORES DE GRUPOS DE MAS DE 10 Y HASTA 20 TNS.	475,69	19,76	568,15	28,68
CONDUCTORES DE GRUPOS DE MAS DE 20 Y HASTA 35 TNS.	492,65	20,53	591,14	29,43
CONDUCTORES DE GRUPOS DE MAS DE 35 Y HASTA 50 TNS.	512,65	21,95	615,30	31,65
CONDUCTORES DE GRUPOS DE MAS DE 45 Y HASTA 50 TNS.	532,82	22,83	639,38	32,64
CONDUCTORES DE GRUPOS DE MAS DE 50 Y HASTA 70 TNS.	559,63	23,51	671,56	33,67
CONDUCTORES DE GRUPOS DE MAS DE 70 Y HASTA 90 TNS.	587,44	24,48	709,93	35,27
CONDUCTORES DE GRUPOS DE MAS DE 90 Y HASTA 110 TNS.	660,03	25,52	816,04	40,28
CONDUCTORES DE GRUPOS DE MAS DE 110 Y HASTA 140 TNS.	714,04	26,75	886,85	43,78
CONDUCTORES DE GRUPOS DE MAS DE 140 Y HASTA 200 TNS.	771,55	28,12	952,39	46,54
CONDUCTORES DE GRUPOS DE MAS DE 200 TNS.	829,55	29,58	1.028,62	49,98
EMBAJADOR	375,95	15,58	448,76	18,78
RECOLECTOR Y/O CLASIFICADOR DE GRUAS	365,66	15,28	438,99	18,28
EMBAJADORES, PEONES ESPECIALIZADOS, PEONES DE BORDADA Y/O REPORTE	357,53	14,96	429,04	17,88
RECOLECTORES DE RESIDUO Y LIMPIEZA	357,53	14,96	429,04	17,88
PEONES	349,27	14,56	419,24	17,47
PEONES GENERALES DE BARRIDO Y LIMPIEZA	349,27	14,56	419,24	17,47
OPERADORES DE SERVICIOS	482,90	20,57	586,88	28,64
DISTRIBUIDOR DOMICILIARIO	402,44	16,68	480,53	23,22
AYUDANTES MAYORES DE 18 AÑOS	482,90	20,57	586,88	28,64
CHOFER DE CAMION BLINDADO	482,90	20,57	586,88	28,64
CHOFER CON FINE	482,90	20,57	586,88	28,64
AGILIA OPERATIVO DE PRIMERA	276,02	12,32	331,22	16,26
AGILIA OPERATIVO DE SEGUNDA	276,02	12,32	331,22	16,26
OFICIAL DE PRIMERA	276,02	12,32	331,22	16,26
OFICIAL COMPLETO DE TALLER	433,36	18,29	520,61	25,25
OFICIAL	381,90	15,91	458,28	22,38
OFICIAL COMERO	433,36	18,29	520,61	25,25
OFICIAL COMERO	381,90	15,91	458,28	22,38
LAVADOR, ENGRASADOR Y AYUDANTE DE TALLER	381,90	15,91	458,28	22,38
PERSONAL ADMINISTRATIVO - PRIMERA CATEGORIA	425,11	17,71	510,13	24,26
PERSONAL ADMINISTRATIVO - SEGUNDA CATEGORIA	357,53	14,96	429,04	17,88
PERSONAL ADMINISTRATIVO - TERCERA CATEGORIA	341,27	14,22	409,52	17,04
MANTENISTA Y/O SERVIDOR	341,27	14,22	409,52	17,04
AGILIA OPERATIVO DE PRIMERA DE CLEARING Y COMBO PRIVADO	426,81	17,78	512,17	24,34
AGILIA OPERATIVO DE PRIMERA DE CLEARING Y COMBO PRIVADO	382,28	15,93	458,74	22,32

Notes: This figure shows the original CBAs for the freight transport sector by road sector in 1995 and 2003.

Figure A.14 – CBA examples: Retail Sector in 2003 and 2005

FAECYS
FEDERACION ARGENTINA DE EMPLEADOS DE COMERCIO Y SERVICIOS

FAECYS - SECRETARIA DE ASUNTOS LABORALES REMUNERACIONES PARA EMPLEADOS DE COMERCIO

AL MES DE JULIO DE 2005

CAJEROS

ANTIGÜEDAD	A	B	C
1	859,30	848,00	857,80
2	840,30	848,70	858,90
3	841,48	849,11	861,10
4	842,57	850,20	862,18
5	843,65	851,28	863,26
6	844,73	852,37	864,34
7	845,81	853,45	865,42
8	846,89	854,54	866,50
9	848,00	855,62	867,58
10	849,11	856,70	868,67
11	850,22	857,78	869,75
12	851,33	858,86	870,83
13	852,44	859,94	871,91
14	853,55	861,02	873,00
15	854,66	862,10	874,08
16	855,77	863,18	875,16
17	856,88	864,26	876,24
18	857,99	865,34	877,32
19	859,10	866,42	878,40
20	860,21	867,50	879,48
21	861,32	868,58	880,56
22	862,43	869,66	881,64
23	863,54	870,74	882,72
24	864,65	871,82	883,80
25	865,76	872,90	884,88
26	866,87	873,98	885,96
27	867,98	875,06	887,04
28	869,09	876,14	888,12
29	870,20	877,22	889,20
30	871,31	878,30	890,28
31	872,42	879,38	891,36
32	873,53	880,46	892,44
33	874,64	881,54	893,52
34	875,75	882,62	894,60
35	876,86	883,70	895,68

NOTA: ACCIONES A LO DISPUESTO EN EL DECRETO P.E.N. 380/03 LA SUMA NO REMUNERATIVA A PERCIBIR EN EL MES DE JULIO SERA DE 175,00

(1) Al Sur del Río Colorado y su continuidad con el Río Barrancas hasta el Río Santa Cruz.
(2) Al Sur del Río Santa Cruz.

Notes: This figure shows the original CBA for the retail sector in 2003 and 2005.

A.4 Comparison with Argentina’s Household Survey for Formal Employment

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

Data description. The primary household survey in Argentina is the Permanent Household Survey. 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 US March Current Population Survey). The questionnaire contains extensive information on labor market participation (e.g., hours worked, labor income, tenure, the industry of occupation) and demographics (e.g., level of education, age). The EPH conducted the survey twice a year from 1995 and 2003 and quarterly from 2004 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.

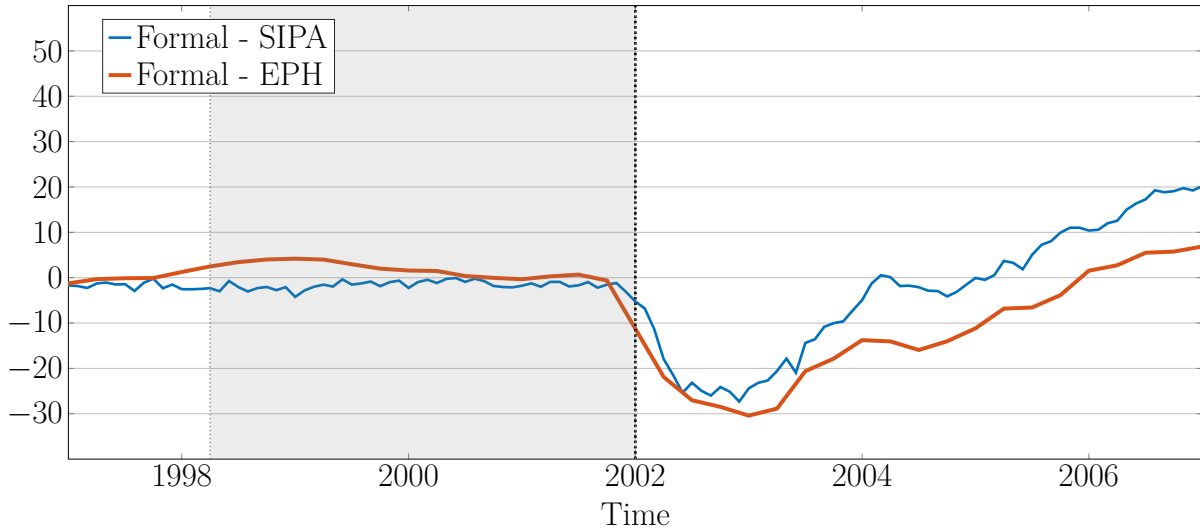
Sample. To compare SIPA and EPH, we follow the same sample selection process. That is, we focus on male workers aged 25-65 who are employed in the formal private sector and earn at least half of the 1996 minimum wage. EPH’s frequency is biannual (i.e., May and October) between 1996 and 2002 and quarterly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

General comparison between SIPA and EPH. The main caveats of the EPH with SIPA are: (i) the household survey is less (resp. more) representative of high (resp. low) income earners, since it is top coded, (ii) stock and flows of employment are computed within 6-month periods due to the frequency of the survey, (iii) statistics are noisier due to a much smaller sample size and the presence of measurement error, (iv) the household survey describes after-tax income, while SIPA includes data on pre-tax income, and (v) there is a rotating sample of households, so we cannot follow households for more than one year.

Main facts with EPH. We organize the discussion around the four facts presented in Section 4. Figure A.15 plots the time series of mean log real income in both datasets.

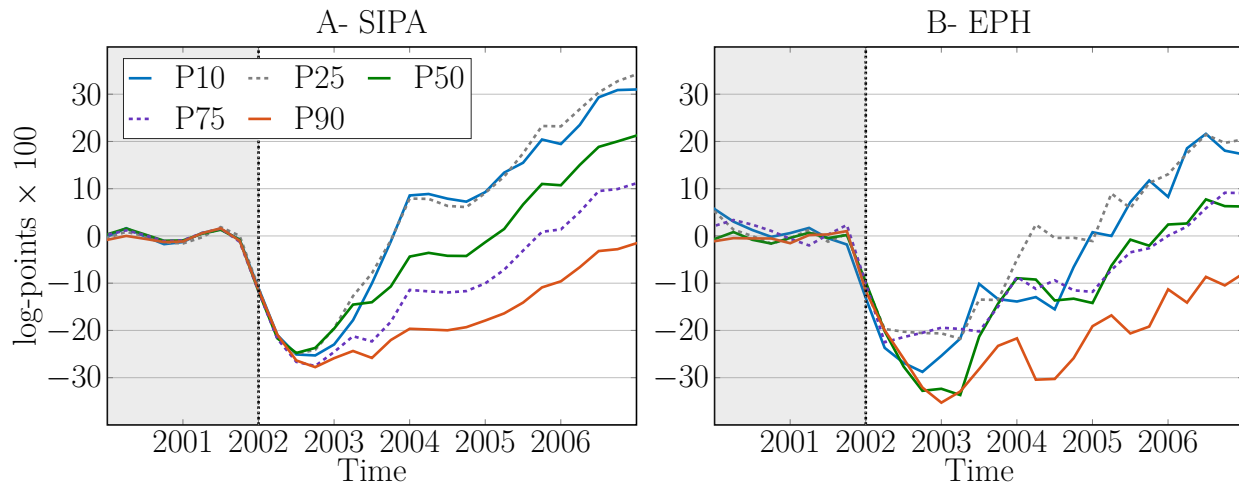
- **Average real income:** Real labor income in the SIPA dataset closely follows real labor income in the EPH in the periods 1997-2007. Figure A.15 plots the time series of mean log real income in both datasets. The levels are different because the SIPA dataset reports the before-tax income, and the EPH data respondents usually report their after-tax income. For this reason, we normalize the 1996 average income to zero in both datasets.
- **Distribution of Income:** The main fact reported in Section 4 is a 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 the cross-sectional facts. Figure A.16 describes 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.15 – Average Log Real Income in Argentina: SIPA and EPH



Notes: This figure plots the mean (log) real labor income in EPH and SIPA for male workers aged 25-65 and employed in the private sector. We normalize average labor income in 1996 to zero in the EPH and SIPA. EPH population estimates are obtained using the survey’s expansion factors.

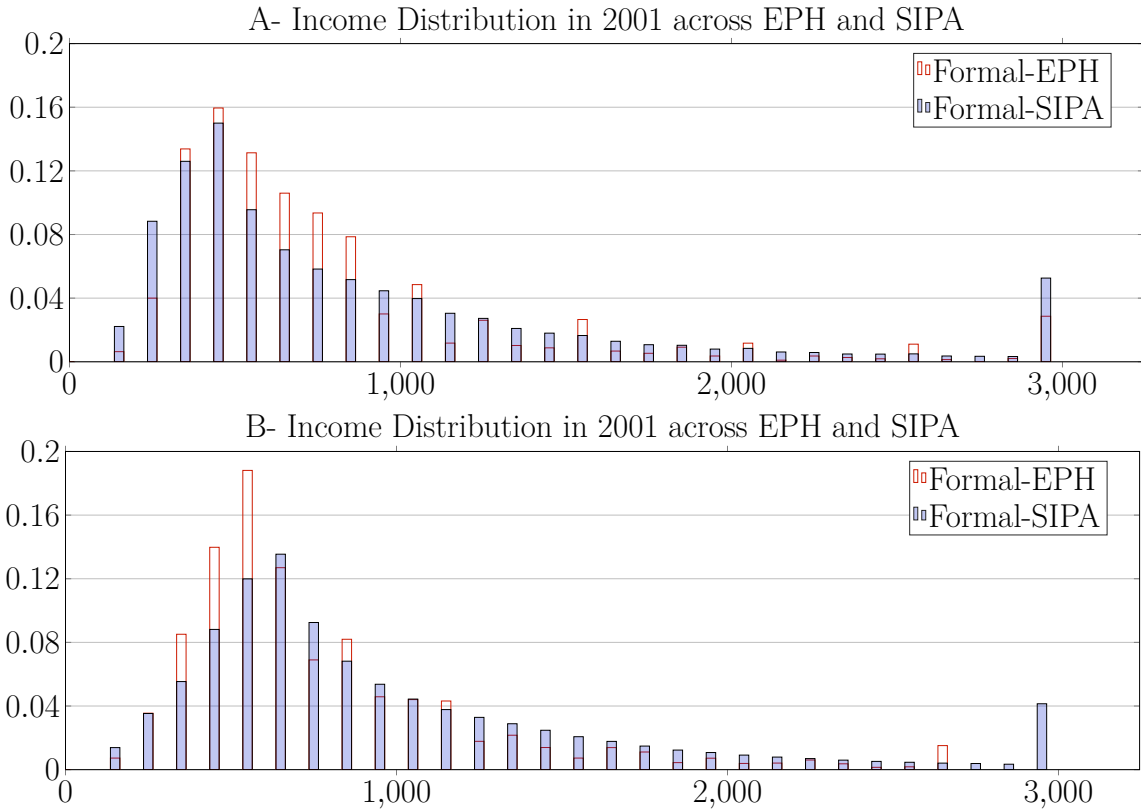
Figure A.16 – Percentiles of labor income: EPH and SIPA



Notes: The figure plots moments of the monthly real income distribution from January 2000 to December 2006. Panel A (B) plots the percentiles of the log real income distribution ($\times 100$) normalized by the average during 2001 from SIPA (EPH). EPH population estimates use the survey’s expansion factors.

Figure A.17 repeats the histogram in the main text across the EPH and SIPA. 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 formal sector are quite similar across datasets.

Figure A.17 – Income Distribution in 2001 and 2006 across EPH and SIPA



Note: The figure plots the income distribution in SIPA and EPH during 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.5 Moments of Labor Income Distribution: Comparison with the US

This section describes statistics across the sample period and compares them with the same statistics computed for the US by [Guvenen et al. \(2014\)](#). For this exercise, and this exercise only, we apply the same filters to our data as the ones used in [Guvenen et al. \(2014\)](#), and report statistics at an annual frequency. We construct annual income for male workers by aggregating monthly income of workers satisfying the following criteria: (i) between 25 and 60 years of age, (ii) annual income is 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 the median annual income. Therefore, by construction, we generate the same statistics for the relative minimum annual income.

The standard deviation and percentiles of annual log income between the US 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. Table [A.7](#) compares average annual labor income statistics in Argentina and the US. By construction, the only statistic that is equal across datasets is the “Min minus Perc. 50.”

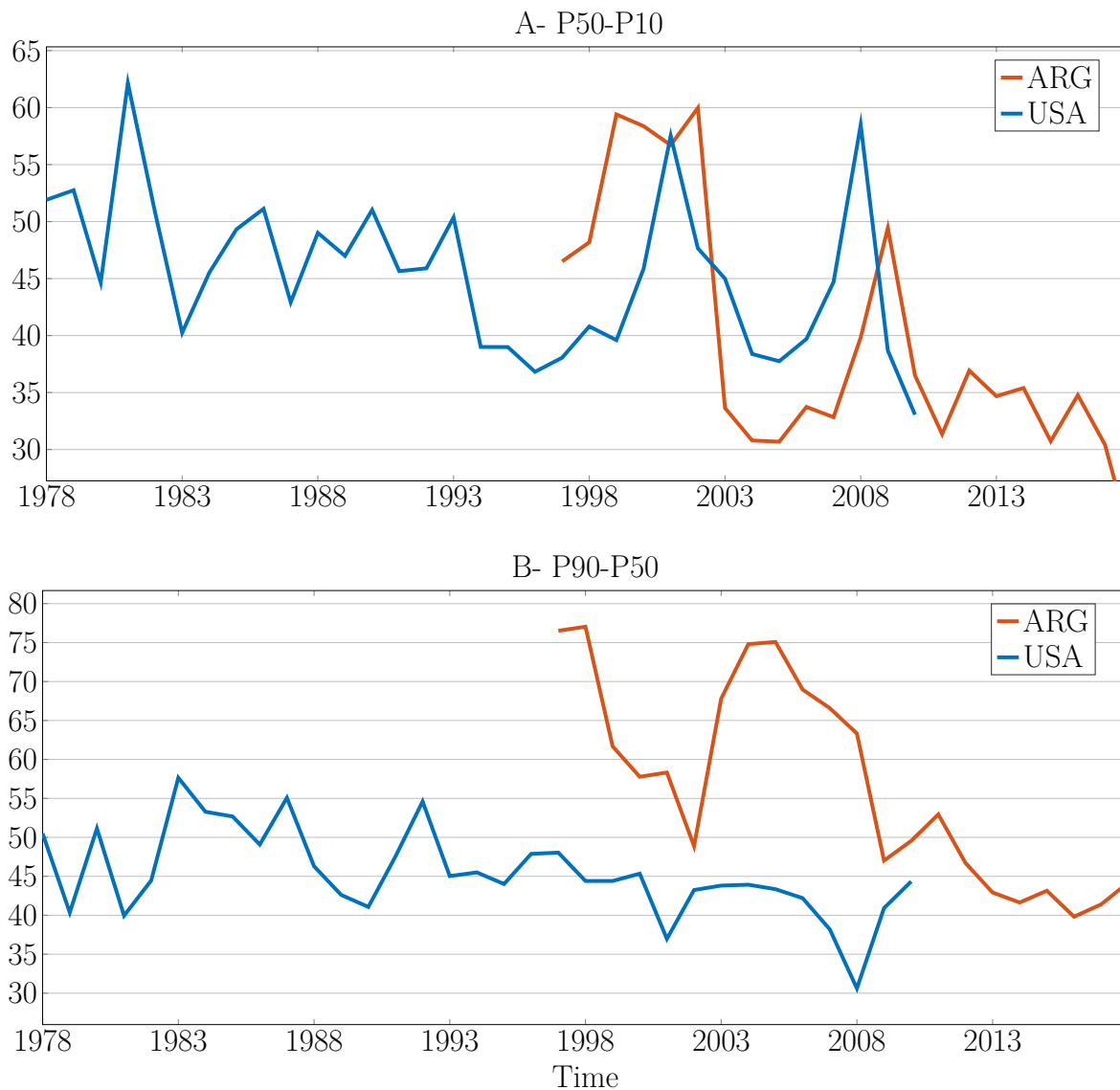
The main fact in [Guvenen et al. \(2014\)](#) is that the skewness of annual income growth is procyclical, while the standard deviation of annual income growth does not present significant fluctuations. We replicate these facts for Argentina. Figures [A.18](#) and [A.19](#) plot the comparison of the same statistics used in [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.18](#)), the reaction to crisis episodes is remarkably similar. This is particularly evident in Figure [A.19](#), in which the skewness of annual income growth follows a similar cyclical pattern.

Table A.7 – Cross-sectional labor income statistics: Argentina and the US

Moments	Argentina	US
Growth Rates		
Standard Deviation	0.59	0.53
Skewness	0.03	-0.31
Perc. 10	-38.00	-43.45
Perc. 50	1.1	2.02
Perc. 90	57.81	47.43
Log-Levels		
Standard Deviation	1.04	0.91
Skewness	-0.48	0.57
Min minus Perc. 50	-3.19	-3.24
Max minus Perc. 50	5.10	5.55
Perc. 1 minus Perc. 50	-2.91	-2.84
Perc. 10 minus Perc. 50	-1.58	-1.30
Perc. 25 minus Perc. 50	-0.62	-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

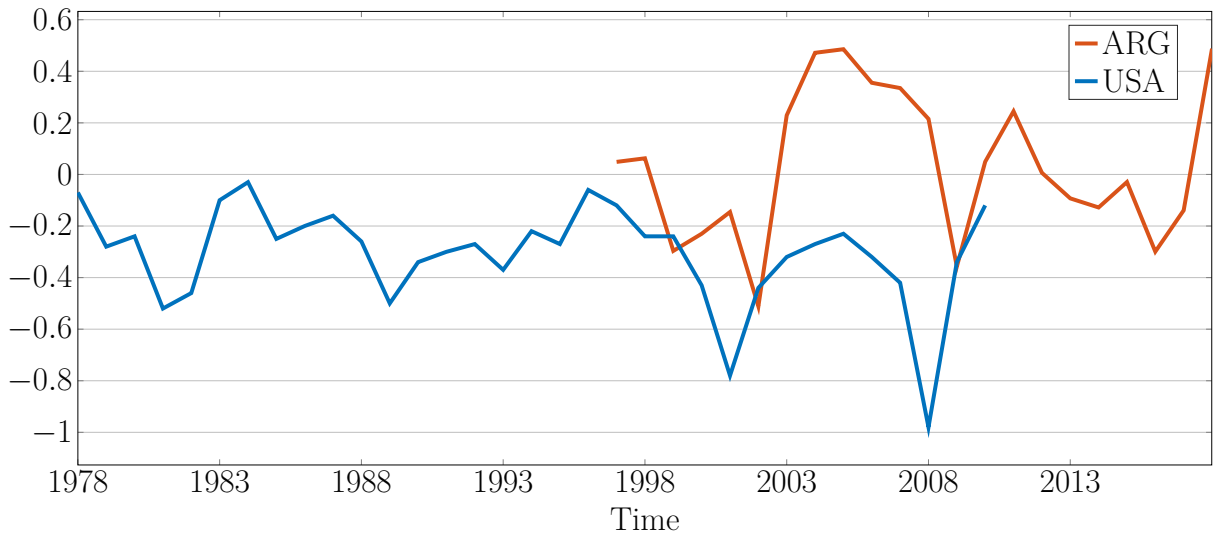
Notes: The table describes the average moments of yearly labor income for working-age males in Argentina and the US. Data for the US are from [Guvenen et al. \(2014\)](#). We set up the minimum annual income each year in Argentina to match the difference between minimum and median income in the US.

Figure A.18 – Moments of Annual Income Growth



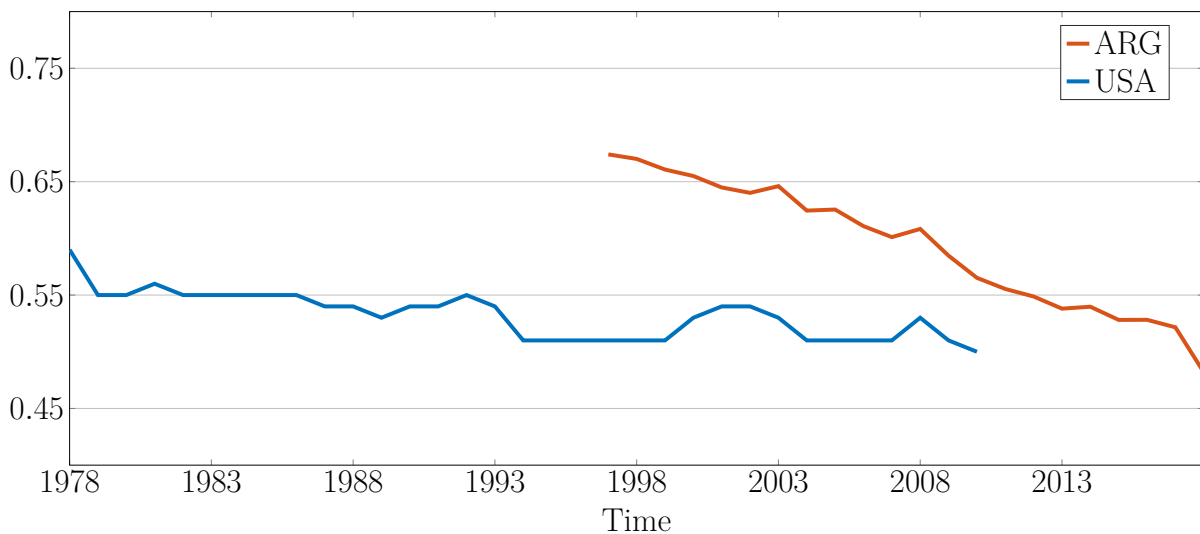
Notes: Panel A plots the log difference of the 50th and 10th percentiles of the annual income growth distribution for the US and Argentina. Panel B plots the log difference of the 90th and 50th percentiles of the annual income growth distribution for the US and Argentina. Workers in the distribution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

Figure A.19 – Skewness of Annual Income Growth



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

Figure A.20 – Standard Deviation of Annual Income Growth



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

B Aggregate Facts after RER Devaluations: Additional Information

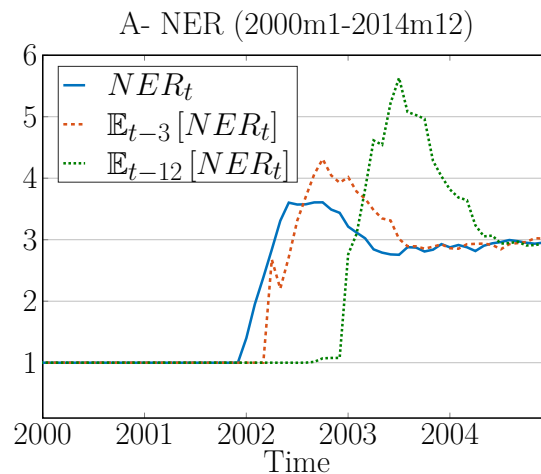
This section describes additional macroeconomic and labor market variables to complement our analysis in Section 3.

B.1 Predictability of the Nominal Exchange Rate

In this section, we examine the predictability of 2002 devaluation. For this analysis, we use survey forecast 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. The resulting dataset includes the average expectations for the 3-month- and 12-month-ahead nominal exchange rate. Figure B.1 shows the realized nominal exchange rate (NER_t), its 3-month-ahead average forecast ($\mathbb{E}_{t-3}[NER_t]$), and 12-month-ahead average forecast ($\mathbb{E}_{t-12}[NER_t]$). For example, when the date on the x-axis is January 2002, we plot the January 2002 NER, as well as the average forecast for the January 2002 NER made in October 2001 and January 2001. We now analyze each episode.

Figure B.1 – Realized and Expected Nominal Exchange Rates



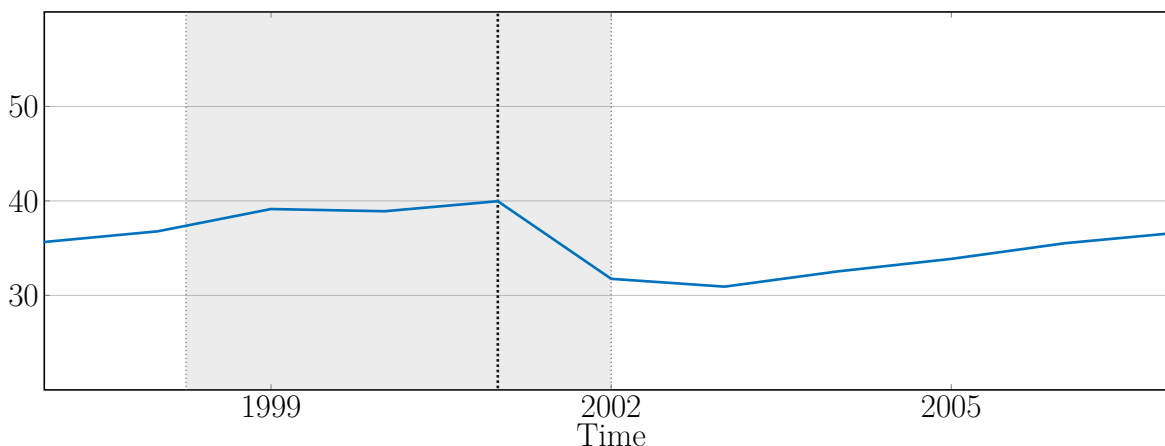
Notes: The figure shows the nominal exchange rate and its 3- and 12-month-ahead expectations in 2000m1-2004m12. We normalize each variable with the nominal exchange rate at the beginning of the sample.

Devaluation in January 2002. On average, professional forecasters failed to predict the 2002 devaluation. Before the devaluation, the 3-month- and 12-month-ahead forecasts were close to one. Notice that after September 2001, the 12-month-ahead forecast increases by 7%, far below the realized rate. Thus, even if professional forecasters had qualitative awareness of an upcoming increase in the nominal exchange rate, they were largely unable to predict its size.

B.2 Additional Aggregate Variables in Argentina

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

Figure B.2 – Labor Share in Argentina



Notes: The figure shows the annual labor share in Argentina from 1997 to 2007. Data were obtained from [Feenstra, Inklaar and Timmer \(2015\)](#) (Penn World Tables 9.1).

Labor share. The main text characterizes the dynamics of real labor income across workers with different permanent incomes. We do not characterize any division of revenue between workers and firms, i.e., the labor share during the 2002 devaluation. The labor share falls in Argentina during the 2002 devaluation, implying a redistribution of real income from workers to firms. Figure B.2 shows the labor share in Argentina from 1997 to 2007.

There is a direct relation between average labor income, labor share, and labor income. The labor share (LS) in a country is the average income per worker $\left(\frac{\sum y_i}{n}\right)$ times workers per income $\left(\frac{n}{Y}\right)$:

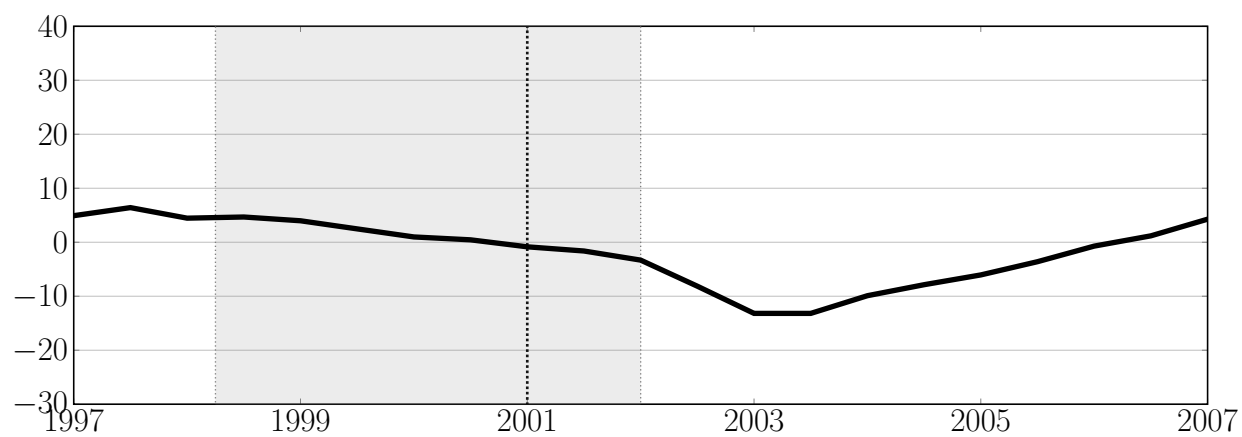
$$LS = \frac{\sum y_i}{Y} = \frac{\sum y_i}{n} \frac{n}{Y} = \text{average labor income} \times \text{inverse output per worker.} \quad (\text{B.2})$$

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

Output per worker. The main text characterizes the recovery across percentiles of the income distribution. Thus, we compare the relative recovery across different workers. However, we did not analyze the main economic driver of labor income, i.e., labor productivity. Figure B.3 shows quarterly log output per worker in Argentina from 1997 to 2007, the measurable variable most related to labor productivity.

The figure exhibits two patterns. First, output per worker was decreasing considerably in Argentina before the 2002 devaluation (i.e., 10% between 1998-2001), while aggregate labor income is constant or weakly increasing. Second, there is a strong recovery of the output per worker after 2003, as we discuss in the main text.

Figure B.3 – Output per Worker in Argentina

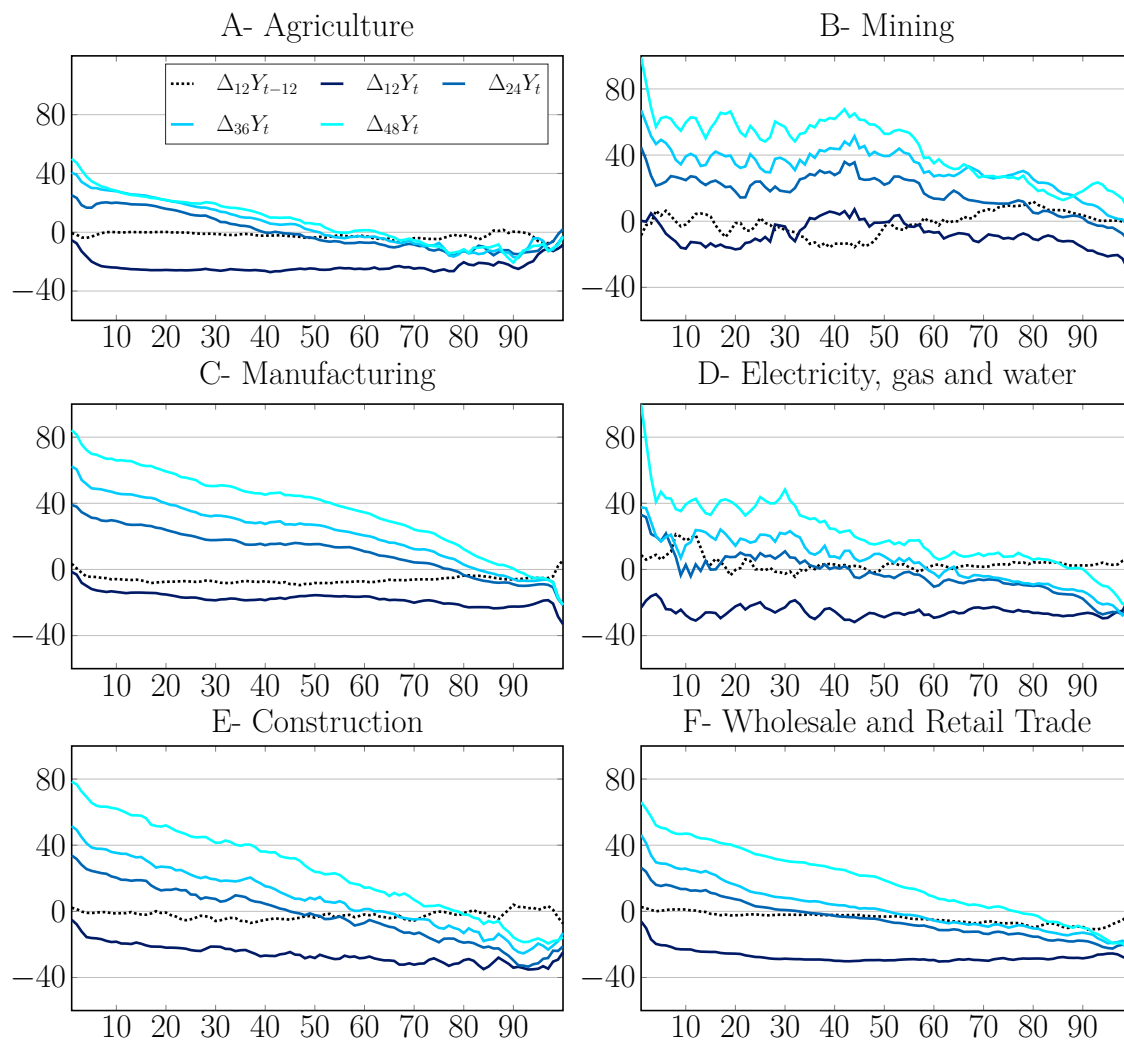


Notes: The figure shows output per worker in Argentina from 1997 to 2007. We compute output per worker as the ratio between real GDP and total employment for the Permanent Household Survey.

C Mechanism Behind the Fall of Inequality: Additional Results

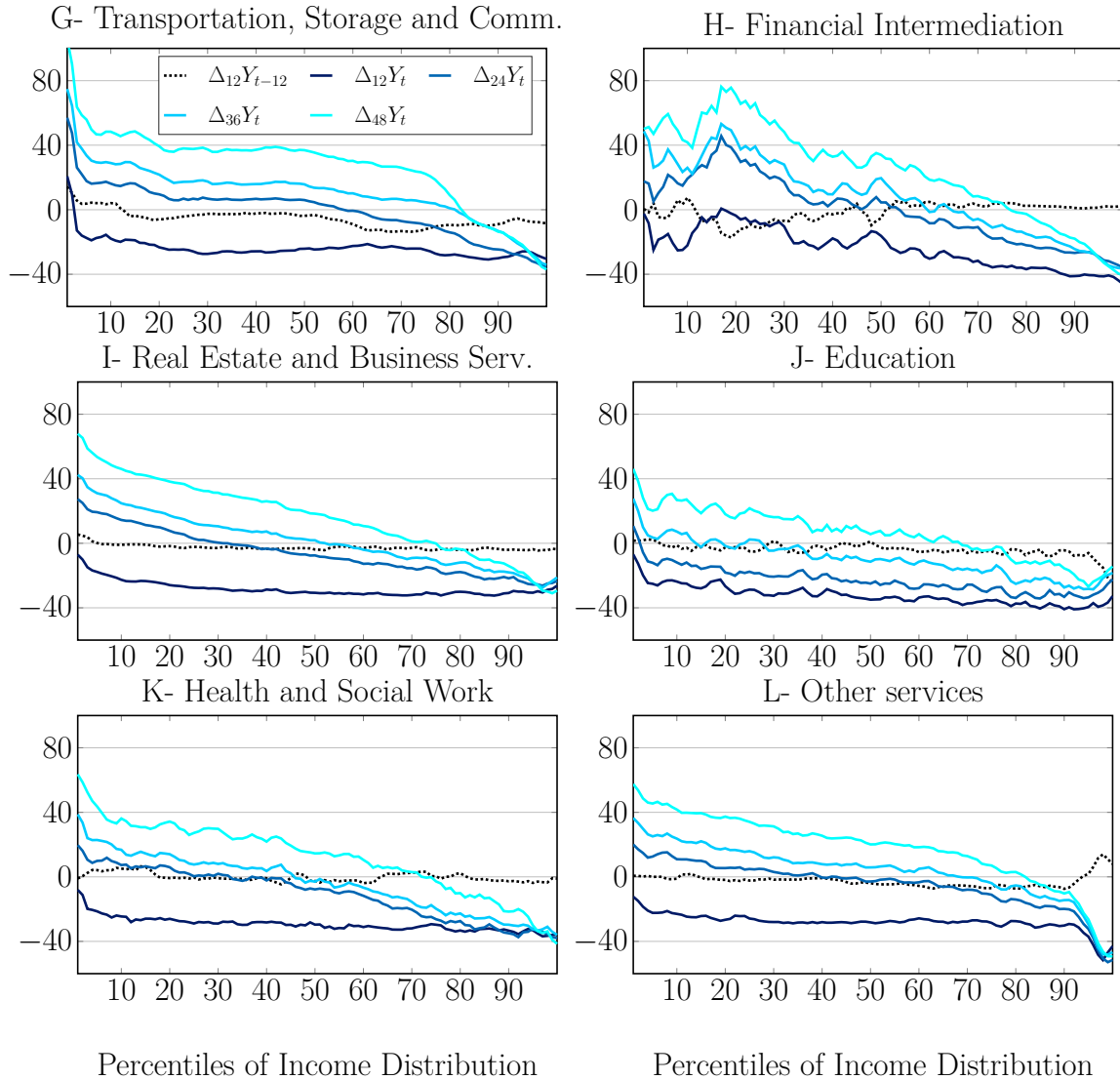
C.1 Robustness Analysis of Parallel Drop and Pivoting

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



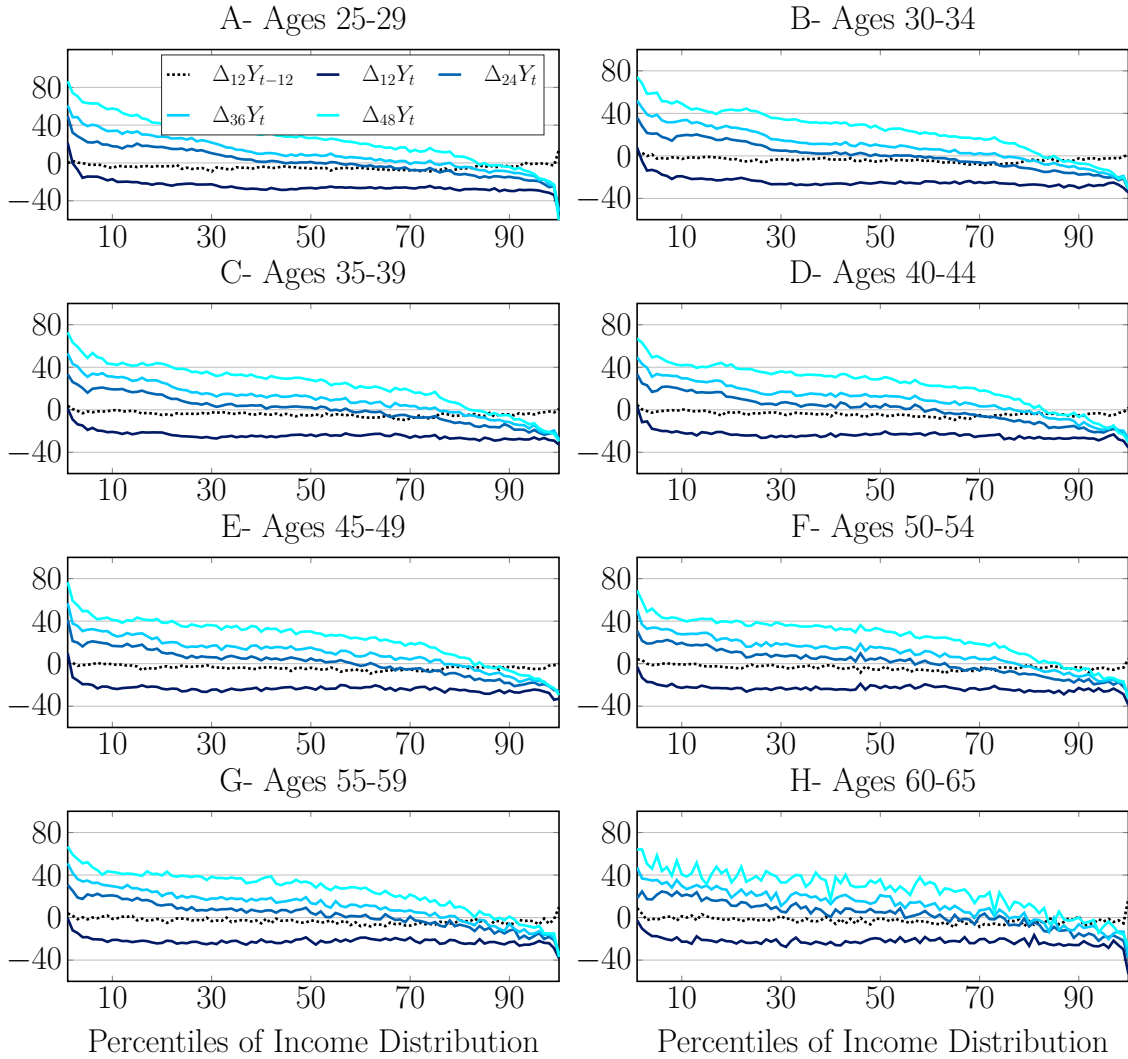
Notes: The figure describes average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. The figures are split according to the sector of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

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



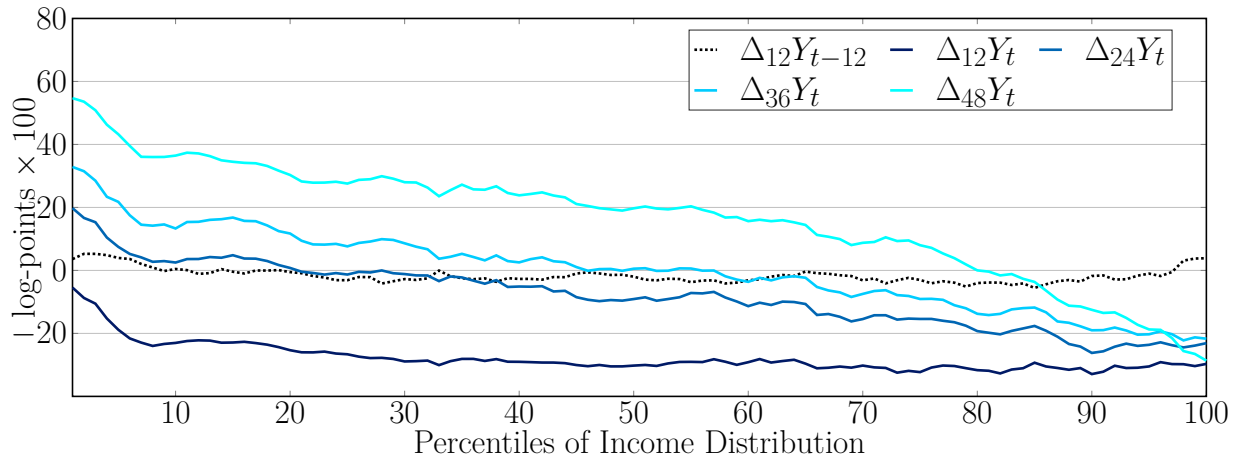
Notes: The figure describes average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. The figures are split according to the sector of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

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



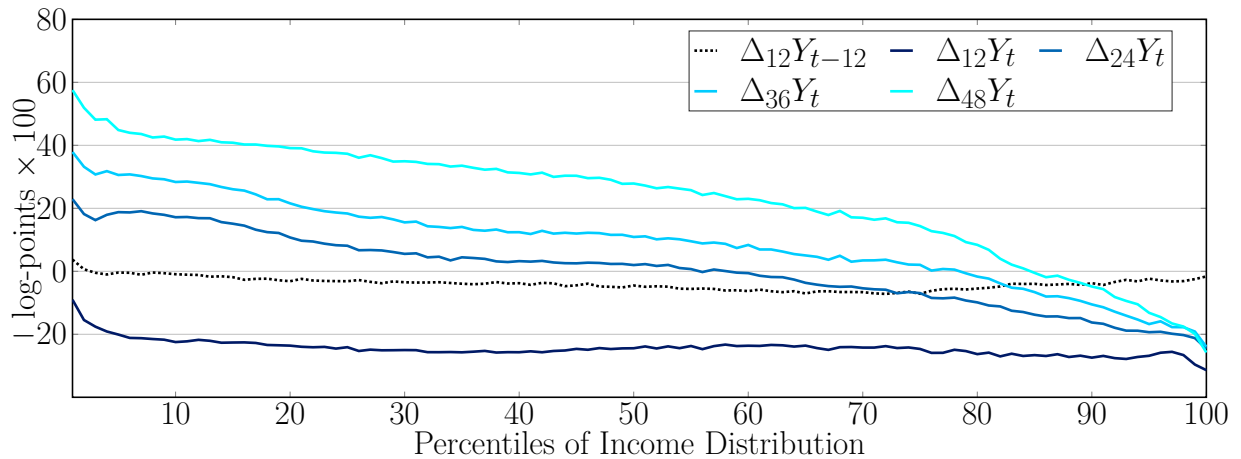
Notes: The figure describes average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. The figures are split according to the age group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

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



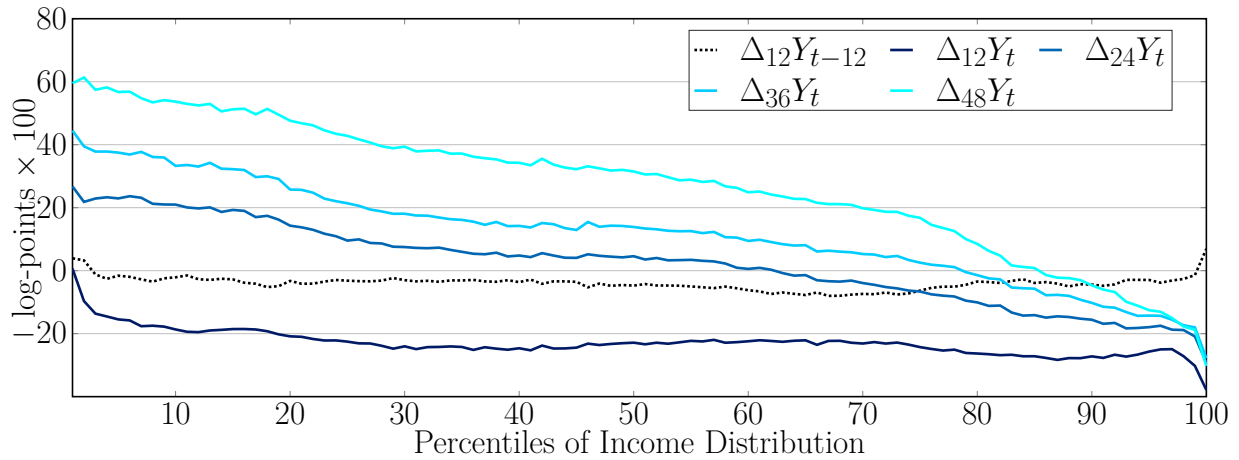
Notes: The figure describes average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period.

Figure C.4 – Average income growth conditional on average income in 1997-2001



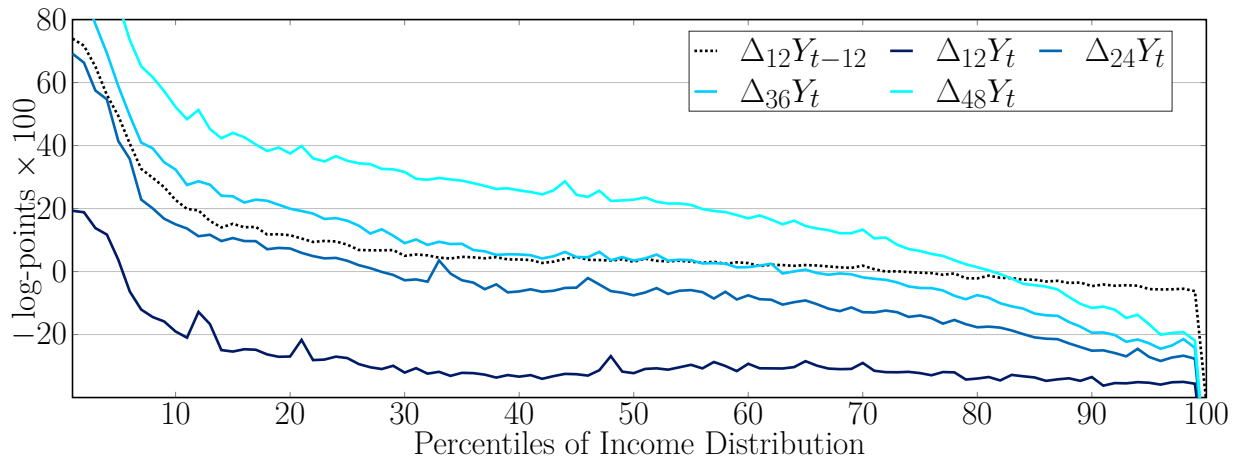
Notes: The figure describes average income growth conditional on the percentile of the distribution of average monthly real income during 1997-2001. The sample is restricted to workers who had at least 6 months of employment during the 1997-2001 period.

Figure C.5 – Avg. income growth conditional on average income in 2000-2001: Full-time workers



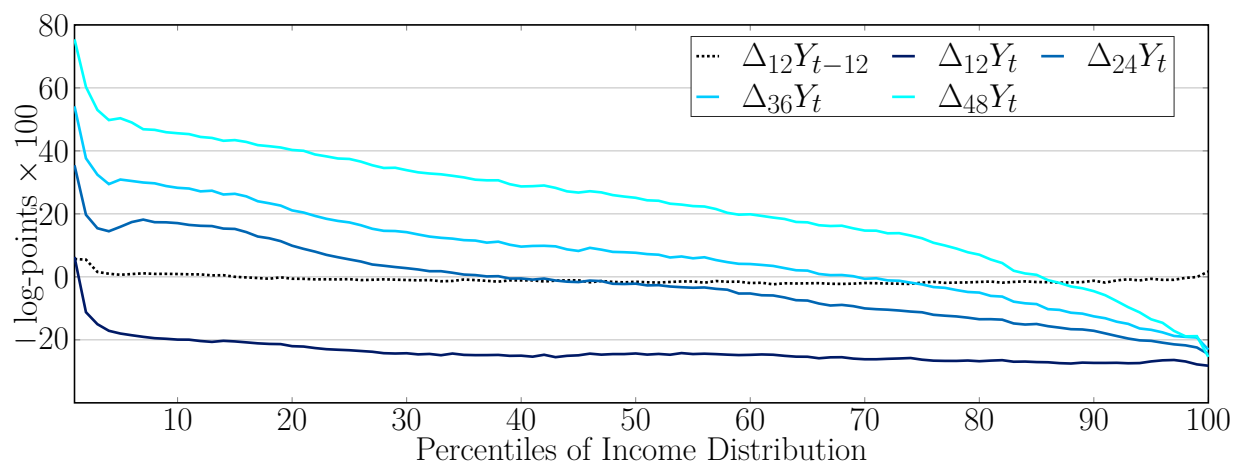
Notes: The figure describes average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period and to full-time jobs only.

Figure C.6 – Avg. income growth conditional on average income in 2000-2001: Including zero-income workers



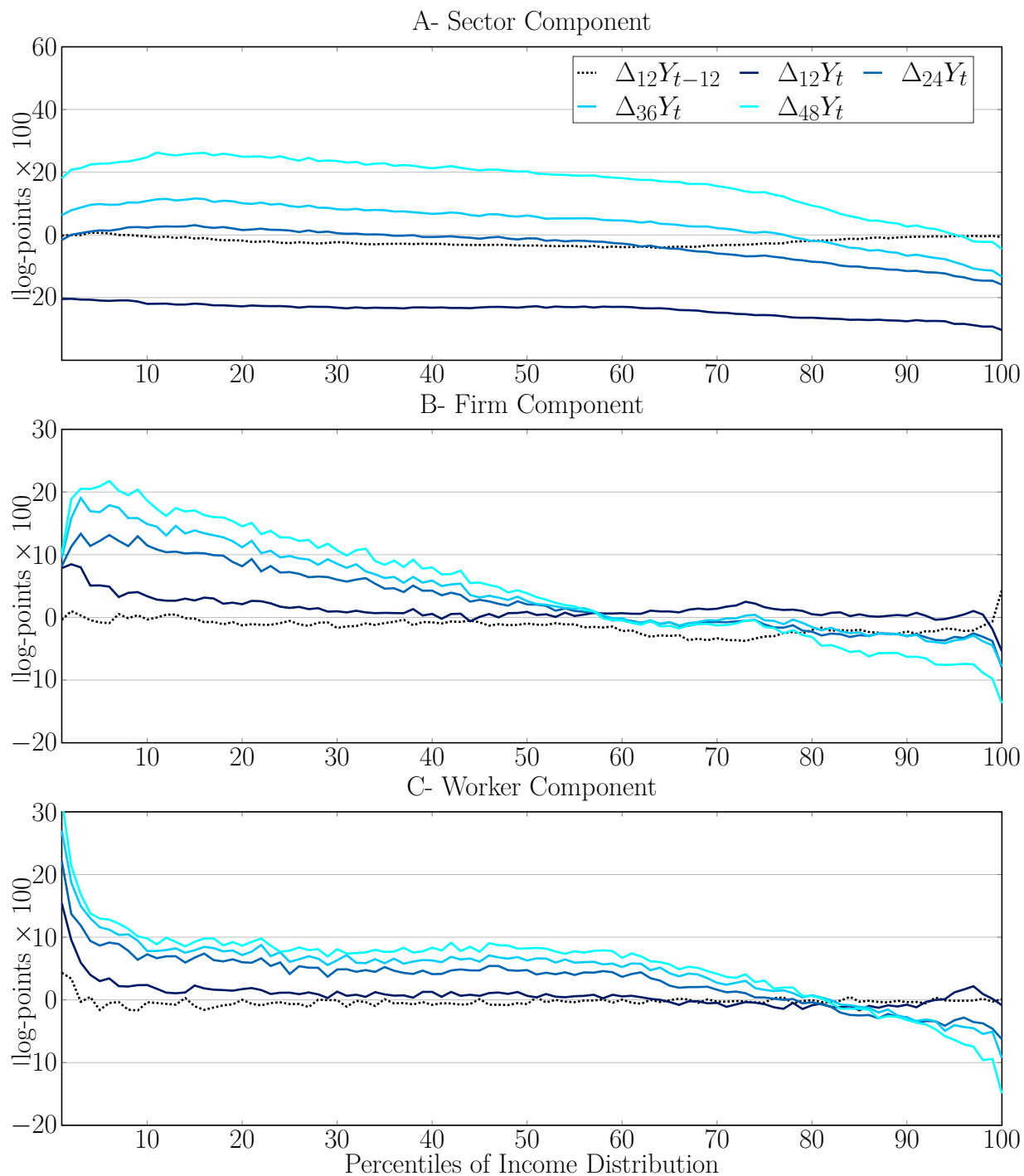
Notes: The figure describes average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period.

Figure C.7 – Avg. income growth conditional on average income in 2000-2001: Quarterly income



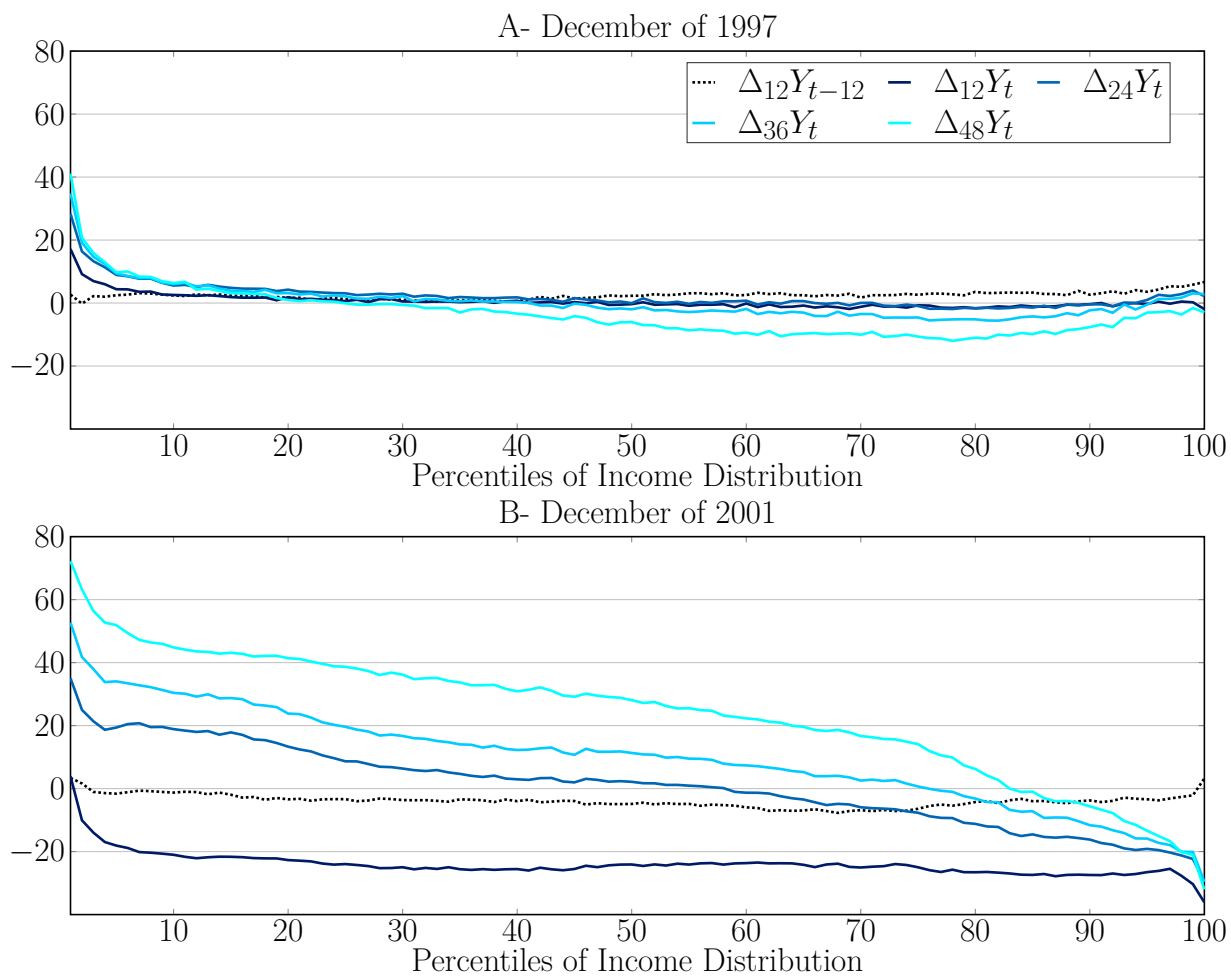
Notes: The figure describes average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period. Average income growth is constructed using data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

Figure C.8 – Decomposition of average income growth conditional on average income in 2000-2001: Workers employed in firms with at least 10 employees



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. 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. 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 C.9 – Average income growth conditional on average income: 1997 vs 2001



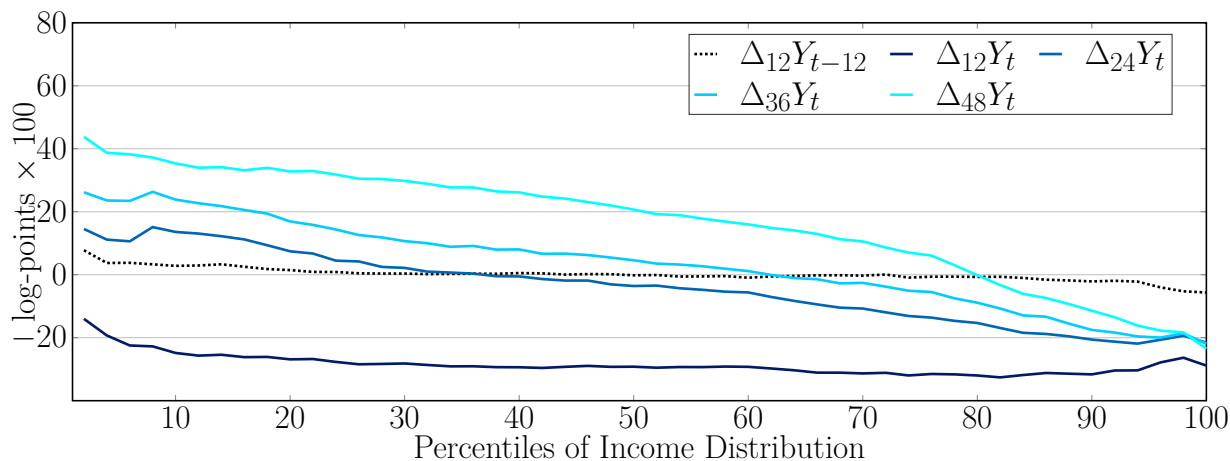
Notes: Panel A (B resp.) plots average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001 (1996-1997 resp.). The sample is restricted to workers who had at least 6 months of employment during the 1996-1997 and 2000-2001 periods.

Here, we control for workers' pre-devaluation trends in income growth to verify whether our main fact is 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 $\Delta\bar{Y}_t^i \equiv \bar{Y}_t^i - \bar{Y}_t^i - 59$ (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 50- and 40- quantile thresholds, respectively. With these thresholds at 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:

$$y_{t+k}^{l,g} - y_t^{l,g} = \sum_{l=1}^{50} \alpha_l \mathbb{1}_{\bar{Y}}\{l\} + \sum_{g=1}^{50} \beta_g \mathbb{1}_{\Delta\bar{Y}}\{g\} + \varepsilon_t^{l,g}, \quad (\text{C.3})$$

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 C.10](#) 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.²⁴

Figure C.10 – Avg. income growth conditional on average income in 2000-2001: Controls for past trends



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 figure plots the coefficients α_l from an OLS estimation of equation (C.3).

²⁴We 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.

C.2 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 in the following way:

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

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:

$$\text{var}(y_{ijst}) \equiv \underbrace{\text{var}_s(\bar{y}_{st})}_{\text{Between-sector dispersion}} + \underbrace{\sum_s \omega_{st} \text{var}_j[\bar{y}_{jst}|j \in s]}_{\text{Between-firm dispersion}} + \underbrace{\sum_j \omega_{jt} \text{var}[y_{ijst}|i \in (j, s)]}_{\text{Within-firm dispersion}}, \quad (\text{C.4})$$

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 mean 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 income.

Figure C.11, Panels A and B, plot the results of the decomposition for each month between January 2000 and December 2006. During this period, the cross-sectional variance of log real income decreased by 21.1 log points. Of this total decrease, a decrease of 7.1 log points was due to the between-sector component, a decrease of 7.2 log points was due to the between-firm component, and a decrease of 6.8 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 compute a further decomposition of the change in the between-sector component in equation (C.4):

$$\begin{aligned} \Delta \text{var}_s(\bar{y}_{st}) &= \underbrace{\sum_s \omega_{st} \left[(\bar{y}_{st} - \bar{y}_t)^2 - (\bar{y}_{st-1} - \bar{y}_{t-1})^2 \right]}_{\text{Fixed weights}} \\ &+ \underbrace{\sum_s (\omega_{st} - \omega_{st-1}) (\bar{y}_{st-1} - \bar{y}_{t-1})^2}_{\text{Fixed dispersion}}. \end{aligned} \quad (\text{C.5})$$

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 C.11-Panel C plots the results of this decomposition. Of the overall decline in the between-sector component of 6.6 log points, 1.4 log points are accounted for by the reallocation of workers across sectors and 5.2 log points by within-sector changes in the deviations from the average labor income. Thus, only 21% of the decline in the between-sector component is due to the reallocation of workers across sectors.

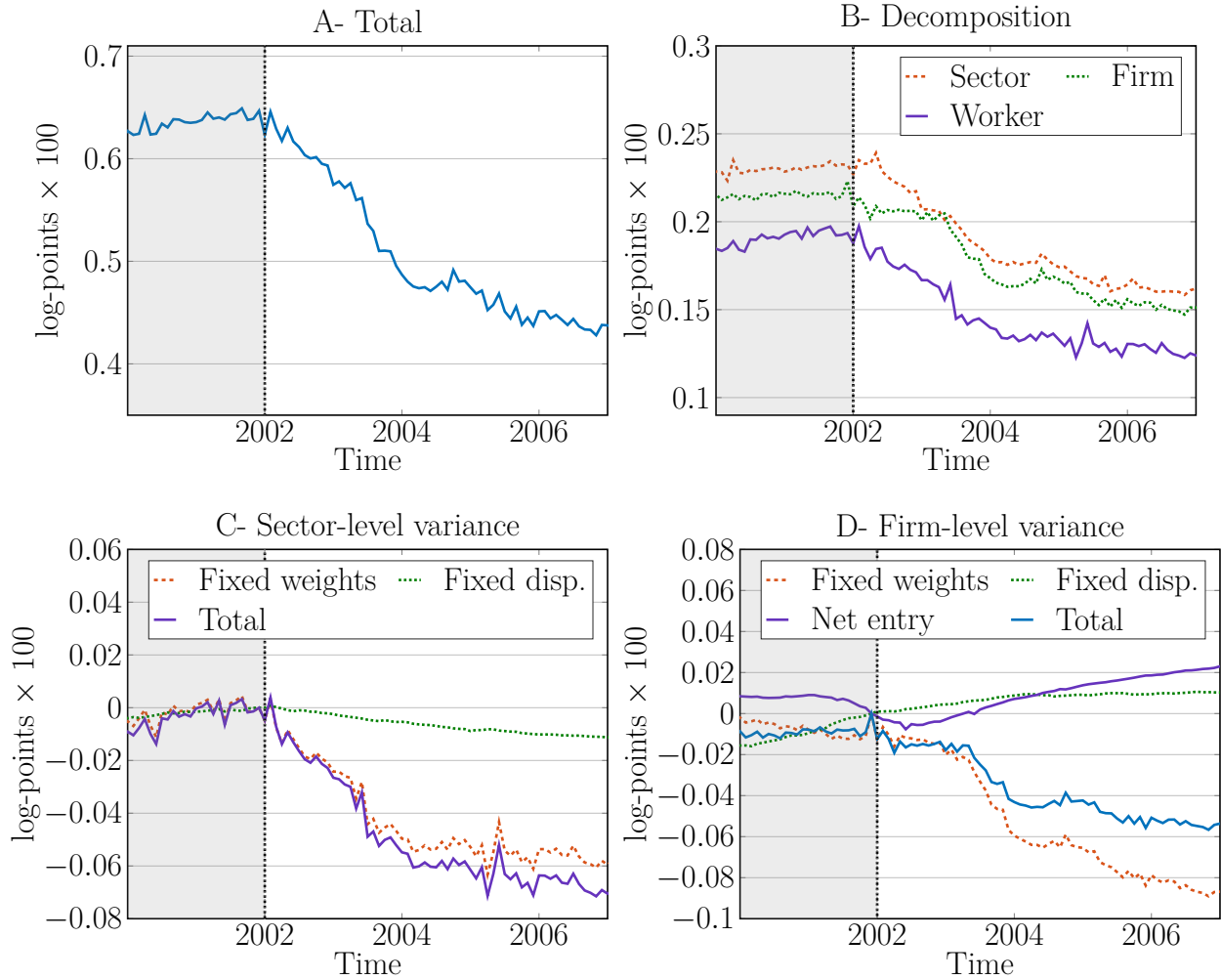
We repeat a similar exercise for between-firm dispersion and find that the variance across firms' wages decreases despite the reallocation of workers. We decompose changes in between-firm dispersion in three

terms according to the following identity:

$$\begin{aligned}
\Delta \sum_s \omega_{st} \text{var}_j [\bar{y}_{jst} | j \in s] &= \underbrace{\sum_{s,j \in \mathcal{J}_{st} \& \mathcal{J}_{st-1}} \omega_{st} \omega_{jst} \left[(\bar{y}_{jst} - \bar{y}_{st})^2 - (\bar{y}_{jst-1} - \bar{y}_{st-1})^2 \right]}_{\text{Fixed weights}} \\
&+ \underbrace{\sum_{s,j \in \mathcal{J}_{st} \& \mathcal{J}_{st-1}} [\omega_{st} \omega_{jst} - \omega_{st-1} \omega_{jst-1}] (\bar{y}_{jst} - \bar{y}_{st})^2}_{\text{Fixed dispersion}} \\
&+ \underbrace{\sum_{s,j \in \mathcal{J}_{st} / \mathcal{J}_{st-1}} \omega_{st} \omega_{jst} (\bar{y}_{jst} - \bar{y}_{st})^2 - \sum_{s,j \in \mathcal{J}_{st-1} / \mathcal{J}_{st}} \omega_{st} \omega_{jst} (\bar{y}_{jst} - \bar{y}_{st})^2}_{\text{Net entry}}.
\end{aligned} \tag{C.6}$$

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 C.11-Panel D plots the decomposition in equation (C.6). The variance increases due to changes in the weights of each firm and net entry. The overall increment is of 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 C.11 – Variance decomposition across sectors, firms, and workers



Notes: The figure plots the total variance and its decomposition according to (C.4) from January of 2000 to December of 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 SIC 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 the firm's j workers share.

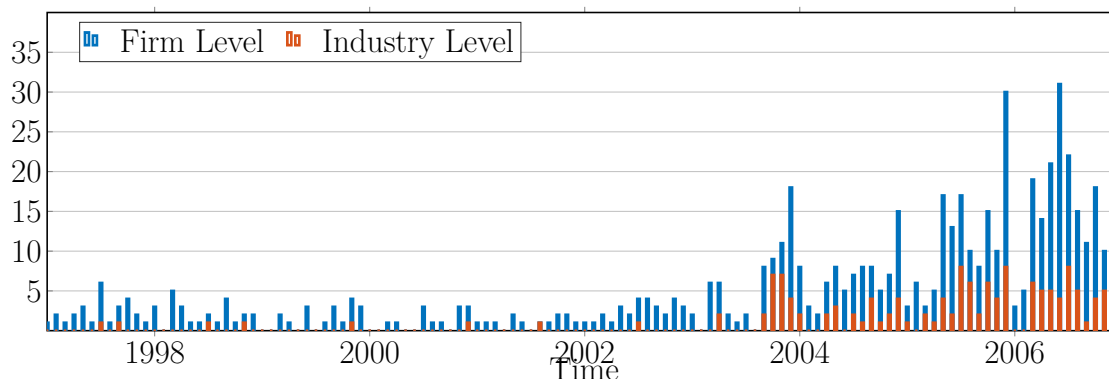
C.3 Economic Mechanism II: Heterogeneous Income Floors

This section presents additional statistics on the role of unions in Argentina’s labor market to complement our analysis in Section 5.

Here we discuss the roles played by unions in contributing to the compression of the income distribution from below. The Argentinian union system is characterized by a high degree of centralization, by which a single union is given the monopoly power by law to represent workers within a specific industry, branch of activity, or type of occupation, irrespective of whether the worker is an union member. Unions tend to negotiate the wages of blue-collar workers and the lower ranks of white-collar workers. Thus, the wages of employees in administrative and managerial jobs are usually not covered by union collective bargaining, and are more subject to competitive forces.

Some of the most impressive evidence for the effects of unionization on the compression of the income distribution is presented in Panel A of Figure C.12, which shows the number of contracts negotiated by unions and firms in 12 sectors between 1996 and 2008. The figure distinguishes between contracts signed between a union and a single firm and those signed between a union and representatives of the entire industry.²⁵ The general pattern that emerges across sectors is that in the years that led to the recession, the overall collective bargaining process was rather weak. This explains the relatively constant average wage of formal workers during the recession period.²⁶ However, after the increase in inflation brought about by the 2002 devaluation, there is a rapid increase in the number of contracts renegotiated. The second piece of suggestive evidence concerns which workers are more likely to benefit from the renegotiation of collective bargaining agreements.

Figure C.12 – Number of Contracts Negotiated by Unions

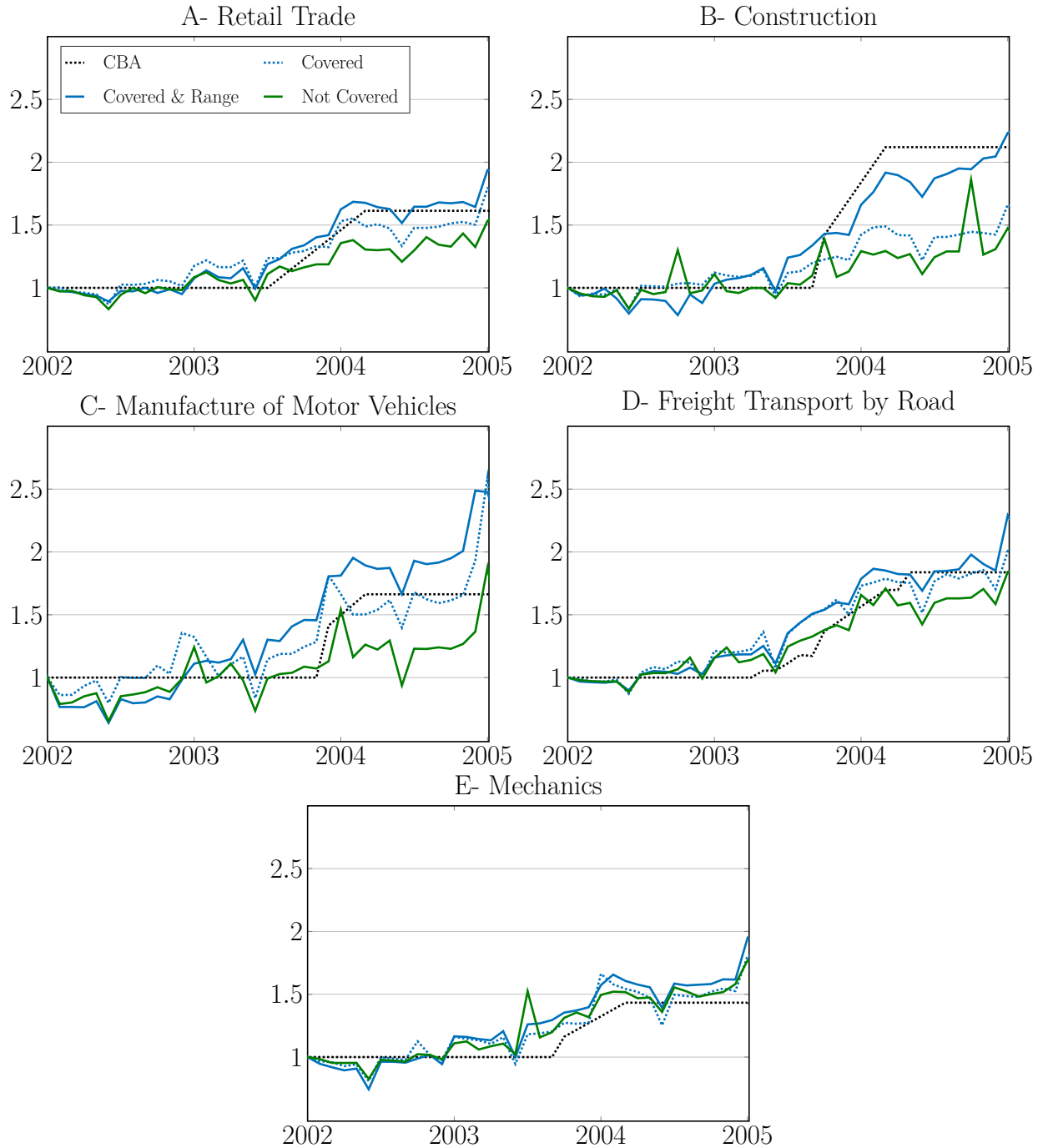


Notes: The figure shows the number of contracts negotiated by unions per month for a subset of industries.

²⁵The source of these data are the original documents signed by the parties in each collective bargaining contract approved by the Argentinian Ministry of Labor. The sample of contracts includes only contracts that modified the scale of basic wages of workers.

²⁶Before 2002, the Argentinian law allowed expired contracts to remain valid until a new contract was 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 weren’t renegotiated after their expiration.

Figure C.13 – Normalized labor income by union coverage and labor income in CBAs



Notes: Panels A to E plot the average labor income across occupations in the CBAs and the average labor income of workers covered and not covered by unions. A worker belongs to the group “Covered” if she is unionized in June 2003. A worker belongs to the group “Covered & Range” if she is unionized in June 2003 and her income is between the lowest and highest incomes across occupations in the CBA in October 2002. A worker belongs to the group “Not Covered” if she is not unionized in June 2003.

D Additional Mechanisms and Robustness: Additional Results

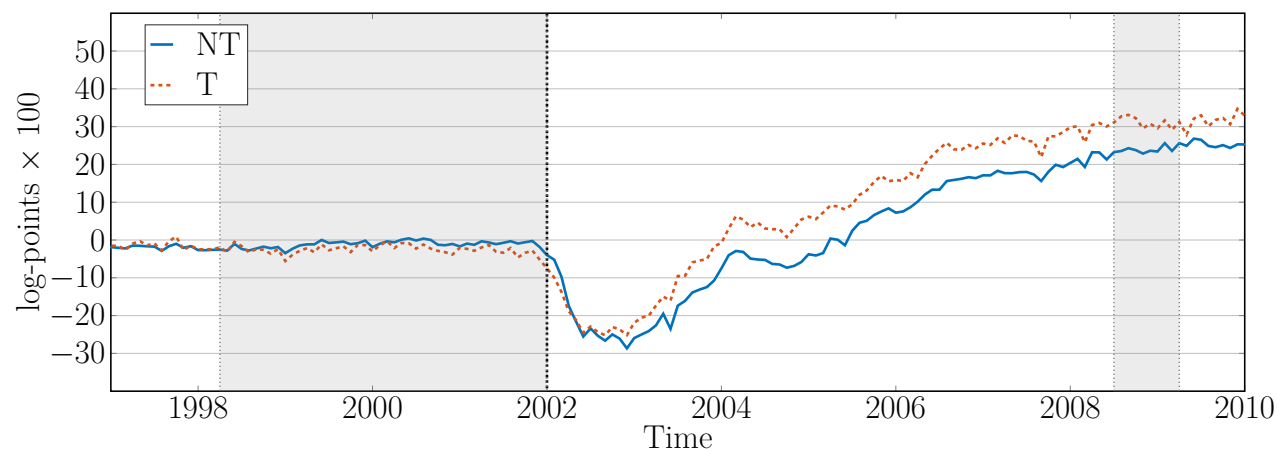
D.1 Sectoral Trade Exposure

This section presents additional statistics on the role of trade in Argentina’s labor market to complement our analysis in Section 6.

Time series of tradable and nontradable sectors. The main text characterizes the distributional impact of trade in Figure 12. Here, we present a time series analysis of tradable and non-tradable sectors to show the reallocation of labor and longer trends of sectoral labor income.

Figure D.1 plots the average real labor income across sectors, normalized by the average income in the nontradable sector in 1996. We can see two clear patterns around the 2002 devaluation. First, there is no pre-devaluation gap across sectors during both the expansion and the recession. If there is any trend, this trend shows a faster decline in tradable sector labor income relative to nontradable. Second, after the 2002 devaluation there is a positive gap between average labor income in the tradable and non-tradable sectors that reached a magnitude of 10% in 2005. The surprising fact in the data is that this gap persists until 2010 (8 years after the 2002 devaluation). In conclusion, there is a significant difference in labor income dynamics across the tradable and nontradable sectors that qualitatively follows the predicted increase in revenue in tradable sectors relative to the nontradable.

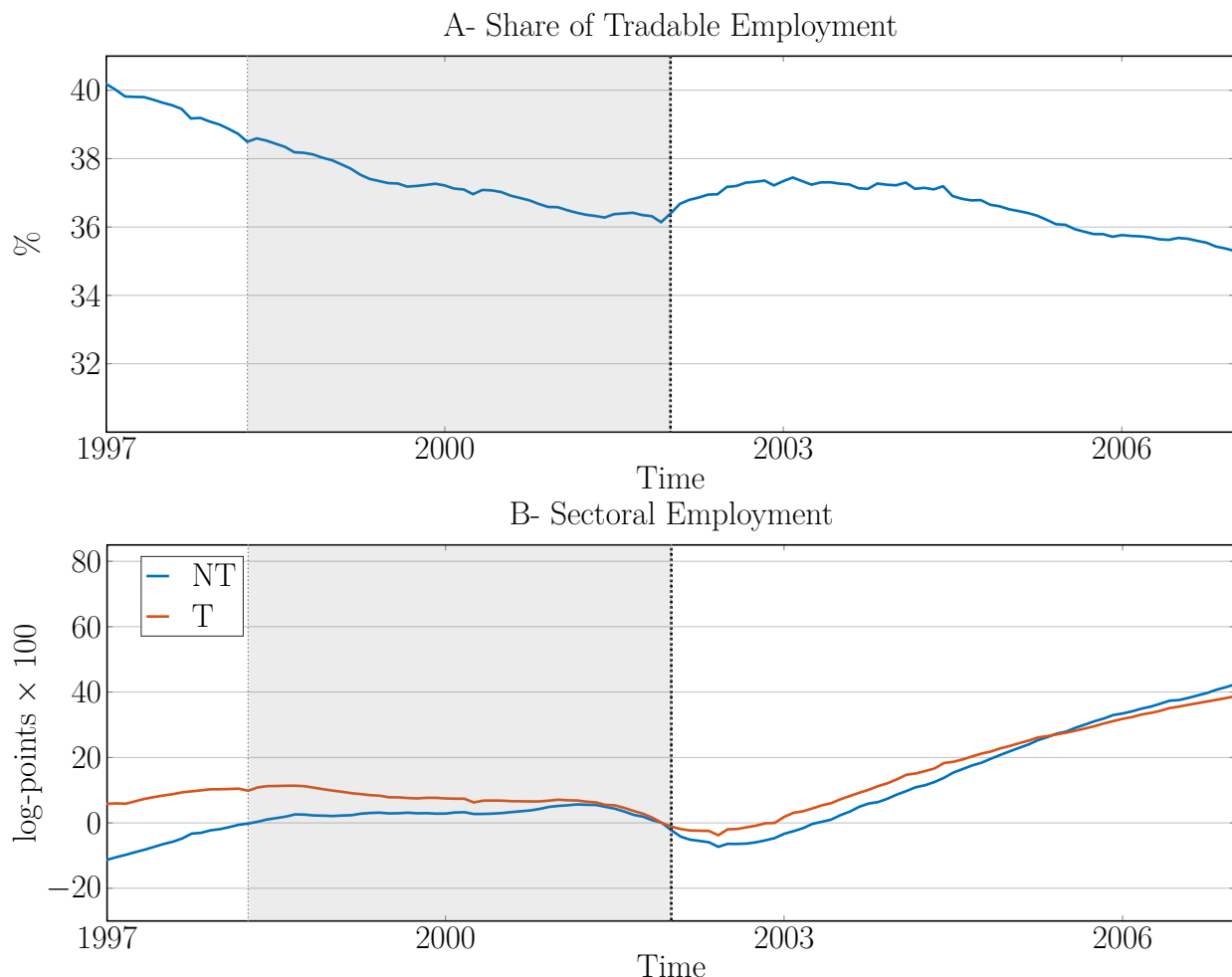
Figure D.1 – Labor income by sector



Notes: The figure shows monthly average (log) real income from 1997 third quarter to 2010 second quarter for the tradable and nontradable sectors. The variables are seasonally adjusted and normalized by the average income in 1996 in nontradable sectors. Recession periods are in gray and monthly devaluations larger than 10% are in dotted black lines.

It is a well-known fact in the literature on structural change that there is a world-wide secular decline in employment in the tradable sector (see Buera and Kaboski (2012)). Argentina is not an exception. Figure D.2-Panel A shows the share of tradable employment from 1997 to 2007. This share declined from 40% to 36% over 10 years, with an average decline of 0.33% per year. 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 100 log-points, the share of tradable employment increased by only 1%.

Figure D.2 – Sectoral employment



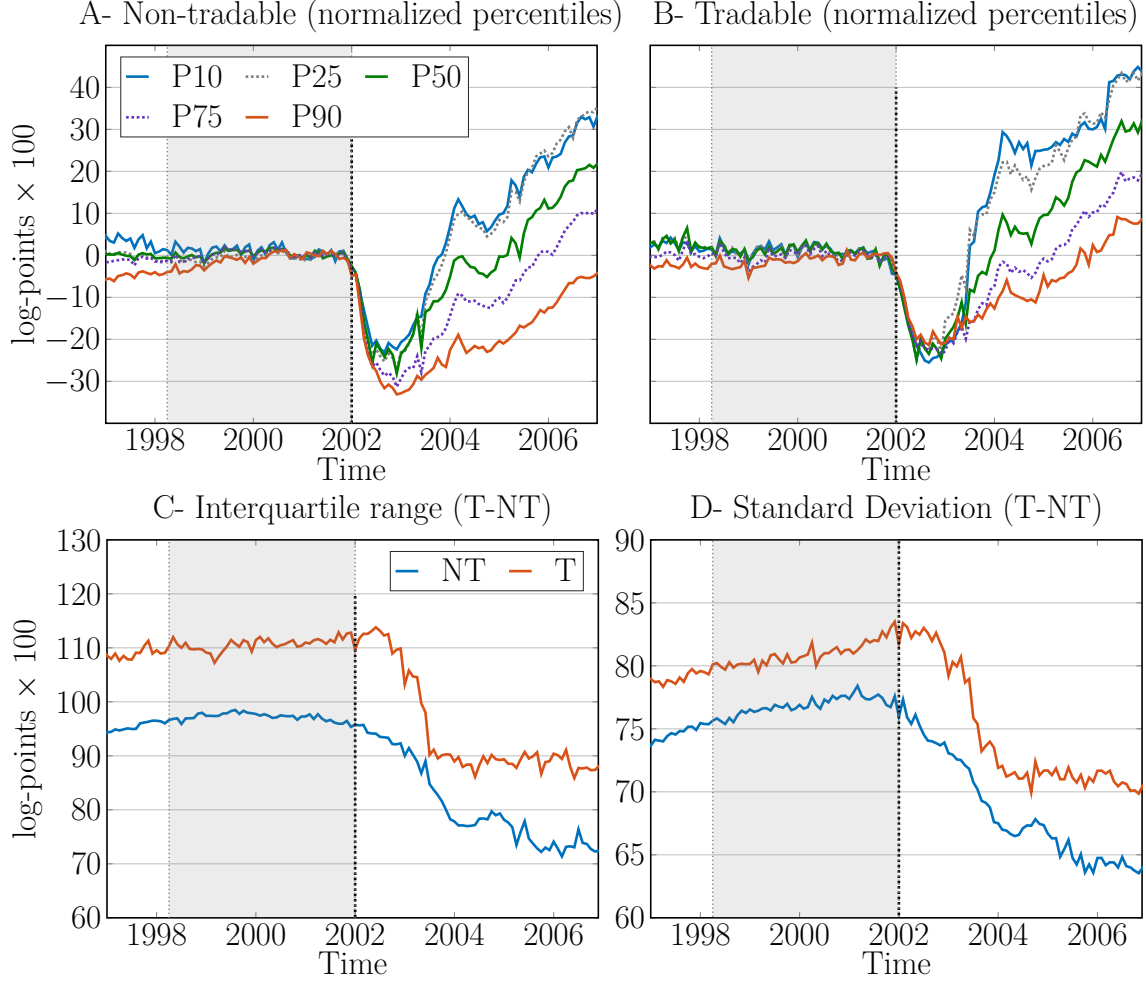
Notes: Panels A and B show the employment share in the tradable sector and the (log) total employment in the tradable and nontradable sectors, respectively. Total employment across sectors is normalized to zero in December 2001. Recession periods are in gray and monthly devaluations larger than 10% are in dotted black lines.

Given the timing of the origination of the permanent gap between sectoral income, we want to understand whether the workers driving this gap are in the bottom or the top of the distribution, or whether it is uniform across the distribution. Figure D.3 answers these questions. Figure D.3 shows, in Panels A and B, the normalized percentiles of the income distribution in each sector, and Panels C and D the interquartile range and the standard deviation.

The first pattern we see in Figure D.3 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 are 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, implying a larger dispersion coming from the top of the distribution.

The second pattern is easier to visually appreciate five years after the devaluation. All of the percentiles of the income distribution in the tradable sector are larger than the percentiles in the nontradable sector. Thus, differences across the entire distribution are responsible for the observed gap in relative real income in tradable relative to nontradable sectors.

Figure D.3 – Percentiles of real labor income distribution by sector



Notes: The figure depicts statistics for monthly real income from January 2000 to December 2006. Panel A (B resp.) describes the percentiles in the NT (T resp.) sector of the log income distribution ($\times 100$) normalized by the average during 2001. We use NT (T resp.) to denote the nontradable (tradable resp.) sector. We use P_x to the x percentile of the distribution. Panels B and C describe the interquartile range ($P_{75} - P_{25}$) and Kelley's skewness ($\frac{P_{90}+P_{10}-2P_{50}}{P_{90}-P_{10}}$) for the same time period across sectors.

Sectoral trade exposure at input-output matrix level. We analyze the determinants of income differences across sectors at a more disaggregated level. Here, the sectors are defined at input-output matrix level, close to a 3-digit SIC classification. More specifically, we reproduce the analysis in Section 6 in two steps. First, we linearly project sectoral labor income growth with RER and its interaction with trade exposure. Second, we use the predicted values to reconstruct average income growth conditional on trade exposure.

Our goal for this analysis is to estimate how sectoral income changes correlate with the RER in response to differences in trade exposure. The usual concern with this type of analysis is that these variables are not exogenous. To alleviate such concerns, we estimate the following equation:

$$\begin{aligned} \Delta outcome_{st} = & \alpha_s + \beta_t + \phi \Delta RER_t \times \text{Ind. Import Share}_{s1997} + \gamma \Delta RER_t \times \text{Ind. Export Share}_{s1997} \\ & + \delta \Delta RER_t \times \text{Import Penetration}_{s1997} + \varepsilon_{st}, \end{aligned} \quad (\text{D.7})$$

where $\Delta outcome_{st}$ is the annual change in some outcome variable in sector s at time t (e.g., labor income growth), ΔRER_t is the annual change in the real exchange rate, and θ_s and β_t are sector and time fixed effects, respectively. The variables of interest are the interactions between the RER with Imp. Share $_s$, Exp. Share $_s$, and Imp Penetration $_s$. The indirect import share and the export share are the indirect share of imported intermediate over total inputs and the indirect export share in sector s over total production from the National Input-Output Matrix in 1997, which are predetermined relative to the sample (see Frías, Kaplan and Verhoogen, 2009, for a similar approach). Import penetration is total imports over output minus trade balance.

The coefficients of the interaction terms ϕ , γ , and δ capture the effect of changes in relative prices due to fluctuation in RER on labor income. Under the assumption that sectoral labor income is proportional to sectoral revenue, theory predicts a positive coefficient for exporting sectors and those with high import penetration, and negative for sectors relying on imported intermediate inputs.

Table D.1 – Sectoral Effects of a Devaluation

	(1)	(2)
	Growth average income	Average income growth
$\Delta RER_t \times IS$	-0.174*** (0.032)	-0.188*** (0.032)
$\Delta RER_t \times ES$	0.240*** (0.017)	0.292*** (0.018)
$\Delta RER_t \times IP$	0.029** (0.014)	-0.002 (0.015)
N	12091	12091
R^2	0.735	0.792

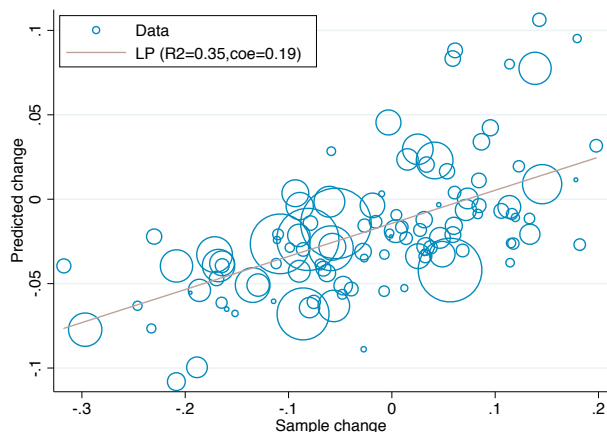
Notes: The dependent variables are the average of within-worker income annual growth by sector and the annual growth rate of average sectoral income. The independent variables include the interaction of the annual change in the RER with the export share by industry, the share of imported intermediate inputs and import penetration, and time and industry fixed effects. The estimation method used in all columns is OLS. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

There is a heterogeneous correlation of sectoral labor income with RER as a function of sectoral trade exposure. Results are shown in Table D.1. In the first and second columns, the outcome variables are the average income growth and the growth rate of average sectoral income. To interpret the coefficient, remember that labor income decreases with RER as we explain in the main text. While income in exporting sectors and sectors with high import penetration falls by less after a devaluation, income in importing sectors falls by more. This pattern across sectors is consistent with the theories described above. The estimated elasticities obtained for the growth rate of average income are larger than the ones obtained for average income growth in the sector. Since the latter is computed using within-worker income growth—thus, controlling for any time-invariant worker characteristics—the difference suggests the presence of compositional effects.

There is a strong correlation between the RER and sectoral labor income as a function of trade exposure at the 3-digit SIC level. Figure D.4 shows the three-year sectoral labor income growth rate at the input-output matrix level and their predictions with the projection estimated in equation (D.7). As the figure shows, the simple linear prediction with only one coefficient interacted with RER estimated in the whole sample has a good fit during the 2002 devaluation. It can generate 35% of the entire variation with an elasticity of 0.19.

The solid (resp. dotted) lines in Figure D.5 show the average sectoral labor income growth rate (resp. average predicted sectoral labor income growth rate) by percentiles of income, aggregated from an input-output matrix sector definition level. By construction, this figure captures the aggregate average increase in labor income at around a 3-digit SIC classification and its correlation with trade exposure. As the figure

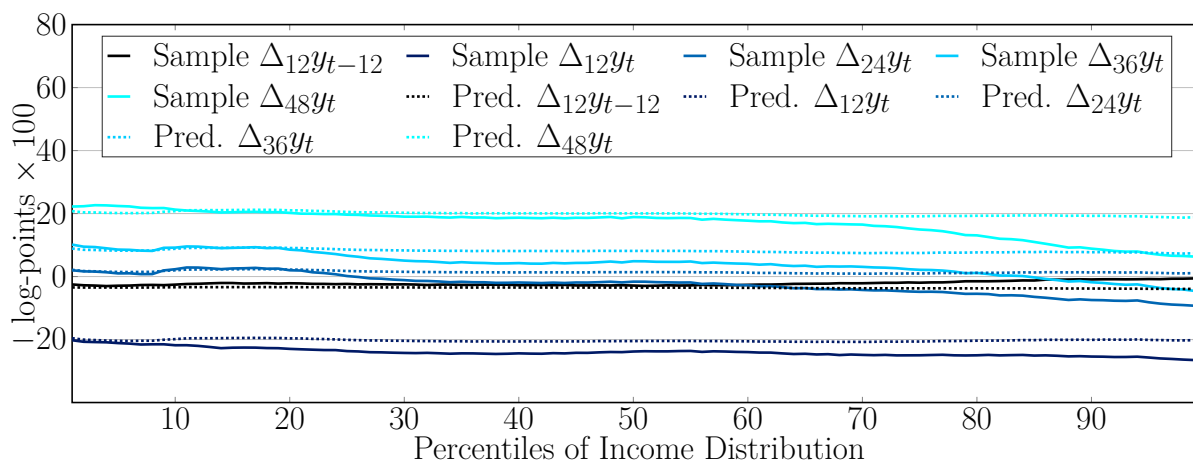
Figure D.4 – Sample and predicted three-year sectoral income growth



Notes: The figure shows real income growth over three years from December 2000 to December 2003 on the x-axis and the predicted real income growth from the projection (D.7). Each blue circle shows the sample size in number of workers. The red line shows the linear projection between the predicted sectoral growth rate and the sample growth rate.

shows, the predicted value of (D.7) does not present almost any heterogeneous sectoral labor income growth. Therefore, our conclusion on the role of trade in the heterogeneous recovery of labor incomes holds at a narrow level of disaggregation.

Figure D.5 – Average conditional income growth for sample and predicted sectoral labor income growth

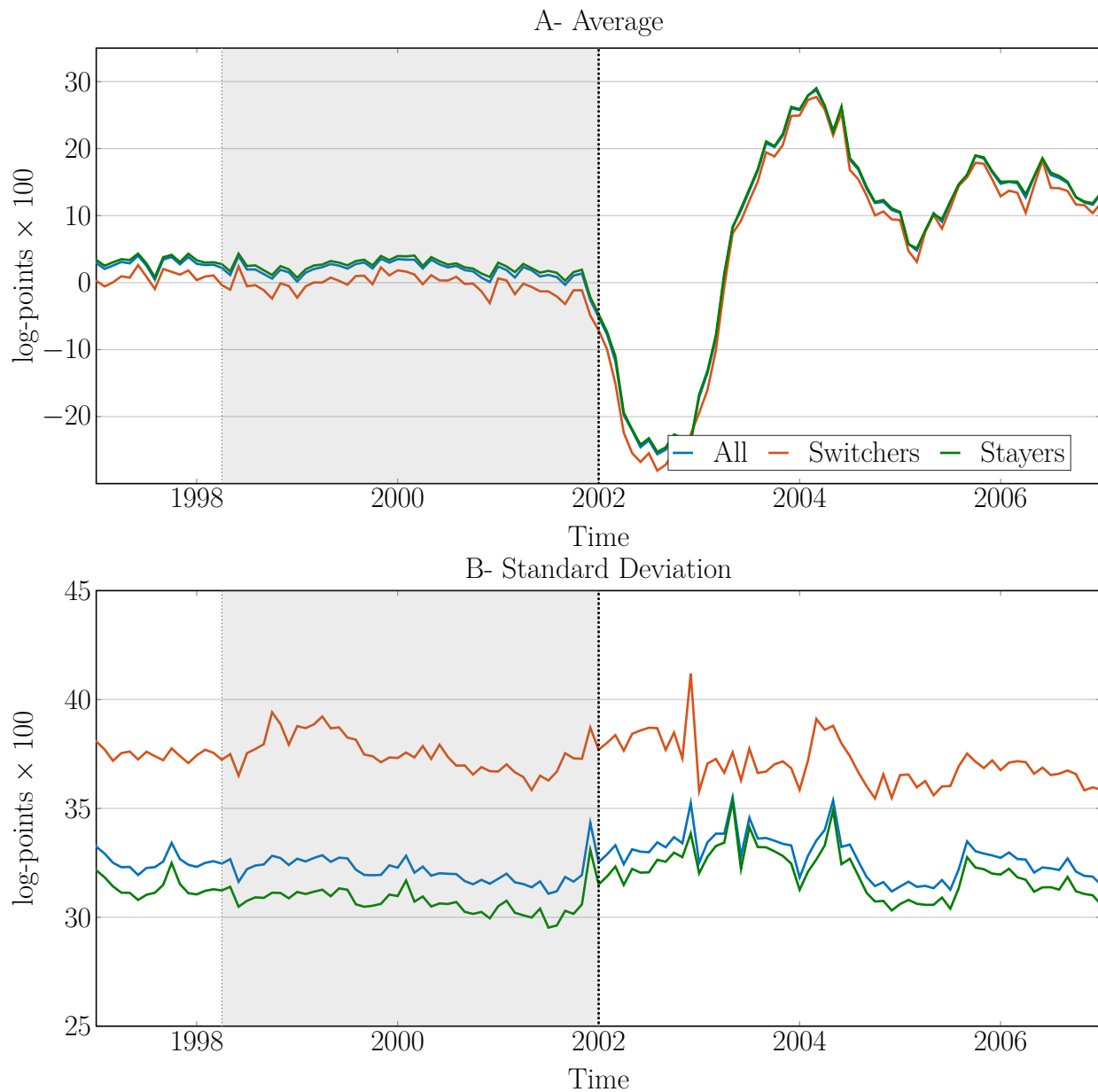


Notes: The figure plots average income growth conditional on the percentile of the distribution of average monthly real income during 2000-2001. The solid lines show average sectoral income growth, aggregated from an input-output-level sectoral classification. The dotted lines show predicted average sectoral income growth, aggregated from an input-output-level sectoral classification from the estimates in equation (D.7). The sample is restricted to workers who had at least 6 months of employment during the 2000-2001 period.

D.2 Changes in Labor Income Risk

This section presents additional statistics about the distribution of income changes to complement our analysis in Section 6.

Figure D.6 – Moments of the Distribution of Labor Income Growth



Notes: Panels A and B plot the average and standard deviation of year-over-year income growth from 1997 first quarter to 2007 first quarter.

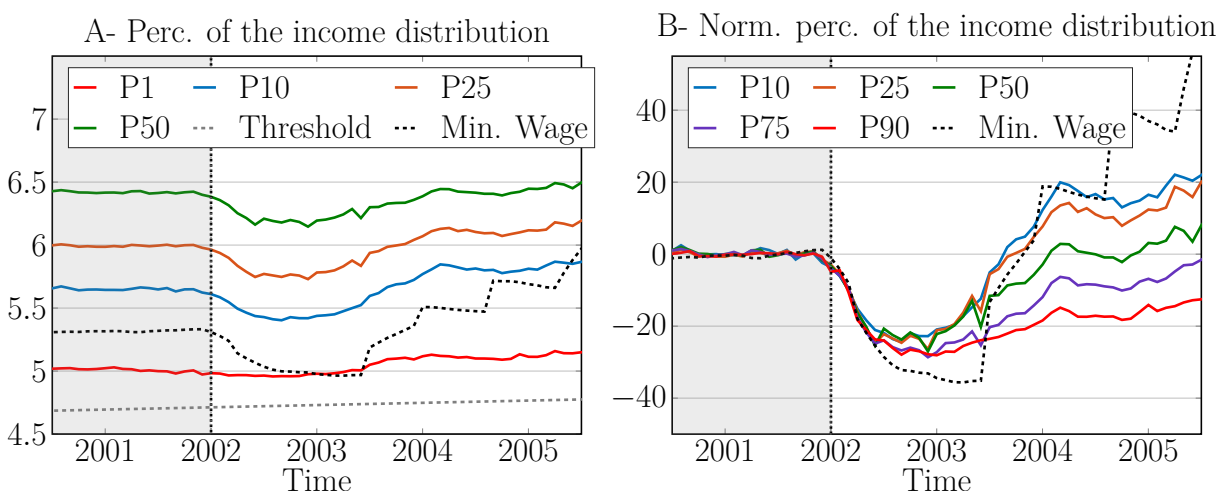
D.3 Changes in the Minimum Wage

Like most countries, Argentina has a minimum wage policy. Given the instability of prices, the length of the period of analysis, and changes of 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 D.7 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 D.7 normalizes percentiles and the minimum wage in order to track their evolution more easily. Although they move in the same direction most of the time (i.e., the real value of minimum wage increases/decreases when percentiles are increasing/decreasing), we see that the minimum wage increases faster after 2003. This is consistent with a series of adjustments in the nominal minimum wage made in that period.

Figure D.7 – 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 and the median are included to facilitate the comparison with the real wage distribution in each period.

D.4 Changes in Hours versus Hourly Wages

A key question about 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 cyclicity of the first moment of the distribution of labor income could be driven by the cyclicity of hours. Here, we show that this is not the case. To show this, we need data on hours of work for each worker. But since our main dataset does not include this information, we rely on data on hours of work 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 performed, we do not find a significant variation in hours that could explain the main facts in Section 4.

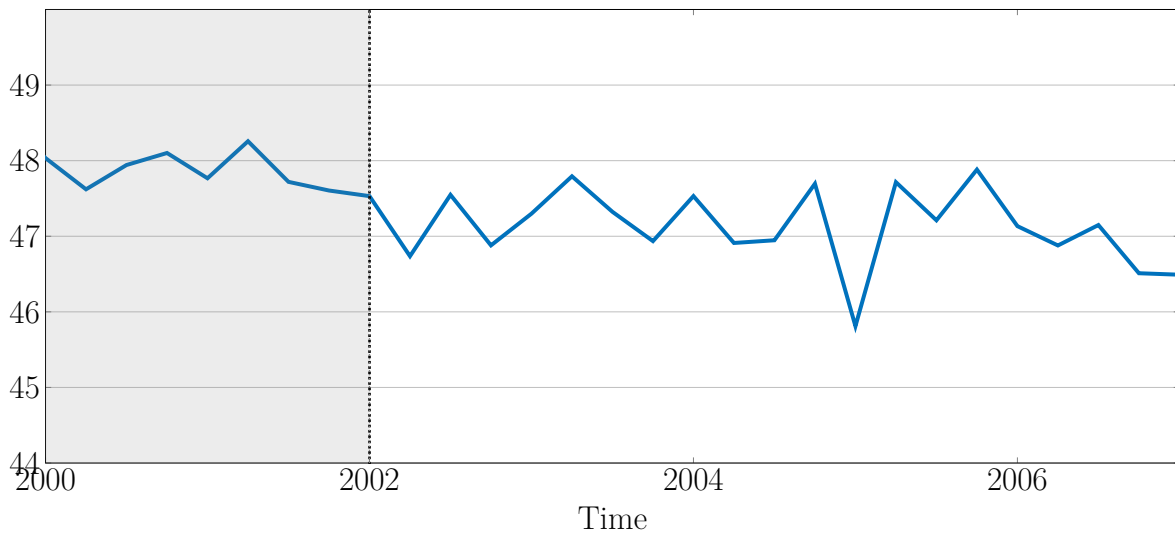
- **Total hours and distribution of hours by income:** Total monthly income in a job can be divided into hours of work and wage per hour. If y_{it} denotes the log-real income, then

$$y_{it} = \log(4) + \log(h_{it}) + \log(w_{it}), \quad (\text{D.8})$$

where h_{it} denotes hours per week and w_{it} denotes wage per hour. Figures D.8 and D.9 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 or changes in the 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.

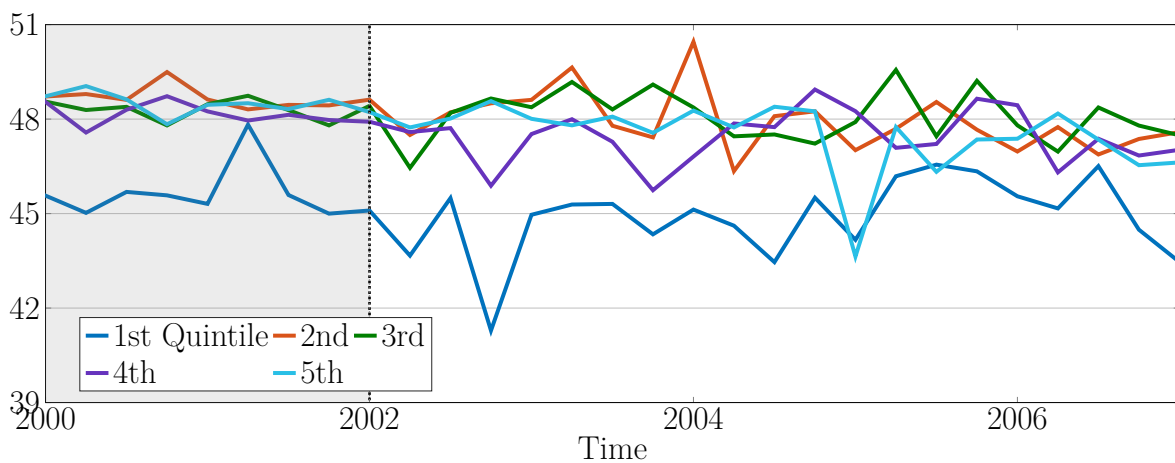
- **The distribution of hourly wages:** Figure D.10 plots the evolution of percentiles of the distribution of log real hourly wages constructed from the national labor force survey based on equation (D.8). Overall, the dynamics of the distribution of hourly wages resemble the dynamics of the distribution of monthly income (see Panel B-Figure A.16). Before the devaluation, all percentiles are almost constant. After the devaluation, there is an 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 overly 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 D.11 plots the evolution of average income for full- and part-time workers. As we can see in this figure, the levels across groups are different, but their cyclical components are similar. Figure D.12 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.

Figure D.8 – Average Hours in the Private Formal Sector



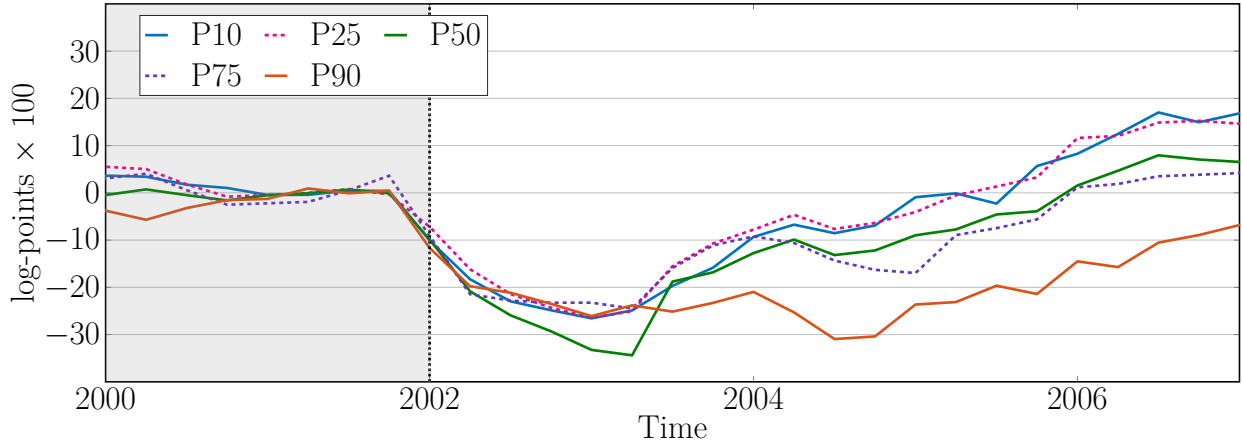
Notes: The figure plots the average hours of work in the primary occupation from January 2000 to December 2006 for male workers aged 25-65 employed in the private formal sector.

Figure D.9 – Average Hours in the Private Formal Sector by Income Quintiles



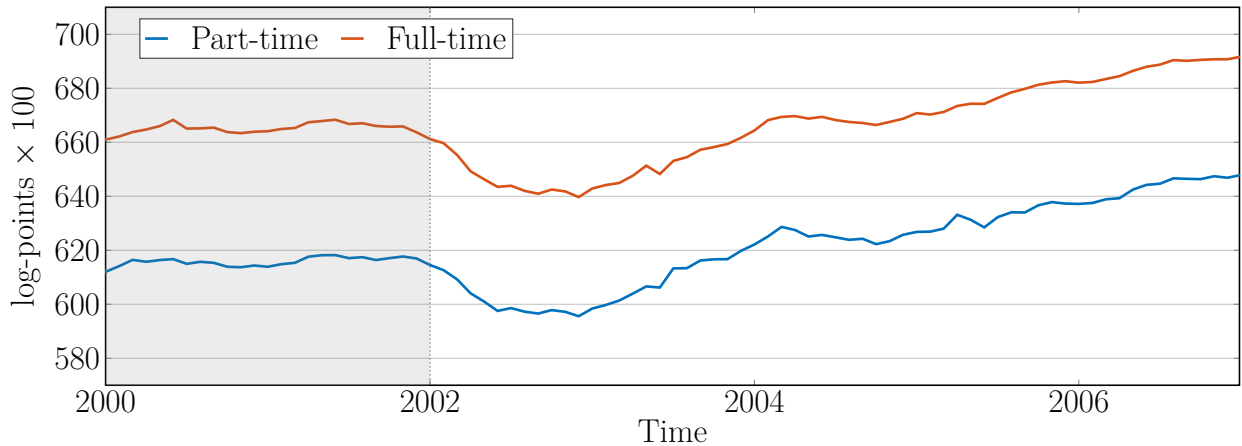
Notes: The figure plots the average hours of work from January 2000 to December 2006 by income quintile in the primary occupation for male workers aged 25-65 employed in the private formal sector.

Figure D.10 – Percentiles of the Distribution of Hourly Wages



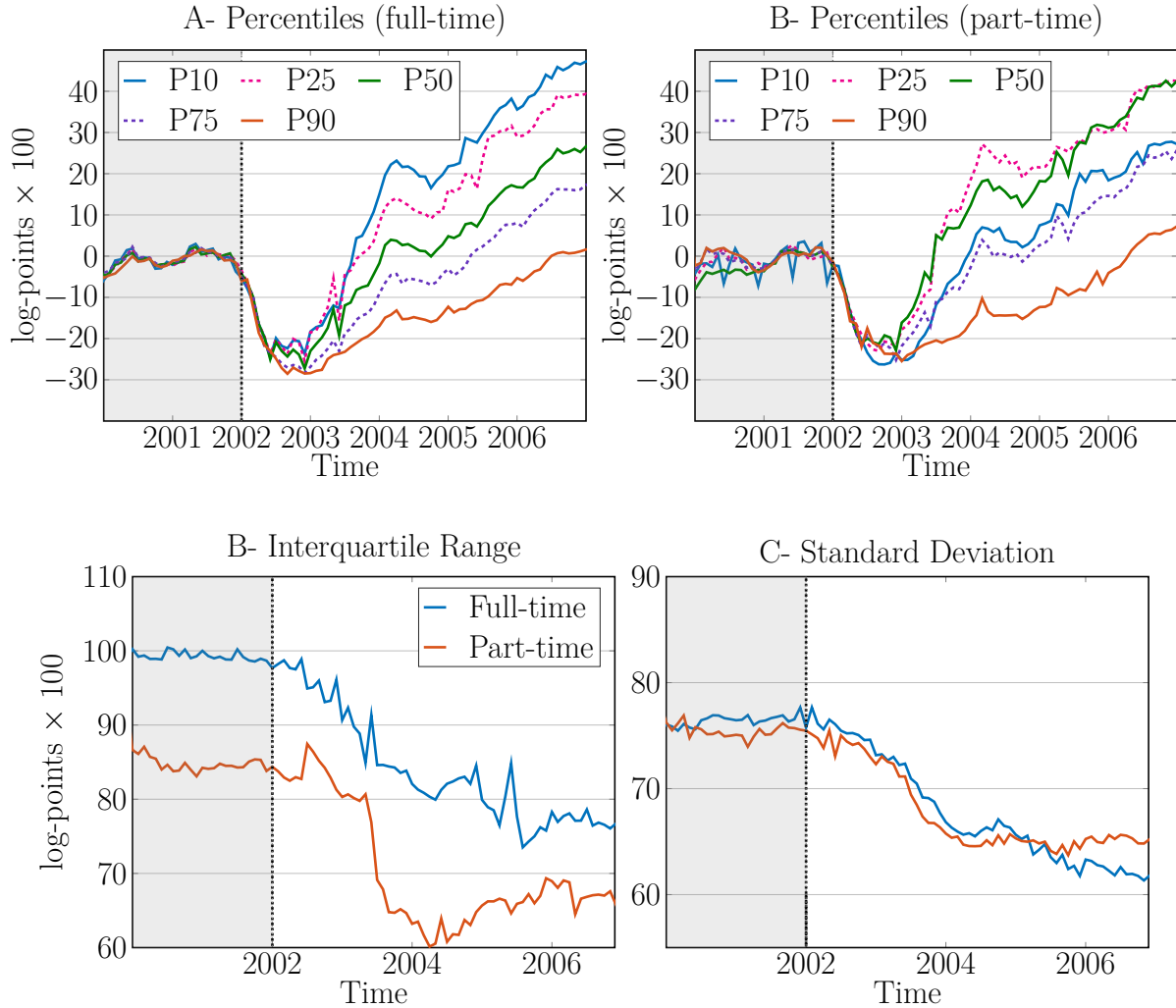
Notes: The figure plots the percentiles of the log real hourly wage distribution ($\times 100$) from January 2000 to December 2006 normalized by their average during 2001. The sample includes male workers aged 25-65 employed in the private formal sector. We use Px to denote the x -th percentile of the distribution.

Figure D.11 – Average Real Labor Income: Full-Time vs Part-Time



Notes: The figure shows monthly average (log) real income from 2000 to 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 10% are in dotted black lines.

Figure D.12 – 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 (B resp.) plots the percentiles of the log income distribution ($\times 100$) normalized by their average during 2001 for full-time workers (part-time workers resp.). We use P_x to the x -th percentile of the distribution. Panels C and D plot the interquartile range ($P_{75} - P_{25}$) and the standard deviation for the same time period.

D.5 Worker-specific Inflation

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, which do not increase their price as much. They find that two 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 micro-data from the survey conducted in 1996, 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 9 broad categories: Food and Beverages, Clothing, Housing, Housing Upkeep, Health, Transportation, Education, Leisure, and Other.²⁷ We then build worker-specific price indices using the weights that correspond to household h according to

$$p_t^h = \sum_g \omega_g^h p_{gt}, \quad (\text{D.9})$$

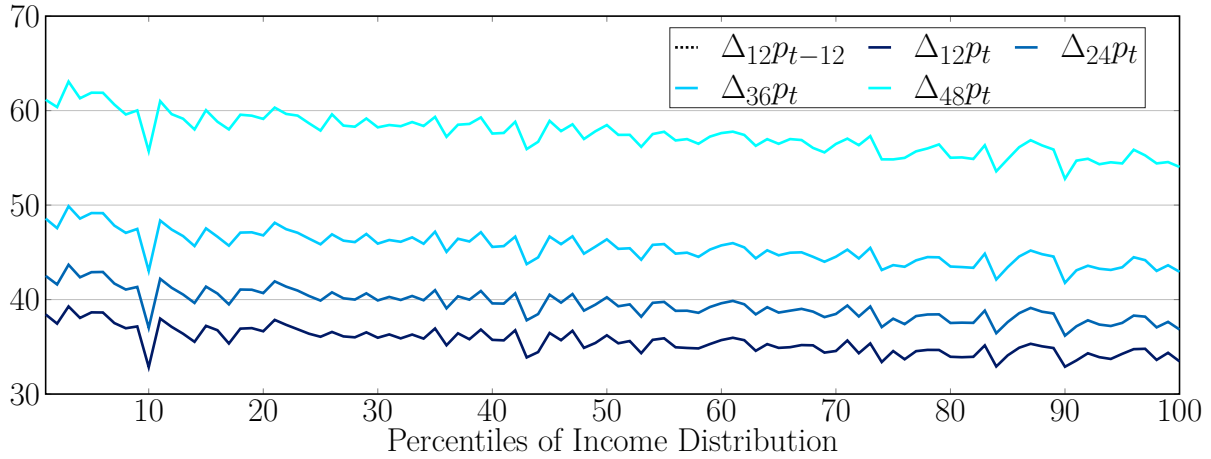
where g denotes the good category, ω_g^h is the share of household’s h expenditure in good category g (computed from the expenditure survey in 1996), and p_{gt} is the price index of good g in month t (obtained from national statistics). These price indices allow us to compute an upper bound of the inflation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

Figure D.13 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 D.14 plots the equivalent of Figure 6 using income-bin-specific inflation rates from Figure D.13 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.²⁸

²⁷Cravino 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 we compute) remains a good approximation of the 9-digit effect.

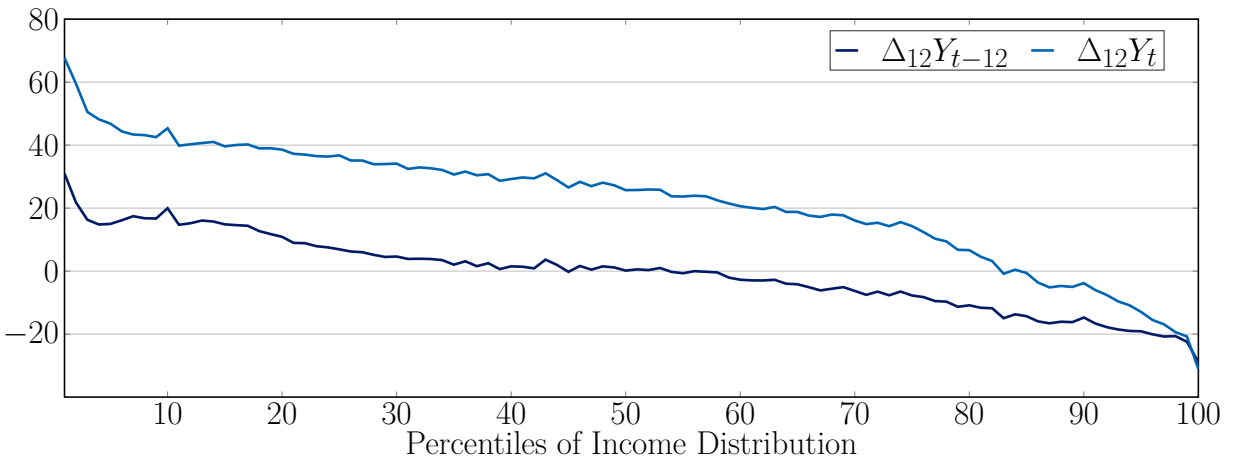
²⁸While the broad definition of expenditure categories does not allow us to estimate the *within* effect, as in Cravino and Levchenko (2017), the difference in growth rates of income across workers is so significant that it should be robust to the expected magnitude of this effect. Cravino and Levchenko (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 D.13 – 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 D.14 – 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.

D.6 The Informal Labor Market

The purpose of this section is to provide a broad picture of the informal sector. Like in many other developing economies, the Argentine informal sector is qualitatively and quantitative important, but the SIPA database only includes information about the formal sector. As we will see, the formal and informal sectors have similar trends and our main aggregate findings are also valid for the informal sector.

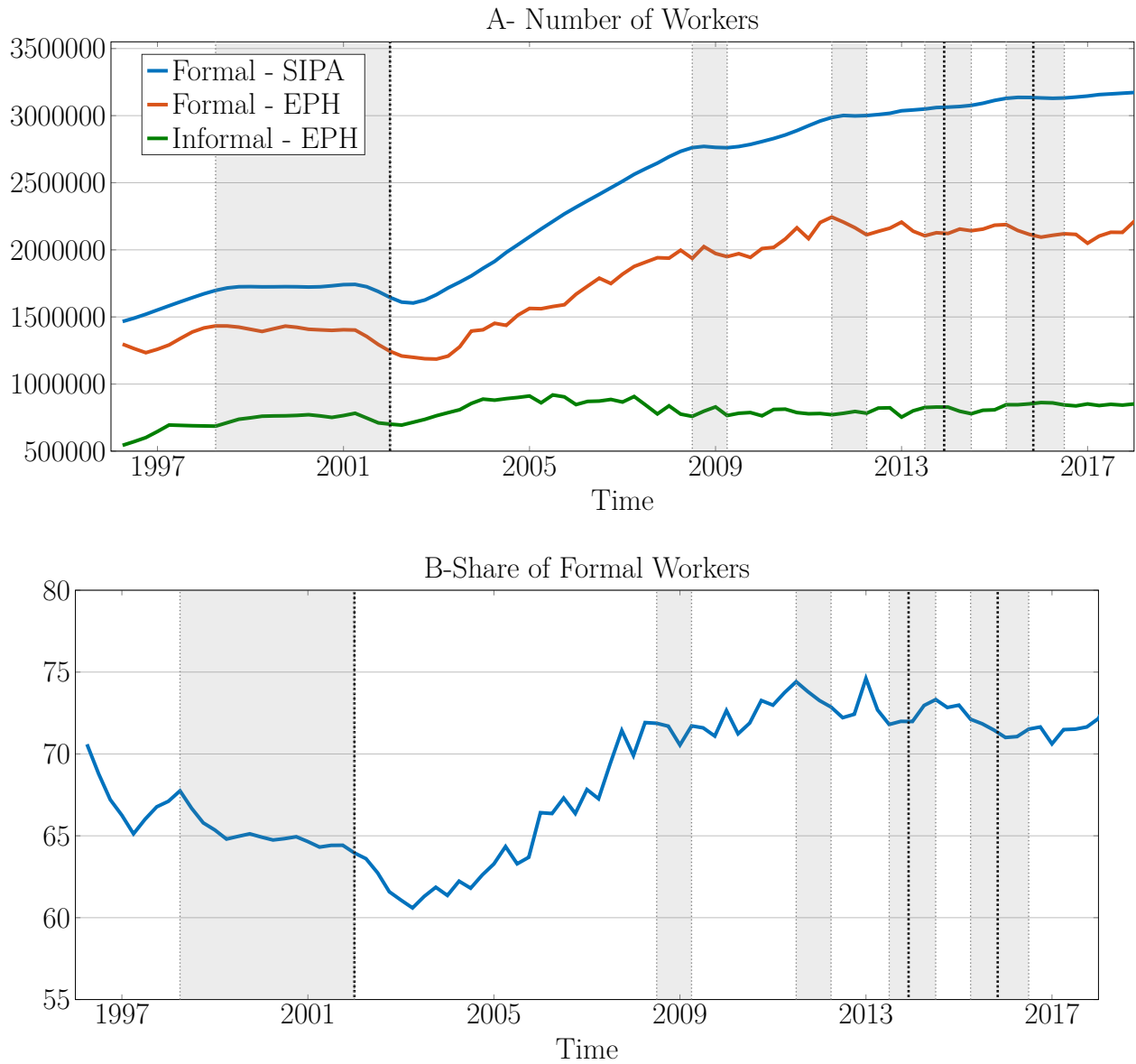
Panel A of Figure D.15 presents the number of formal and informal workers obtained from the labor force survey (EPH) and also the number of formal workers registered in the SIPA database. The number of formal workers we obtain from the EPH is systematically lower than its SIPA's counterpart. This is 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 D.15 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%, showing the importance of the informal sector in the Argentine economy.

The evolution of real income in both sectors is presented in Figure D.16. As one might expect, the direction of changes in real income in a given period is more 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 D.17 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 D.17, with one exception: When analyzing the speed of recovery, there is no difference across percentiles.

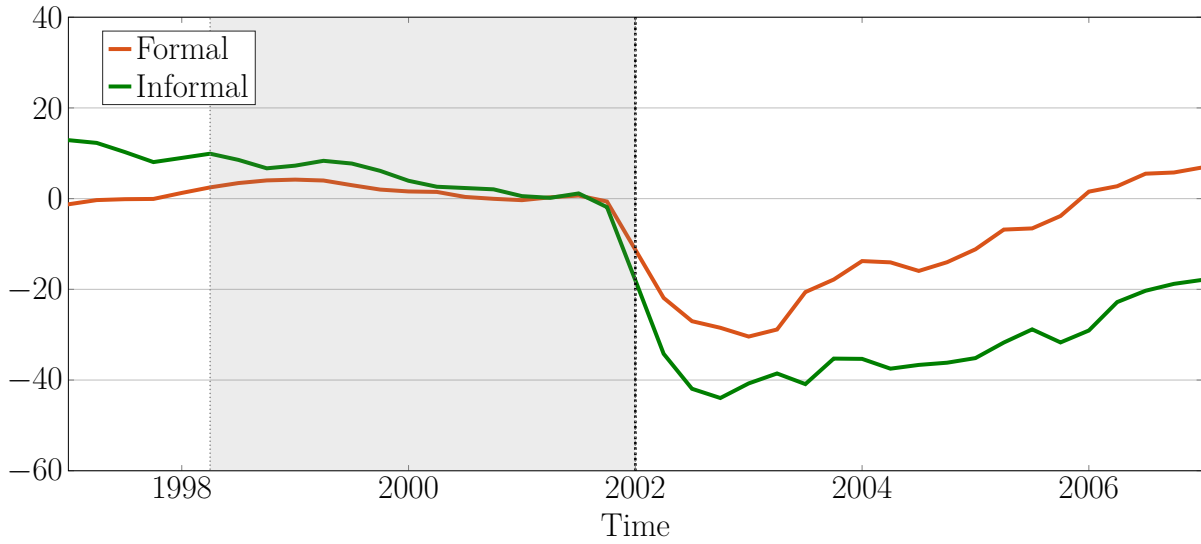
These patterns are consistent with the fact that unions, which are present only in the formal sector and do not cover the right tail of the distribution, explain a faster recovery of real incomes. In addition, if the decline in the informality rate is associated with transitions from the informal to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

Figure D.15 – Number of Formal and Informal Workers in Argentina: SIPA and EPH



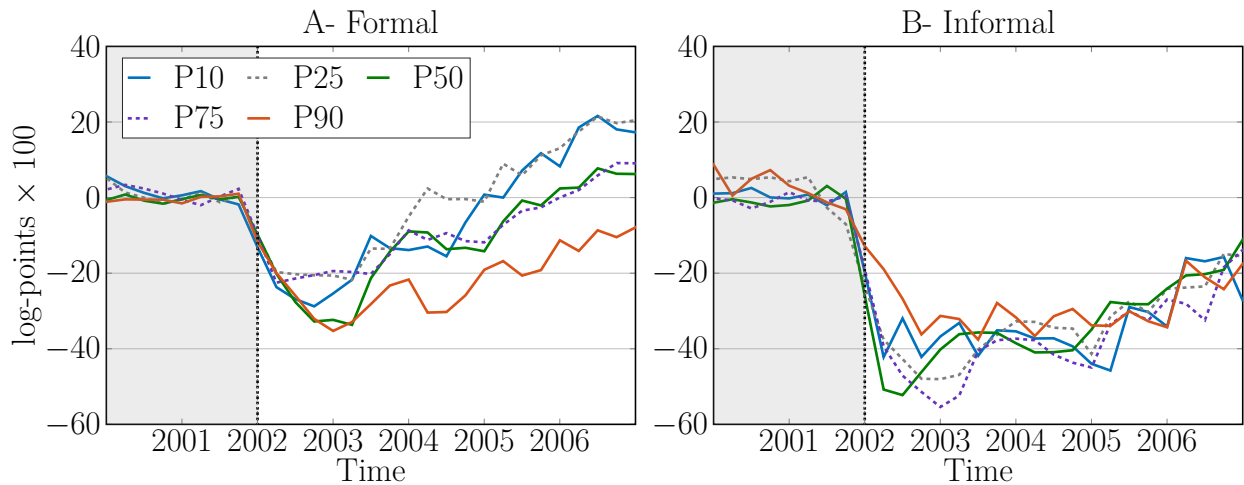
Notes: The figure compares the populations in SIPA and EPH. Panel A plots the number of private male workers aged 25-65 in SIPA and EPH, where EPH population estimates were obtained using the survey's expansion factors. Panel B plots the share of formal workers in EPH. Recession periods are in gray and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

Figure D.16 – Average Log Real Earnings in Argentina: Formal vs. Informal



Notes: The figure plots the mean (log) real wages in EPH for male workers aged 26-65 employed in the formal and informal sectors. EPH population estimates are obtained using the survey's expansion factors. Trajectories are normalized to their values before the 2002 devaluation.

Figure D.17 – 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 (B resp.) plots the percentiles of the log income distribution ($\times 100$) in the formal (informal resp.) sector normalized by the average during 2001. EPH population estimates are obtained using the survey's expansion factors.