

The Unexpected Upside of Depreciation: Bridging Europe's Income Divide*

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Abstract

This paper investigates the impact of foreign exchange (FX) shocks on income inequality across 31 European countries from 2003 to 2021. Leveraging a unique database of household-level longitudinal data from the European Union Statistics on Income and Living Conditions (EU-SILC) and exchange rate data from the Bank of International Settlements, we investigate how currency devaluations and appreciations influence income distribution. Our findings indicate that a 1% currency devaluation decreases income inequality by 15 basis points within one year, while appreciations have the reverse effect. Contrary to previous studies focused on Latin America, which credit reductions in inequality to both labor mobility and union influence, our analysis identifies labor mobility as the primary factor in Europe. Furthermore, we discover that income changes are predominantly driven by variations in income per hour rather than hours worked.

Keywords: Foreign exchange, income inequality, labor mobility, EU-SILC

JEL Codes: F31, F41, F44.

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1 Introduction

Income inequality has emerged as a pressing concern in the global economic landscape, with significant implications for social and political stability as well as political choice. While much of the literature has focused on the effects of trade, technology, and fiscal policies on inequality, the role of foreign exchange (FX) shocks remains under-explored, particularly in the context of advanced economies. This paper aims to fill this gap by investigating how FX shocks influence income inequality in Europe.

Recent research documents that large currency devaluations *reduce* income inequality in Latin America, driven by mechanisms like labor mobility and union coverage. However, the extent to which these findings apply to Europe, where economic structures and institutional settings differ significantly, remains unclear. Using a harmonized household-level dataset covering 31 European countries over 19 years, we examine the impact of FX shocks on income distribution, accounting for regional and temporal variations.

Most closely related to our work, [Blanco et al. \(2024\)](#) analyze the evolution of income inequality following significant currency devaluations, defined as those exceeding 30%. Drawing on a comprehensive dataset that primarily includes Latin American countries such as Brazil, Mexico, and Argentina, alongside a smaller selection of European and Asian nations, the authors document a consistent pattern: large devaluations reduce income inequality. On average, a 30% devaluation decreases the Gini coefficient by 3.5% within four years, highlighting a substantial and lasting effect. To investigate the underlying mechanisms, the authors focus on Argentina’s 2002 devaluation, a well-documented example of a large currency shock. Using detailed microdata, they observe that while all income deciles experience an initial decline in real incomes, lower-income households recover much faster than higher-income ones, driving the overall reduction in inequality. This differential recovery emerges as a central factor in their findings.

Three mechanisms are proposed to explain these dynamics. Labor mobility accounts for 23% of the reduction in inequality, as lower-income workers, more likely to change jobs following the devaluation, often secure higher wages through these transitions. Higher-income workers, being less mobile, face prolonged income losses. Union coverage explains another 19%, with workers in lower and middle-income brackets benefiting from unions’ ability to negotiate higher nominal wages in response to inflationary pressures. These wage increases help unionized workers recover more quickly than their non-unionized counterparts, who are typically higher earners. Trade exposure, while less influential, contributes 7% to

the observed reduction. The modest impact of trade exposure is attributed to the relatively even distribution of households across tradable and non-tradable sectors along the income distribution, limiting its role in driving changes in inequality.

Our paper builds on this framework by examining the evolution of income inequality after currency swings, including both devaluations and appreciations, with a focus on European countries spanning both developed and developing economies. We find that a 1% devaluation reduces income inequality by approximately 15 basis points after one year. Comparing this to [Blanco et al. \(2024\)](#), our findings imply that a 30% devaluation could reduce income inequality by 4.5% within the first year, suggesting a stronger and more immediate effect than what they document over a four-year horizon.

In terms of mechanisms, we explore the roles of labor mobility and unions. In contrast to [Blanco et al. \(2024\)](#), who find that both labor mobility and union coverage contribute to reducing inequality, our results indicate that only labor mobility drives this effect in the European context. Specifically, we observe little to no differential income change along the income distribution for union members following devaluations, which suggests that unions play a limited role in mitigating inequality in these settings. Together, these findings enrich the understanding of how currency fluctuations affect income inequality, highlighting regional differences in the underlying mechanisms and their relative impacts.

Our paper is related to other recent literature on how exchange rate shifts have heterogeneous effects. [Cravino and Levchenko \(2017\)](#) is an empirical study of the 1994 Mexican devaluation with a focus on the effect on prices of different households. Since poor households spend more on tradeables, their price index rises more than for rich households, suggesting that depreciation may rather worsen inequality. [Hottman and Monarch \(2020\)](#) reach similar conclusions for US households. [Yilmazkuday \(2022\)](#) looks at the exchange rate pass-through (ERPT) into prices and how this shapes the income loss for different household categories in Turkey; he finds some redistributive effects of an exchange rate shock going through prices.

Perhaps surprisingly, there is a scarcity of theoretical papers on the heterogeneous effects of currency swings. One exception is [Tille \(2006\)](#), whose theoretical analysis of the distributional consequences of devaluations suggests that the sector that is more exposed to exports stands to benefit more, which is intuitive. [Auclert et al. \(2021\)](#) also offer a theoretical model with quantitative calibration for Mexico. Other papers have focused on the role of foreign currency debt, for example [Verner and Gyöngyösi \(2020\)](#), however this is more relevant for wealth rather than income inequality.¹ [Lane and Stracca \(2018\)](#) is an empirical

¹Related, [Drenik et al. \(2018\)](#) document that the likelihood of having assets in foreign currency is

study for the euro area countries, where the authors find that the terms of trade effect of appreciations (which is expansionary) may more than compensate for the (contractionary) effect of expenditure switching. This in turn may have distributional consequences, with the export-exposed sectors benefiting more, in line with [Tille \(2006\)](#).²

The rest of the paper is organized as follows. Section 2 describes the data and empirical methodology. Section 3 presents the main findings, including robustness checks. Section 4 delves into the mechanisms underlying these results, focusing on labor mobility and union dynamics. Section 5 concludes.

2 Data and Background

In this study, we investigate the relationship between exchange rate shocks and income inequality across Europe. Central to our approach is the utilization of harmonized household-level data from the European Union Statistics on Income and Living Conditions (EU-SILC).³ This dataset enables us to analyze household income responses to exchange rate fluctuations while controlling for household characteristics and allowing for differential effects based on income levels. Our primary objective is to understand how income inequality evolves following currency shocks.

This dataset encompasses a comprehensive sample of 31 European countries between 2003 to 2021.⁴ It includes both household and individual-level data, covering a wide range of topics such as income, social exclusion, housing conditions, labor, education, and health. Two main types of data are provided: cross-sectional data, which captures a snapshot of information at a specific point in time, and longitudinal data, which tracks individual-level changes over a period of up to four years. For this paper, we focus exclusively on the longitudinal data.

The application process for accessing EU-SILC microdata involves several steps and can be quite rigorous due to the need to protect sensitive information and ensure data security. To access EU-SILC microdata, you must first be affiliated with a recognized research institu-

increasing in households' income within many emerging economies, which leads to heterogeneous exposures of wealth to exchange rate movements. After exchange rate devaluations wealth is redistributed from low income to high income households, which is the opposite of what we find for income.

²Other models with heterogeneous agents look at the distributional impact of shocks, without necessarily focusing on exchange rates; see for example [de Ferra et al. \(2020\)](#) and [Debortoli and Galí \(2017\)](#)

³Website: <https://ec.europa.eu/eurostat/web/microdata/european-union-statistics-on-income-and-living-conditions>

⁴See Figure A.1 in Appendix for a Complete list of countries and years.

tion. This requirement ensures that the data is used responsibly and for legitimate research purposes. Recognized institutions typically include universities, research centers, and other organizations that have a proven track record in conducting high-quality research. Secondly, the researcher needs to submit an application including detailed information about the research project, objectives, methodology, and the specific data needed. Once the application is submitted, it undergoes a review process by Eurostat and the statistical agencies of the EU member states.

The difficulty in obtaining access to EU-SILC data stems from several factors. The data is highly sensitive, containing detailed information about individuals' income, living conditions, and social situations. To protect respondents' privacy, strict anonymization rules are applied, and access is tightly controlled. Additionally, the review process involves multiple agencies, which adds to the complexity and duration of the application process.

Despite these challenges, the longitudinal format of the dataset offers a unique advantage: it enables the construction of income changes over consecutive years, allowing for an in-depth analysis of the impact of currency fluctuations on income distribution, as households are surveyed for up to four years.

Table 2.1 provides a synthetic example illustrating how this panel data is structured. Each household contributes data until it is replaced by a new respondent. Wave year represents the most recent year where the household was interviewed and shared information of current and past years. For instance, Household 1 from Austria (AT) was surveyed in 2006, providing income data from 2004 to 2006. In subsequent years, new households (e.g., Households 2 and 3) join the sample. By stacking the most recent waves for each household, we compile a comprehensive dataset covering all possible households.

The dataset also includes detailed personal information such as occupation, sex, education, and age for each individual within a household. Eurostat provides explicit guidelines for merging household and individual datasets. In our analysis, we assign personal characteristics to households based on the individual with the highest labor income, defining this person as the head of household. In cases of income ties, the oldest individual is selected. For example, if a household comprises three members with varying occupations, we assign the occupation of the highest earner to the household as a whole.

Table 2.1: Data Synthetic Example

Year	Country	Household ID	Income	Wave	Year
2003	AT	1	902		2006
2004	AT	1	900		2006
2005	AT	1	903		2006
2006	AT	1	1000		2006
2004	AT	2	300		2007
2005	AT	2	305		2007
2006	AT	2	400		2007
2007	AT	2	420		2007
2004	AT	3	600		2007
2005	AT	3	650		2007
2006	AT	3	570		2007
2007	AT	3	580		2007
2003	BE	1	750		2006
2004	BE	1	850		2006
2005	BE	1	904		2006
2006	BE	1	1500		2006
2004	BE	2	350		2007
2005	BE	2	403		2007
2006	BE	2	500		2007
2007	BE	2	600		2007

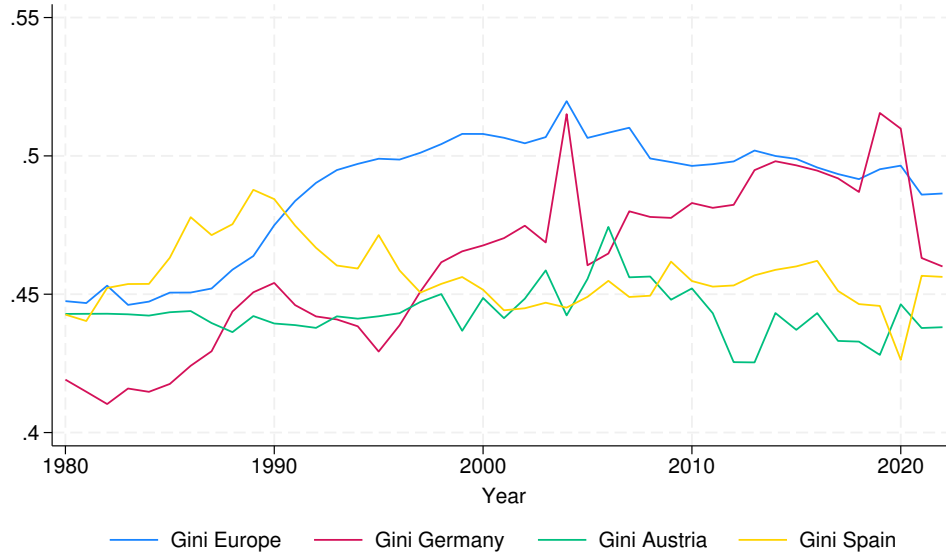
Notes. This Table shows a simple synthetic example of the dataset.

2.1 Income Inequality in Europe

Understanding the causes and implications of rising income inequality has gained significant importance in recent years, particularly in Europe. Global trends, alongside country-specific factors, have contributed to the observed increase in inequality. Figure 2.1 illustrates the evolution of the Gini index for Europe as a whole and for selected European countries. Since the 1980s, Europe has experienced a notable rise in inequality, driven by diverse national trends.

For example, Germany has seen a steady increase in inequality over recent decades, reflecting structural economic changes and labor market dynamics. In contrast, Spain experienced a sharp rise in inequality during the 1980s, followed by a return to its long-run average in the 1990s. Austria, on the other hand, has maintained relatively stable levels of inequality, demonstrating resilience against broader global trends. These patterns highlight the heterogeneity in inequality trajectories across European countries, emphasizing the need for region-specific analyses to understand underlying drivers and implications.

Figure 2.1: Gini Index in Europe



Notes. This figure shows the evolution of the Gini Index for a selection of European countries.
Source: World Inequality Database.

2.2 Household Income Summary Statistics

Table 2.2 presents summary statistics on income distribution within the EU-SILC dataset, employing both pre-tax and post-tax measures of income. All income figures are reported in Euros to ensure comparability across countries. There is evidence that the tax system can have large implications on income inequality as the distribution of income might be substantially different depending on the measure analyzed.

To calculate these statistics, the sample for each year and country is divided into ten income deciles. The table highlights the average income for each decile, demonstrating the disparities across the income distribution. For instance, households in the second decile report an average annual income of approximately 11,200 Euros, while those in the eighth decile earn an average of 46,500 Euros. Additionally, the distribution of observations across deciles is well-balanced, with each decile containing around 300,000 observations. These findings underscore the value of the EU-SILC dataset in capturing income variations across different segments of the population.

Table 2.2: Summary Statistics Household Income

Variable	Statistic	Bin Income									
		1	2	3	4	5	6	7	8	9	10
Pre tax Nominal Income (Euros)	Mean	7,527.05	11,261.67	15,398.50	19,640.67	24,502.50	30,537.83	37,731.46	46,528.70	58,596.19	80,317.68
	Std. Dev	7,156.98	8,881.39	11,526.94	14,077.70	16,999.57	20,520.04	24,627.59	29,486.81	34,929.65	42,358.55
	Num. Obs.	299,647	336,810	344,425	354,002	359,364	360,956	362,262	362,991	362,916	329,359
Post tax Nominal Income (Euros)	Mean	6,229.89	9,647.50	12,859.10	16,154.93	19,812.72	24,201.28	29,314.94	35,500.67	43,586.65	58,463.03
	Std. Dev	4,580.60	6,507.56	8,356.98	10,193.13	12,282.59	14,708.42	17,414.69	20,582.47	23,708.09	27,961.77
	Num. Obs.	315,957	354,191	361,842	371,734	377,368	379,333	380,950	382,385	381,518	346,530

Notes. This table shows summary statistics on pre tax and post tax nominal income (in Euros) for each income bin in the EU-SILC database (2003-2021). Households were divided into income bins for each country and year. The table only shows statistics for the bin combining all years and countries.

2.3 Exchange Rates

We use exchange rate data from the Bank of International Settlements, focusing on nominal exchange rates measured as bilateral rates between each country’s currency and the US dollar. The dataset categorizes countries into three distinct exchange rate regimes. The first group comprises euro area countries, which adopted the euro as their official currency throughout the sample period, including Germany, Finland, and France. The second group includes countries with currencies formally pegged to the euro, such as Denmark. Finally, the third group consists of countries with independent exchange rate regimes, like Sweden and the United Kingdom, which manage their exchange rates independently of the euro. We refer to this group as flexible regime countries. Table 2.3 summarizes these regimes by country.

Table 2.3: Exchange Rate Regimes / Currencies

Country ID	Country name	Currency Regime (2003-2021)
AT	Austria	Euro
BE	Belgium	Euro
BG	Bulgaria	Euro pegged
CH	Switzerland	Flex. Non Euro
CY	Cyprus	Euro pegged, switched to euro in 2008
CZ	Czechia	Flex. Non Euro
DE	Germany	Euro
DK	Denmark	Euro Pegged
EE	Estonia	Euro pegged, switched to euro in 2011
ES	Spain	Euro
FI	Finland	Euro
FR	France	Euro
GB	United Kingdom	Flex. Non Euro
GR	Greece	Euro
HR	Croatia	Flex. Non Euro
HU	Hungary	Flex. Non Euro
IE	Ireland	Euro
IS	Iceland	Flex. Non Euro
IT	Italy	Euro
LT	Lithuania	Euro pegged, switched to euro in 2015
LU	Luxembourg	Euro
LV	Latvia	Flex 2005, 2006. Then pegged till 2014, then Euro
MT	Malta	Euro pegged, switched to euro in 2008 (although 1-1 NER with euro)
NO	Norway	Flex. Non Euro
PL	Poland	Flex. Non Euro
PT	Portugal	Euro
RO	Romania	Flex. Non Euro
RS	Serbia	Flex. Non Euro
SE	Sweden	Flex. Non Euro
SI	Slovenia	Euro pegged, switched to euro in 2007
SK	Slovakia	Flex till 2006, then pegged to Euro till 2009, then Euro

Notes. This table summarizes the exchange rates regimes for countries in the dataset.

Descriptive statistics shown in Table 2.4 reveal key differences across these regimes. For euro area and euro-pegged countries, the mean devaluation is approximately 5%, while the mean appreciation is about -4.6% . These values are calculated based on the exchange rate as the value of one US dollar relative to foreign currencies. Increases in the exchange rate indicate dollar appreciation and local currency devaluation, while decreases reflect dollar depreciation and local currency appreciation.

In contrast, countries with flexible exchange rate regimes experience greater fluctuations, as reflected in their higher standard deviations. The mean devaluation is around 8%, and the mean appreciation is approximately -5.3% . These findings provide a foundational understanding of the scale and nature of currency shocks under different exchange rate regimes, setting the stage for further empirical analysis.

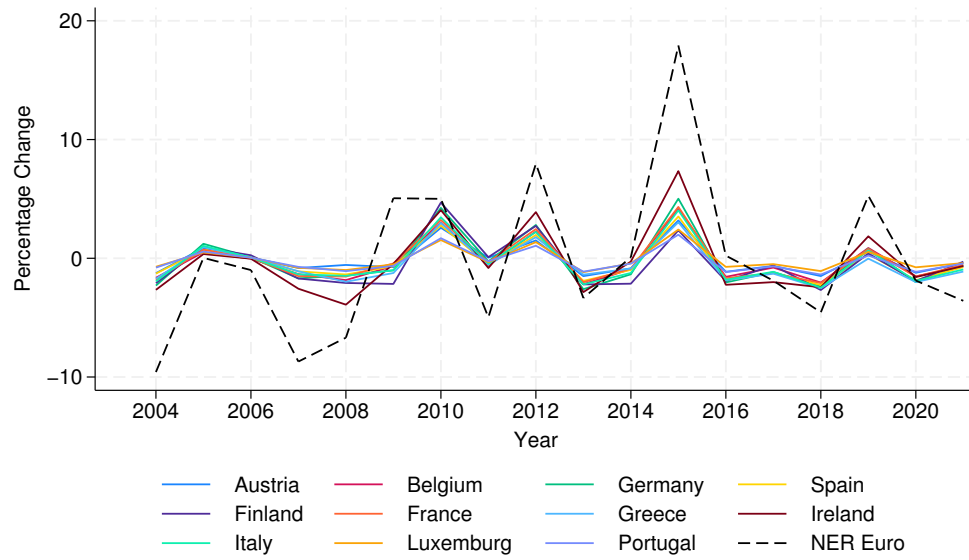
Table 2.4: Nominal Exchange Rate Statistics

Variable	Statistic	Euro Area		Euro Pegged		Flexible Regime	
		Devaluation	Appreciation	Devaluation	Appreciation	Devaluation	Appreciation
% change	Mean	5.2	-4.62	5.36	-4.64	8.12	-5.38
	Std. Dev.	5.59	2.78	5.57	3.15	7.45	4.04

Notes. This table shows summary statistics on FX changes by currency regime.

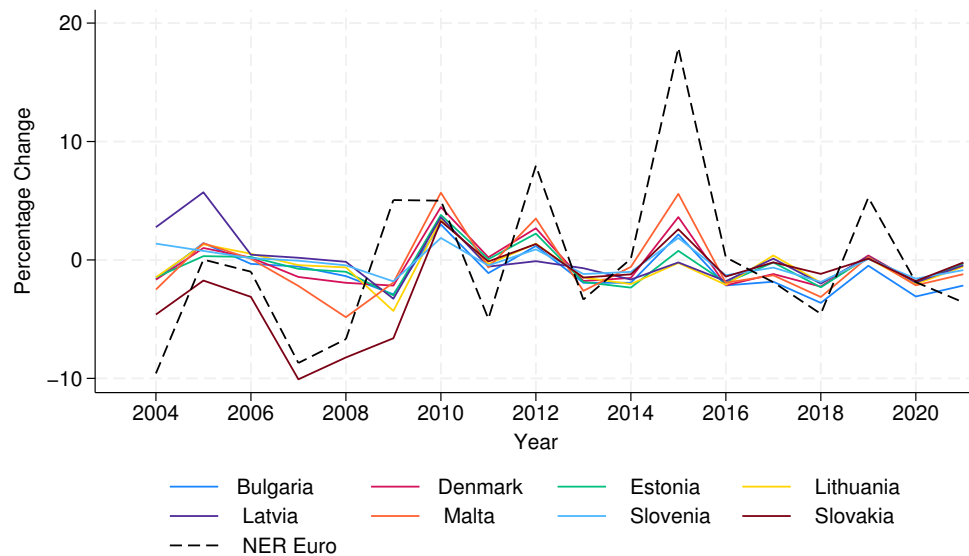
We also present the percentage change over time for each group in the figures below. To highlight differences in volatility, we compare these changes with the Nominal Effective Exchange Rate (trade-weighted) from BIS, showing that the bilateral exchange rate exhibits greater volatility. Notably, the Euro area and currencies pegged to the Euro experienced significant devaluations, exceeding 10%, in 2015, as well as in 2012 and 2019. Conversely, the largest appreciations occurred in 2005 and 2011. For countries with flexible exchange rate regimes, the patterns are more varied. Noteworthy examples of substantial currency shocks include the depreciation of the Icelandic króna, Polish złoty, and British pound in 2008, and the appreciation of the Swiss franc in 2011.

Figure 2.2: Evolution Exchange Rates - Euro Area



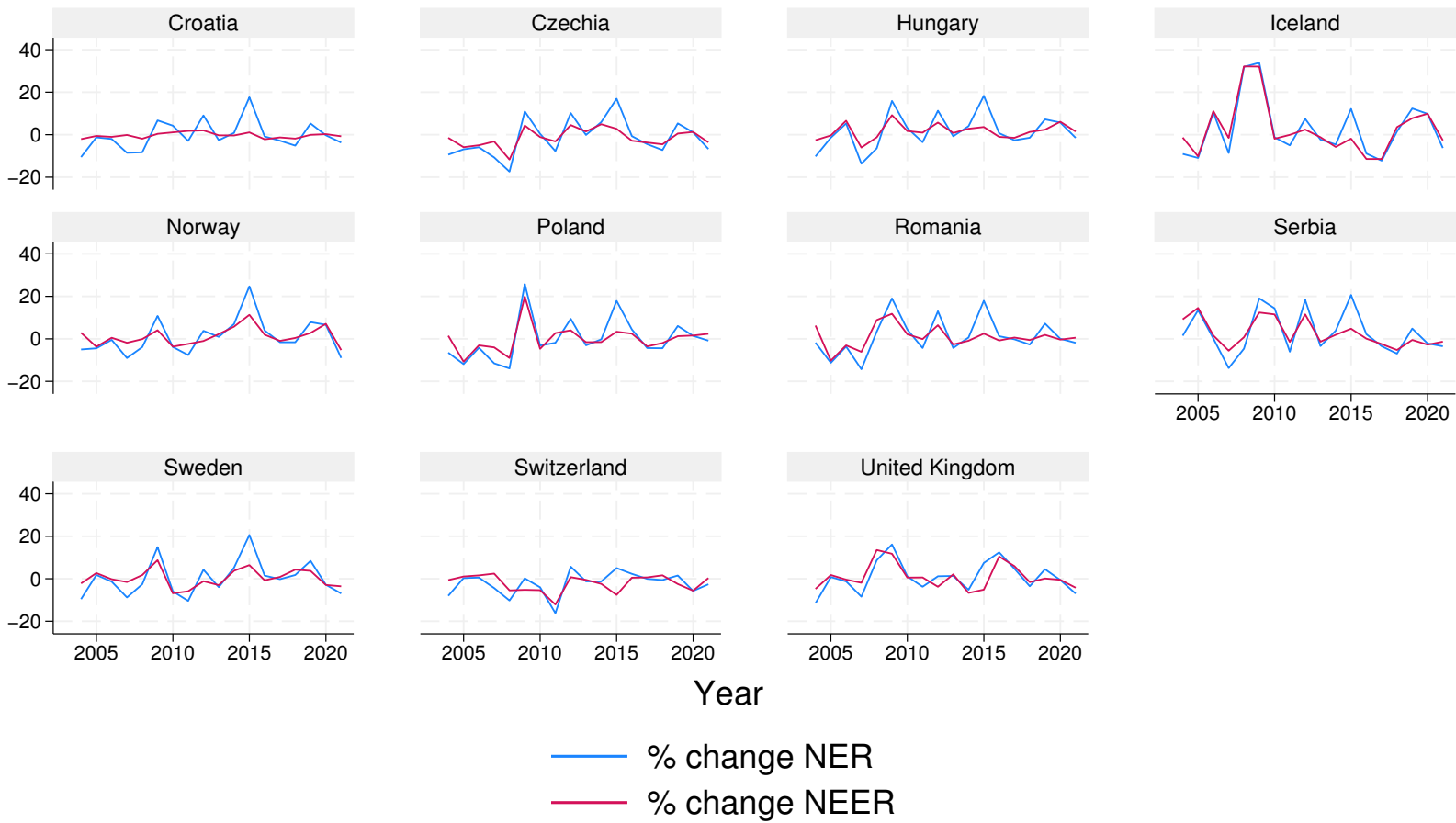
Notes. This figure shows percentage changes of nominal effective exchange rates (trade-weighted) for Euro Area countries and bilateral nominal exchange rate for the euro (relative to U.S. dollar).

Figure 2.3: Evolution Exchange Rates - Euro Pegged



Notes. This figure shows percentage changes of nominal effective exchange rates (trade-weighted) for Euro pegged countries and bilateral nominal exchange rate for the euro (relative to U.S. dollar).

Figure 2.4: Evolution Exchange Rates - Flexibe Regimes



Notes. This figure shows percentage changes of exchange rates relative to U.S. dollar (bilateral and trade-weighted) for non-Euro Area and flexible regimes.

3 Empirical Findings

This paper investigates the evolution of income inequality following currency shocks. In this section, we explore various econometric models to demonstrate that income inequality decreases (increases) after currency devaluations (appreciations). The baseline empirical model we estimate is:

$$\begin{aligned} \text{dlog Real Pre-Tax Income}_{hct} = & \alpha \\ & + \beta_{Deva} \times \mathbb{I}(Deva.)_{ct} \times \text{dlog NER}_{ct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Median Nom. Pre-Tax Inc.}_{c,t-1}) \\ & + \beta_{Appre} \mathbb{I}(Appre.)_{ct} \times \text{dlog NER}_{ct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Median Nom. Pre-Tax Inc.}_{c,t-1}) \\ & + \text{Controls}_{h,t-1} + \lambda_{r,t} + e_{ht} \end{aligned} \tag{1}$$

where h , c , and t represent household, country, and time, respectively. The regression estimates the correlation between log changes in real pre-tax income at the household level and currency fluctuations, measured as log changes in the nominal exchange rate. We include indicator variables to capture differential effects of devaluations and appreciations. The key coefficient of interest measures the differential impact of currency changes along the income distribution. To capture this, we incorporate the household's pre-tax nominal income relative to the median pre-tax nominal income at the country-year level, enabling us to assess how currency swings affect income inequality by examining their impact on households across different income levels. All income values are expressed in thousands.

We control for region-year fixed effects to account for unobserved variables and include lagged household characteristics (pre-tax nominal income, sex, education, and age).⁵ To compute real pre-tax income, we divide the household's pre-tax income in local currency by the country-year Consumer Price Index from Eurostat. Standard errors are clustered at the region level.

We present the results in Table 3.1, comparing three models with different fixed effects. Additionally, we control for the log changes in nominal exchange rates to capture aggregate effects that may not be fully addressed by the region and region-year fixed effects.

⁵Regions are defined according to the NUTS-1 division. See Figure A.2 in the Appendix for further details.

Table 3.1: Baseline Results

	(1)	(2)	(3)
lag Relative Income * dlog NER (Appreciations)	0.0144*** (0.00269)	0.0135*** (0.00251)	0.0139*** (0.00265)
lag Relative Income * dlog NER (Devaluations)	-0.00190* (0.00104)	-0.00196* (0.00102)	-0.00222** (0.00108)
dlog NER (Appreciations)	-0.289*** (0.0608)	-0.226*** (0.0724)	0 (.)
dlog NER (Devaluations)	0.00795 (0.0392)	-0.0957** (0.0422)	0 (.)
lag Relative Income	-0.00337*** (0.000216)	-0.00339*** (0.000214)	-0.00337*** (0.000215)
lag Occupation	-0.00871*** (0.00112)	-0.00853*** (0.00101)	-0.00830*** (0.00102)
lag Education	0.0000471*** (0.00000771)	0.0000681*** (0.0000168)	0.0000889*** (0.0000168)
lag Sex	-0.00761*** (0.00226)	-0.00723*** (0.00232)	-0.00737*** (0.00231)
lag Age	-0.000247 (0.000150)	-0.000195 (0.000149)	-0.000183 (0.000150)
Constant	0.111*** (0.0102)	0.109*** (0.00852)	0.105*** (0.00836)
Adjusted R^2	0.071	0.074	0.087
Observations	1,072,171	1,072,171	1,072,171
FE	Region	Region, Year	Region-Year
Standard Errors	Cluster Region	Cluster Region	Cluster Region

Notes. This table shows the baseline results for different fixed effects specifications.

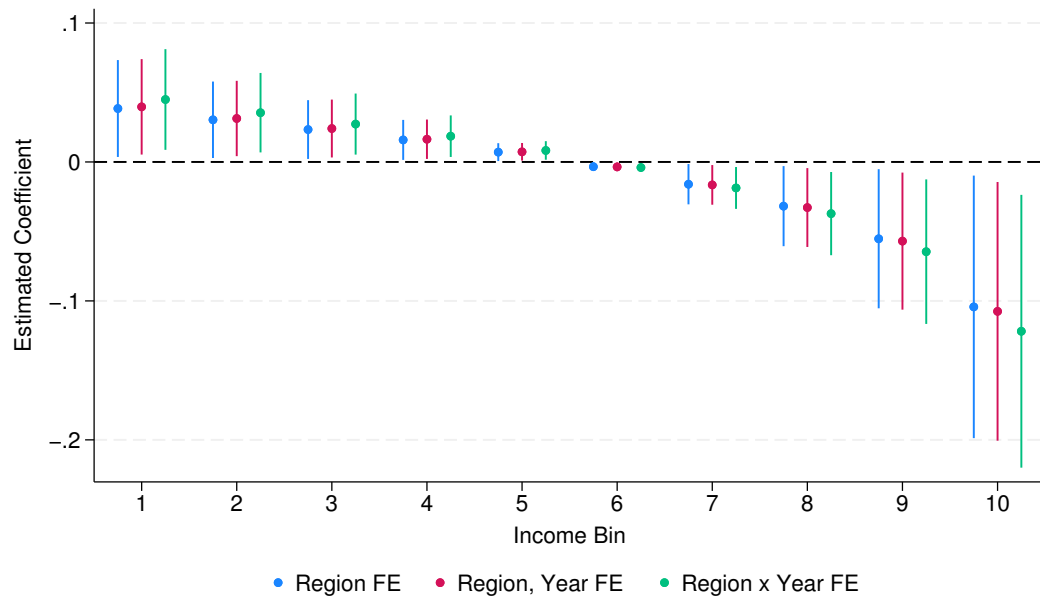
The results indicate that devaluations are associated with a decline in real income for households above the mean (second row). This is because wealthier households typically earn more than the median. In contrast, for appreciations, wealthier households benefit from higher income after a currency appreciation.

To better understand the estimated coefficients, we compute the implied elasticities of real income in response to currency changes across different income deciles. For each country-year pair, we divide households into income deciles and calculate the average pre-tax nominal income for each decile. We then derive the implied elasticity of real income to currency changes using the estimated coefficients. The results are presented in Figure (3.1).

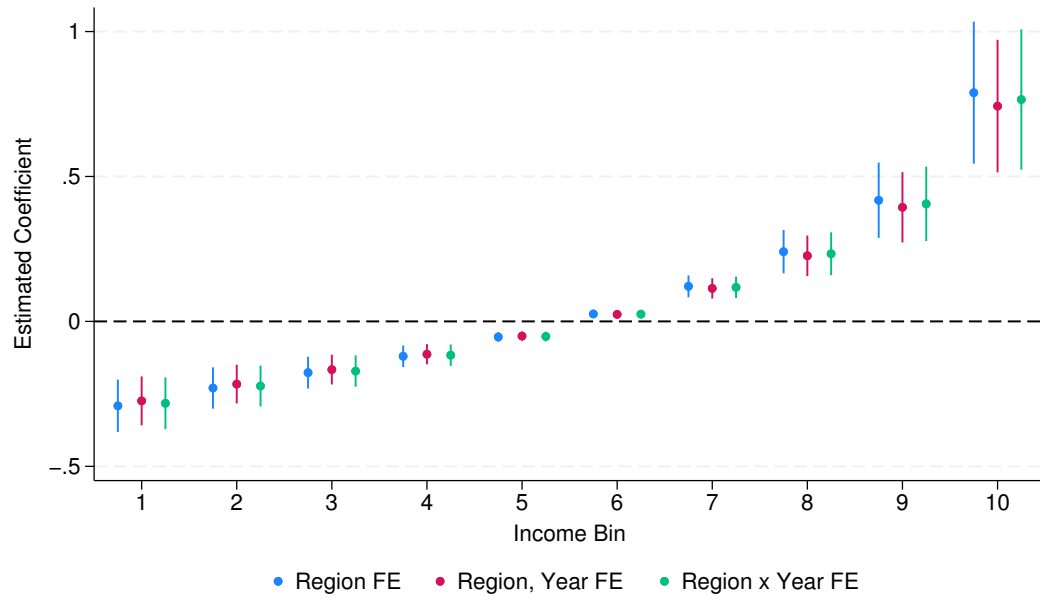
The plot reveals a positive correlation between income and devaluations for households below the median income. For those above the median, the correlation is negative, providing evidence of a reduction in income inequality following a currency devaluation. Conversely, for currency appreciations, the results are reversed: income inequality increases. A simple back-of-the-envelope calculation estimates the magnitude of these changes. The difference in estimated elasticities between the bottom and top deciles shows that income inequality improves by 0.16% after a 1% currency devaluation.⁶

⁶Specifically: bottom decile elasticity - top decile elasticity = 0.05 - (-0.11) = 0.16

Figure 3.1: Baseline Estimates



(a) Devaluations



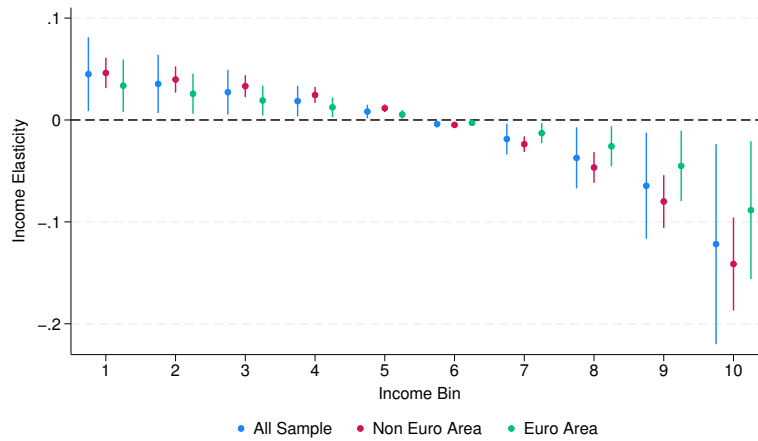
(b) Appreciations

Notes. This figure shows estimated income elasticities by income deciles after a 1% currency change (devaluations for Panel a and appreciations for Panel b). Standard errors are clustered at the region level (NUTS-1).

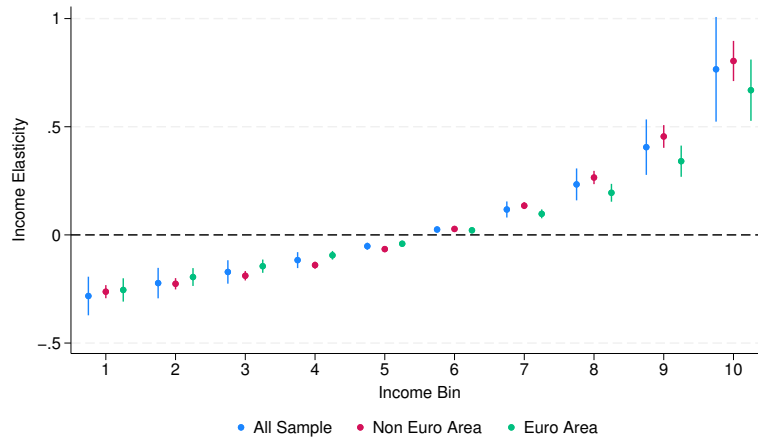
3.1 Robustness

Euro vs Non-Euro Area. We assess the degree on which the type of currency can affect the results by dividing the sample between countries that use the euro for the whole sample (e.g. Finland) and countries with a different currency (e.g. United Kingdom). We include an additional indicator to capture the differential effect for these two country groups. Results are consistent with the baseline estimates and shown in Figure 3.2 based on regression estimates from Table A.1.

Figure 3.2: Euro vs Non-Euro Area



(a) Devaluations

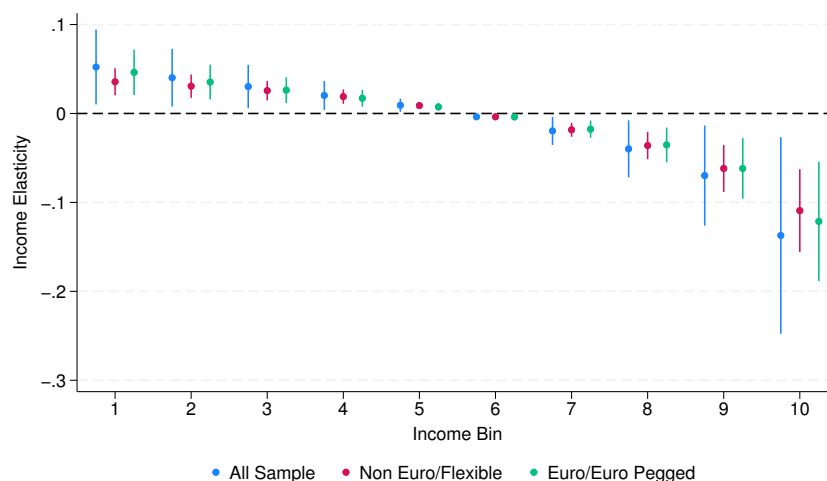


(b) Appreciations

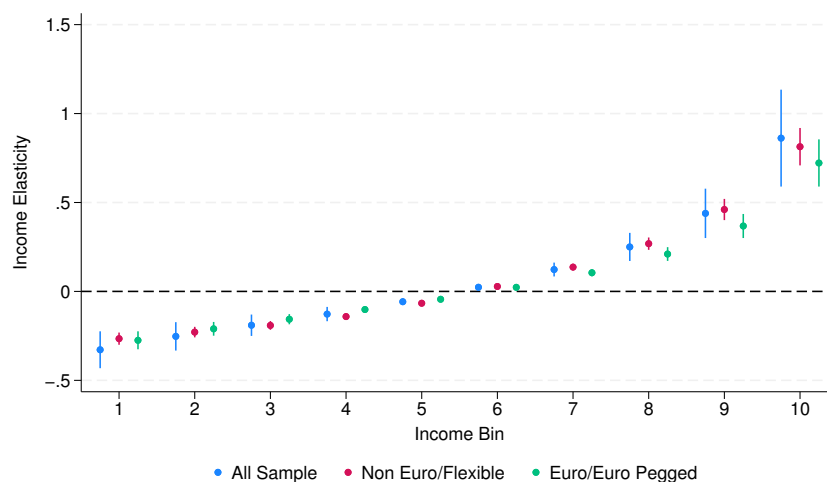
Notes. This figure shows estimated income elasticities by income deciles after a 1% currency change (devaluations for Panel a and appreciations for Panel b). Fixed effects are included at the country-year. Standard errors are clustered at the region level (NUTS-1) for baseline and Heteroskedacity Robust for FX regime model. Estimates are divided according to currency area using indicators. Income is measured as real income pre-tax.

FX Regime: Flexible vs Euro/Euro Pegged. To complement the previous robustness, we also study the differential effects when comparing countries with fixed or flexible exchange rate relative to the Euro. To do this, we use a indicator to split countries that use the euro throughout the sample (e.g. Finland) plus countries with a fixed exchange (e.g. Denmark) relative to countries with a different regime (e.g. United Kingdom). Results are consistent with the baseline estimates and shown in Figure 3.3 based on regression estimates from Table A.2.

Figure 3.3: Flexible vs Euro/Euro Pegged



(a) Devaluations

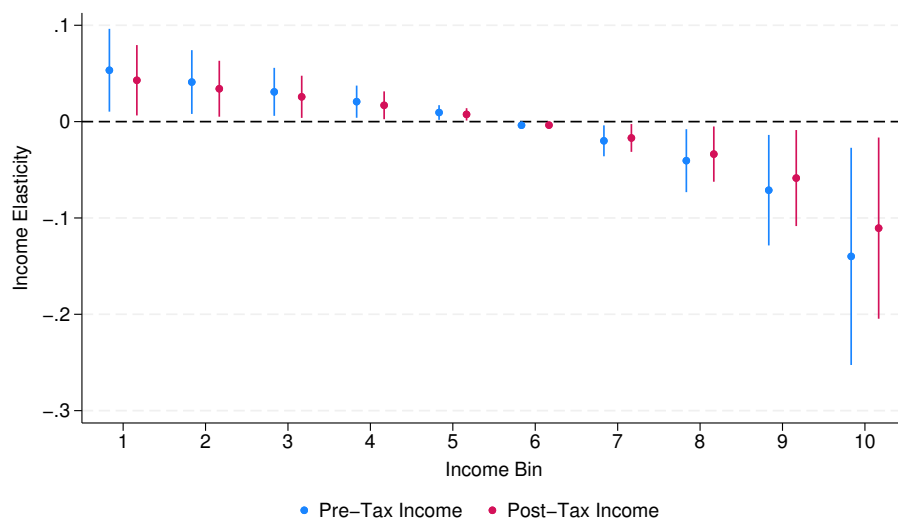


(b) Appreciations

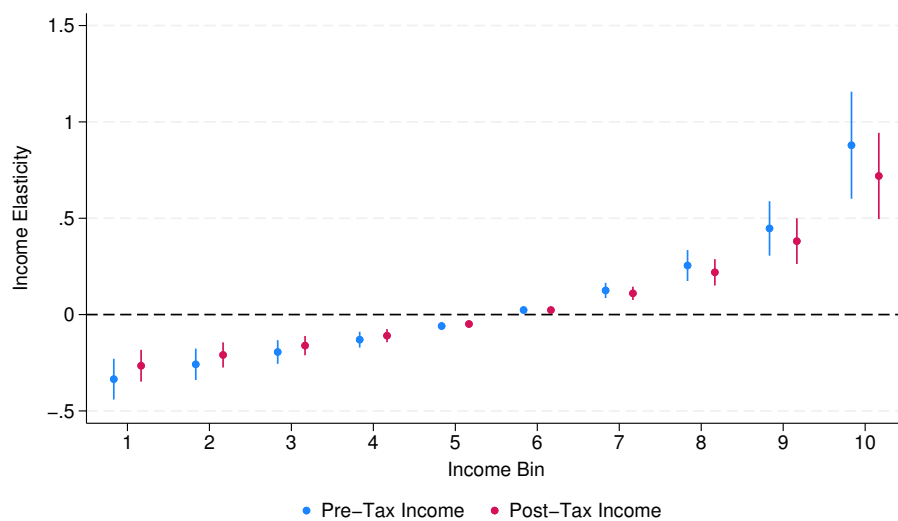
Notes. This figure shows estimated income elasticities by income deciles after a 1% currency change (devaluations for Panel a and appreciations for Panel b). Fixed effects are included at the country-year. Standard errors are clustered at the region level (NUTS-1) for baseline and Heteroskedacity Robust for FX regime model. Estimates are divided according to FX regime using indicators. Income is measured as real income pre-tax.

Post-Tax Income. We show that the results also hold for post-tax income. We estimate the baseline regression but using post-tax real income as the left hand side variable. Figure (3.4) plots the estimated coefficients comparing with baseline, based on estimates from Table A.3.

Figure 3.4: Pre-Tax vs Post-Tax



(a) Devaluations

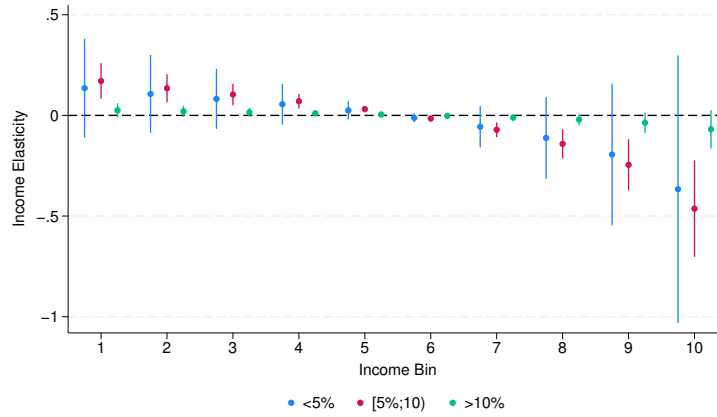


(b) Appreciations

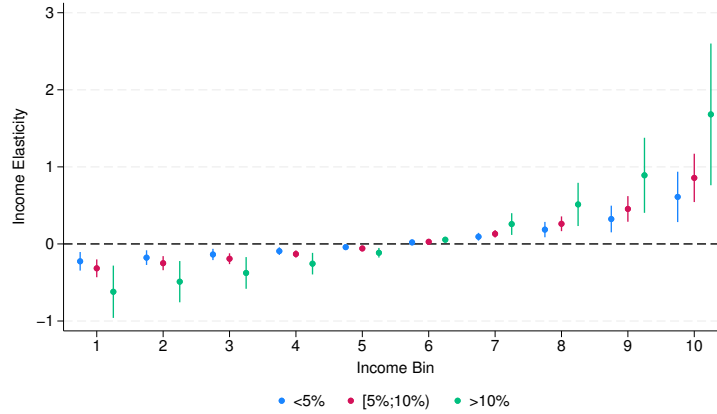
Notes. This figure shows estimated income elasticities by income deciles after a 1% currency change (devaluations for Panel a and appreciations for Panel b). Fixed effects are included at the region-year levels. Standard errors are clustered at the region level (NUTS-1). Income is measured as real income pre-tax (blue) and real income post-tax (red).

Thresholds: FX swings depending on size. In this robustness exercise we explore the differential effects of the size of the currency change. We split the sample into three categories using indicators for both appreciations and devaluations: small (below 5%), medium (between 5% and 10%) and large (over 10%). Results are plotted below on Figure 3.5 based on estimates from Table A.4. For devaluations (Panel a) most of the results are coming from medium devaluations, as small and large devaluations do not generate a statistically significant differential effect over the income distribution. For appreciations (Panel b) all the currency changes create differential effects over the income distribution. The largest appreciations are the ones generating the largest effects.

Figure 3.5: Thresholds



(a) Devaluations

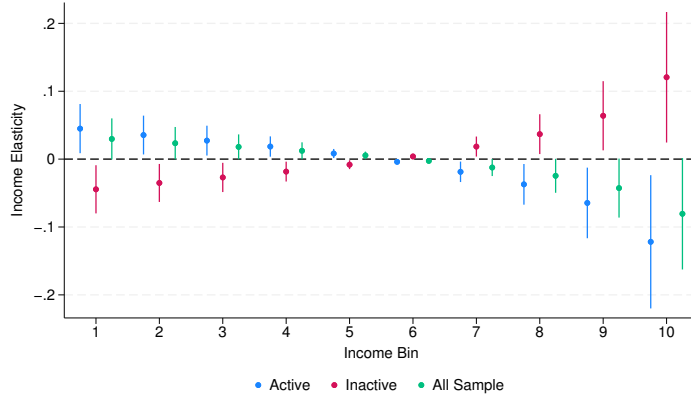


(b) Appreciations

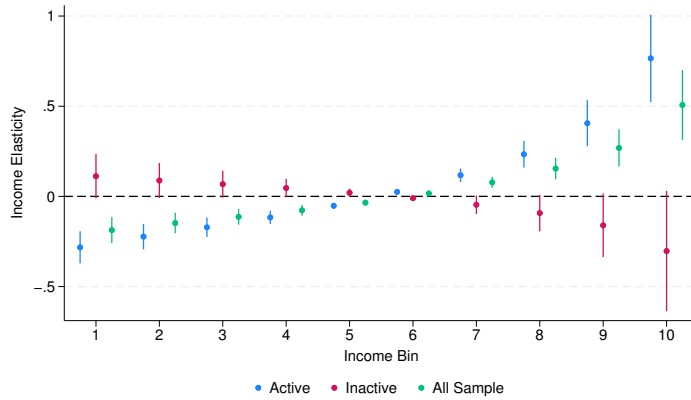
Notes. This figure shows estimated income elasticities by income deciles after a 1% currency change (devaluations for Panel a and appreciations for Panel b). Fixed effects are included at the region-year levels. Standard errors are clustered at the region level (NUTS-1). Income is measured as real income pre-tax. Estimates are divided according to size of currency changes using indicators.

Labor Force Participation: Active vs Inactive. All previous estimations focus on Active workers (employed or unemployed). In this robustness, we study how inactive (retired) workers are affected by currency swings. We follow the same baseline specification but limiting the observations to inactive workers and all sample. Figure (3.6) shows the results comparing with baseline (Active), based on estimates from Table A.5. The results are interesting as inactive workers have the opposite correlation. Inactive households in the bottom deciles of the income distribution see a relative decline in the real income after a currency devaluation. On the other hand, top earners improve their income. Although this finding is beyond the scope of the paper, this could be explained by the fact that rich retired households have retirement accounts in dollars and benefit from a dollar appreciation.

Figure 3.6: Active vs Inactive



(a) Devaluations



(b) Appreciations

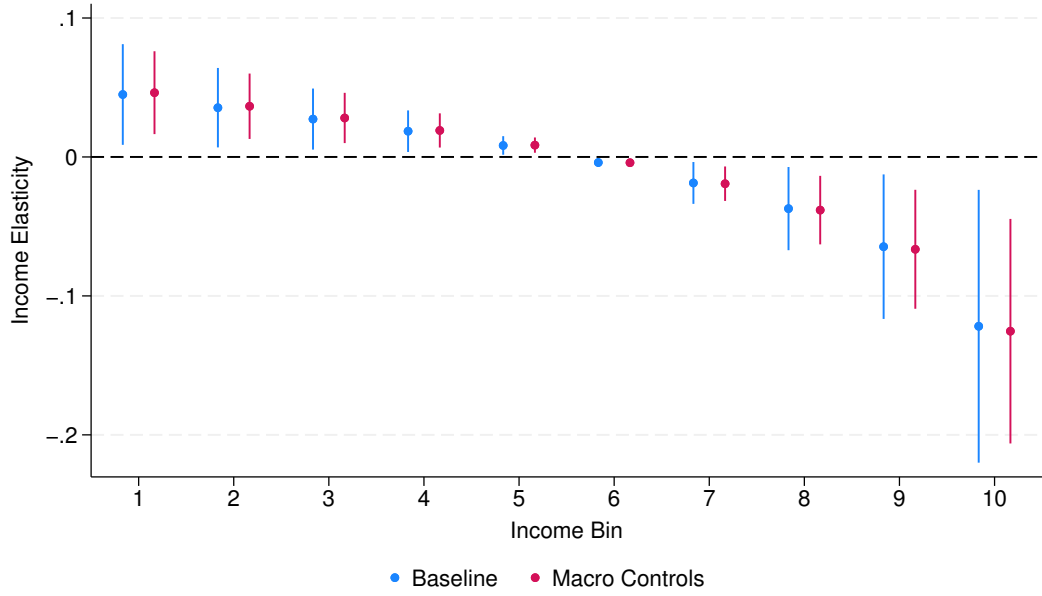
Notes. This figure shows estimated income elasticities by income deciles after a 1% currency appreciation (devaluations for Panel a and appreciations for Panel b). Fixed effects are included at the region-year. Standard errors are clustered at the region level (NUTS-1). Sample is divided by labor force participation. Income is measured as real income pre-tax.

Adding Macroeconomic Controls. Omitted variables at the aggregate level could create bias in the estimates. More fundamentally, the effect of exchange rates depend on the nature of the shock driving them, as emphasized notably in [Forbes et al. \(2018\)](#). In this paper we are mostly interested in the impact of exchange rate movements in themselves, not as a reflection of other shocks such as productivity and monetary policy shocks. To address this potential issue, we include macroeconomic controls to the baseline regression, which as shown by [Lloyd and Manuel \(2024\)](#) may be a better way to achieve identification than considering orthogonalized shocks from an identification scheme. With this purpose in mind, we include real GDP growth, inflation and unemployment as controls that can capture aggregate effects explaining household income and exchange rates. All three variables are interacted with pre-tax nominal income to control for the correlation of aggregate variables on household income. The estimated model is

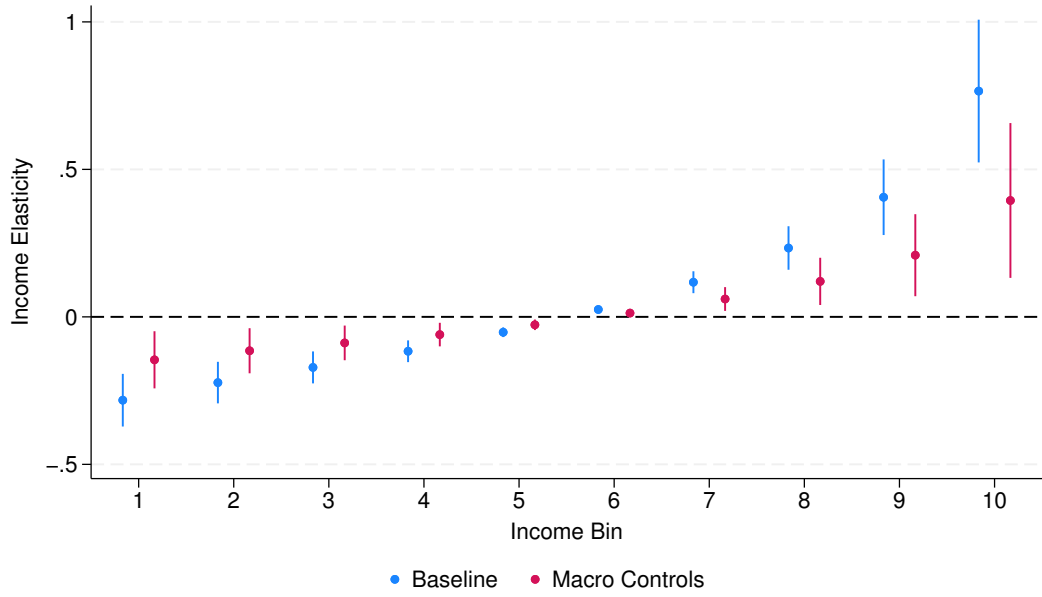
$$\begin{aligned}
\text{dlog Real Pre-Tax Income}_{hct} = & \alpha \\
& + \beta_{Deva} \times \mathbb{I}(Deva.)_{ct} \times \text{dlog NER}_{ct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Median Nom. Pre-Tax Inc.}_{c,t-1}) \\
& + \beta_{Appre} \mathbb{I}(Appre.)_{ct} \times \text{dlog NER}_{ct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Median Nom. Pre-Tax Inc.}_{c,t-1}) \\
& + \sum_s \beta_{Deva}^s \times \mathbb{I}(Deva.)_{ct} \times \text{Agg. Control}_{sct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Median Nom. Pre-Tax Inc.}_{c,t-1}) \\
& + \sum_s \beta_{Appre}^s \mathbb{I}(Appre.)_{ct} \times \text{Agg. Control}_{sct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Median Nom. Pre-Tax Inc.}_{c,t-1}) \\
& + \text{Controls}_{h,t-1} + \lambda_{r,t} + e_{ht}
\end{aligned} \tag{2}$$

where $s = 1, 2, 3$ representing the aggregate controls. Figure [3.7](#) presents the results using the estimated coefficients from Table [A.6](#). Incorporating macroeconomic controls slightly diminishes the coefficients for appreciations, but the overall pattern observed in the baseline results remains consistent.

Figure 3.7: Macroeconomic Controls



(a) Devaluations



(b) Appreciations

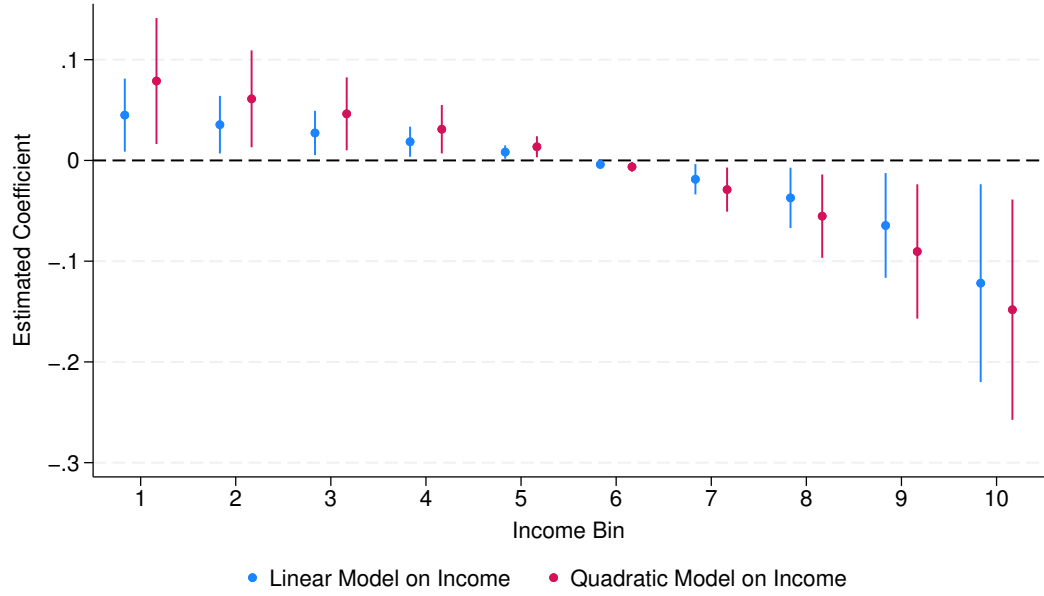
Notes. This figure shows estimated income elasticities by income deciles after a 1% currency change (devaluations for Panel a and appreciations for Panel b). Fixed effects are included at the region-year levels. Standard errors are clustered at the region level (NUTS-1). Income is measured as real income pre-tax. Regression in red includes macroeconomic controls interacted with relative income level (GDP growth, inflation and unemployment).

Quadratic Effects. In this robustness we test if there are non-linear effects of currency changes on income inequality. In particular, we include a quadratic term for pre-tax nominal income (relative to median). The estimated model is the following:

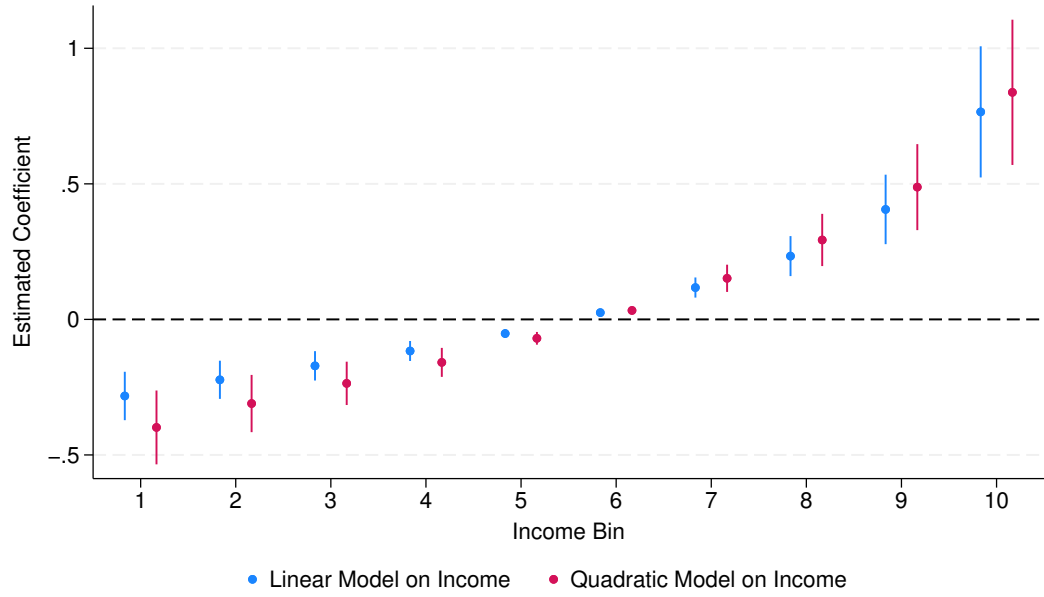
$$\begin{aligned}
\text{dlog Real Pre-Tax Income}_{hct} = & \alpha \tag{3} \\
& + \beta_{Deva}^{(1)} \times \mathbb{I}(Deva.)_{ct} \times \text{dlog NER}_{ct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Median Nom. Pre-Tax Inc.}_{c,t-1}) \\
& + \beta_{Appre}^{(1)} \times \mathbb{I}(Appre.)_{ct} \times \text{dlog NER}_{ct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Median Nom. Pre-Tax Inc.}_{c,t-1}) \\
& + \beta_{Deva}^{(2)} \times \mathbb{I}(Deva.)_{ct} \times \text{dlog NER}_{ct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Median Nom. Pre-Tax Inc.}_{c,t-1})^2 \\
& + \beta_{Appre}^{(2)} \times \mathbb{I}(Appre.)_{ct} \times \text{dlog NER}_{ct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Median Nom. Pre-Tax Inc.}_{c,t-1})^2 \\
& + \text{Controls}_{h,t-1} + \lambda_{r,t} + e_{ht}
\end{aligned}$$

where the lag relative income squared is also used as a control. Results are show below on Figure 3.8 based on estimated coefficients from Table A.7. In summary, including a quadratic term does not change drastically the results: income inequality declines after currency devaluations.

Figure 3.8: Linear vs Quadratic



(a) Devaluations



(b) Appreciations

Notes. This figure shows estimated income elasticities by income deciles after a 1% currency change (devaluations for Panel a and appreciations for Panel b). Fixed effects are included at the region-year levels. Standard errors are clustered at the region level (NUTS-1). Income is measured as real income pre-tax. Regression in red includes a quadratic term for pre-tax nominal income (relative to median).

4 Mechanisms

In this section we explore the mechanisms that explain the empirical findings. First, we show that income changes mainly by total income and not hours worked, suggesting that income per hour is the driver of income inequality changes. Second, we follow the literature to assess the implication of labor mobility and unions to explain our empirical results. We find that only labor mobility allows to explain the results as union members do not see their income change differentially after currency swings.

4.1 Income and Employment

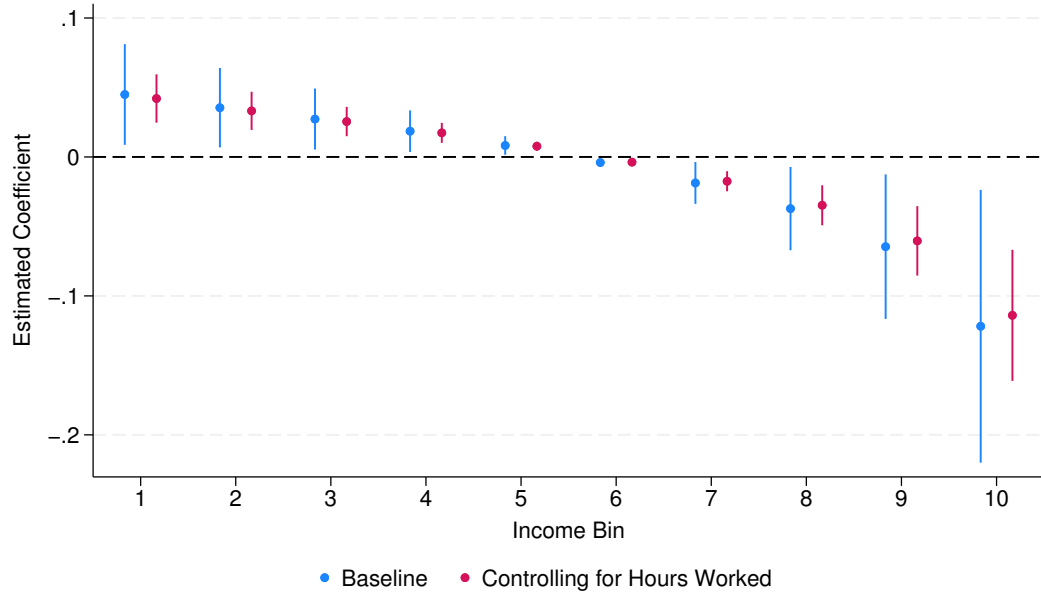
We estimate the following empirical model

$$\begin{aligned} \text{dlog Real Pre-Tax Income}_{hct} = & \alpha \\ & + \beta_{Deva} \times \mathbb{I}(Deva)_{ct} \times \text{dlog NER}_{ct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Median Nom. Pre-Tax Inc.}_{h,t-1}) \\ & + \beta_{Appre} \times \mathbb{I}(Appre)_{ct} \times \text{dlog NER}_{ct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Median Nom. Pre-Tax Inc.}_{h,t-1}) \\ & + \text{Controls}_{h,t-1} + \text{Hours Worked}_{h,t-1} + \text{Hours Worked}_{h,t} + \lambda_{r,t} + e_{ht} \end{aligned} \tag{4}$$

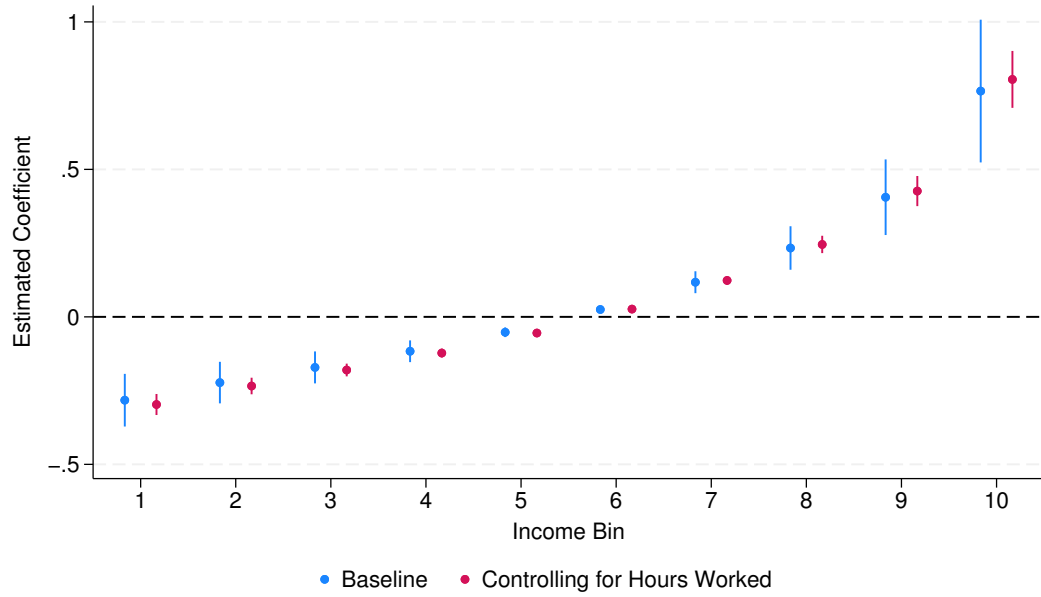
Basically, we repeat the baseline specification but controlling for hours worked before and after the shock. The idea is to estimate the correlation between real pre-tax income and changes in nominal exchange rate by income but keeping hours worked constant. This allows us to isolate the effects of income per hour and hours worked.

We show income elasticities in Figure 4.1 based on regression estimates from Table A.8. The estimated elasticities display almost identical results as the baseline. Therefore, we conclude that hours worked do not explain the change in income after a currency swing. All the effect comes from income per hour.

Figure 4.1: Income and Employment



(a) Devaluations



(b) Appreciations

Notes. This figure shows estimated income elasticities by income deciles after a 1% currency change (devaluations for Panel a and appreciations for Panel b). Fixed effects are included at the region-year levels. Standard errors are clustered at the region level (NUTS-1). Income is measured as real income pre-tax. Regression in red controls by hours worked before and after the currency change.

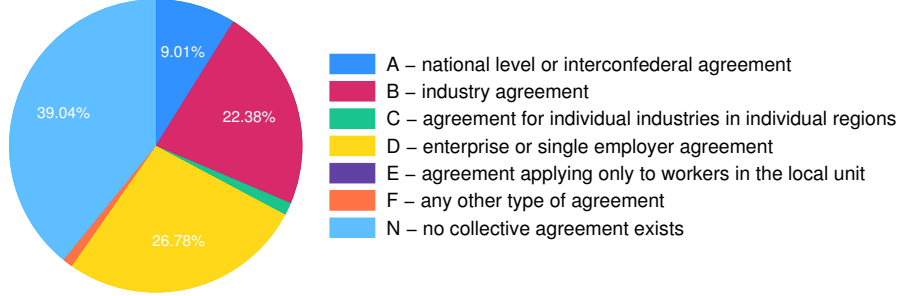
4.2 The Role of Union Membership

To analyze the role of unions, we use the Structure of Earnings Survey (SES) from Europe. This is a large-scale survey that covers employee data across most European countries, conducted every four years from 2002 to 2018. The SES includes detailed information about employee characteristics such as country, year, income, occupation, gender, education, and union affiliation.

Our primary goal is to estimate the probability of union membership based on these characteristics. We then integrate these probabilities with income data to assess how union membership influences income dynamics, specifically looking at the impact of currency devaluations and appreciation. We compare the real income changes between union and non-union workers using the estimated probabilities of union membership.

The SES dataset includes information from a cross-section of workers and firms in selected years: 2002, 2006, 2010, 2014, and 2018. It covers all European countries included in the EU-SILC, except for Austria, Switzerland, Ireland, and Serbia. The key variables in the dataset include annual gross employee income (pre-tax), occupation, age, education, and trade union affiliation. Union affiliation is determined at the firm level; if more than 50% of the workers in a firm are union members or belong to a collective pay agreement, all workers in that firm are classified as union members. The unions are categorized into national agreements, industry agreements, individual or enterprise agreements, local agreements, other types of agreements, or no agreement. Figure (4.2) shows the share of each category among all observations. Approximately 40% of workers are not part of a union. The remaining union members are primarily in industry agreements (22%) and enterprise agreements (26%).

Figure 4.2: Union Membership by type



Notes. This figure shows the share of each collective pay agreement for all the SES sample. Luxembourg and Germany are excluded as they have a different classification system.

Estimation. Our approach involves a two-stage model. In the First Stage, we use a logit model to estimate the probability of union membership, controlling for country, income level, and occupation. Occupations are grouped into categories such as managers, professionals, technicians, service workers, and others. High-income workers are mostly found in managerial or professional occupations, while low-income workers tend to occupy technical, service, or agricultural roles. Figure 4.3 shows the share of each occupation for the whole EU-SILC dataset and Figure 4.4 for each income decile.

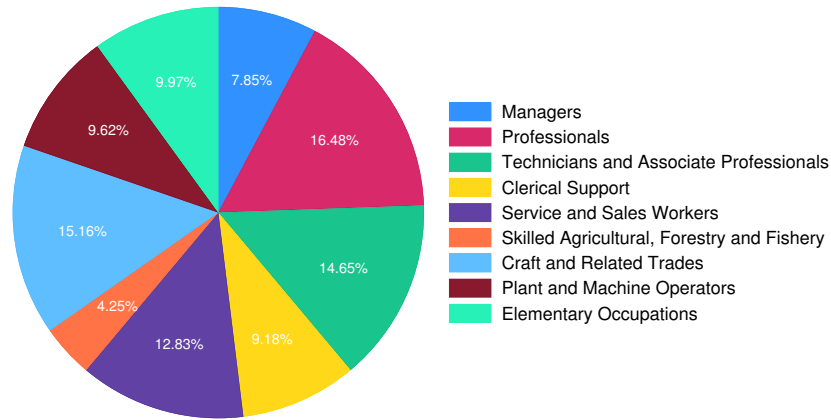
The empirical model for the First Stage is

$$g(\mathbb{I}_{h \in \text{union}}) = \theta + \sum_c \gamma_c \mathbb{I}_{h \in c} + \sum_b \gamma_b \text{Pre-Tax Nominal Income}_{h,t} + \sum_o \gamma_o \mathbb{I}_{h \in o} + e_{h,t} \quad (5)$$

$$g^{-1}(x) = \frac{e^x}{1 + e^x}$$

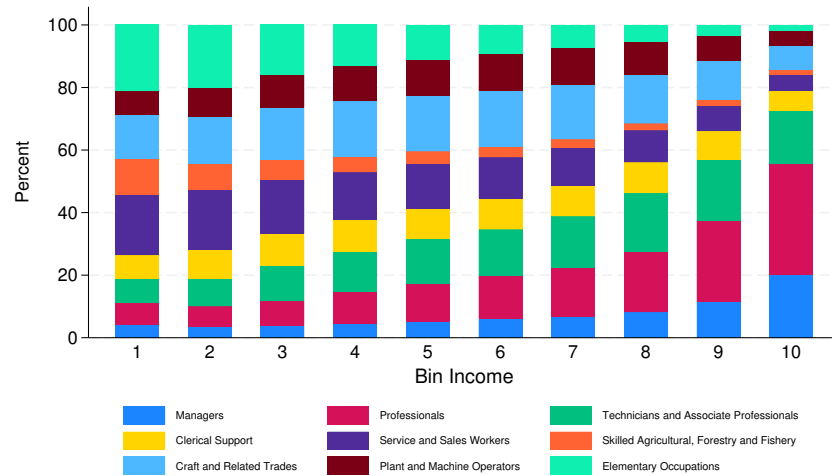
Figure A.3 in Appendix shows the model fit. The logit model performs well, predicting union membership with an 82% accuracy using just three variables: country, occupation, and nominal income.

Figure 4.3: Occupations in Europe



Notes. This figures show the percentage share of each occupation in EU-SILC.

Figure 4.4: Occupations in Europe by Income



Notes. This figures show the percentage share of each occupation in EU-SILC by income deciles.

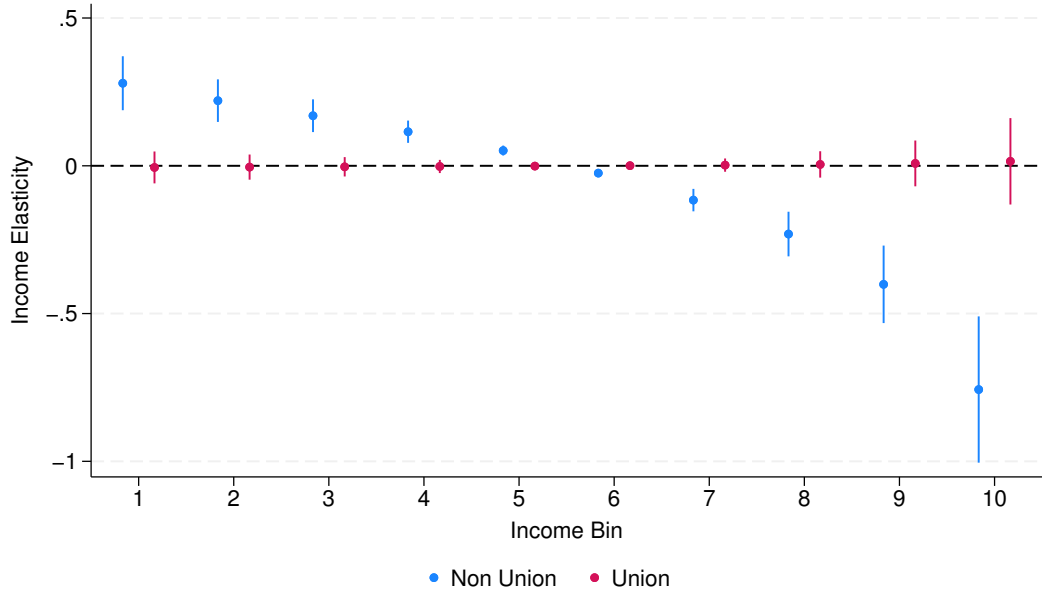
The Second Stage involves using the estimated union membership probabilities as a control variable in baseline regression model. Specifically, we estimate real income evolution after currency swings controlling for predicted union probability from First Stage. The empirical model is

$$\begin{aligned}
\text{dlog Real Pre-Tax Income}_{hct} = & \alpha \\
& + \beta_D^{Non\ Union} \times \mathbb{I}(D)_{ct} \times \text{dlog NER}_{ct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Med. Nom. Pre-Tax N.Inc.}_{h,t-1}) \\
& + \beta_D^{Union} \times \mathbb{I}(D)_{ct} \times \text{dlog NER}_{ct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Med. Nom. Pre-Tax N.Inc.}_{h,t-1}) \times P(Union)_{hc,t-1} \\
& + \beta_A^{Non\ Union} \times \mathbb{I}(A)_{ct} \times \text{dlog NER}_{ct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Med. Nom. Pre-Tax Inc.}_{h,t-1}) \\
& + \beta_A^{Union} \times \mathbb{I}(A)_{ct} \times \text{dlog NER}_{ct} \times (\text{Nom. Pre-Tax Inc.}_{h,t-1} - \text{Med. Nom. Pre-Tax Inc.}_{h,t-1}) \times P(Union)_{hc,t-1} \\
& + \text{Controls}_{h,t-1} + P(Union)_{hc,t-1} + \lambda_{r,t} + e_{ht}
\end{aligned} \tag{6}$$

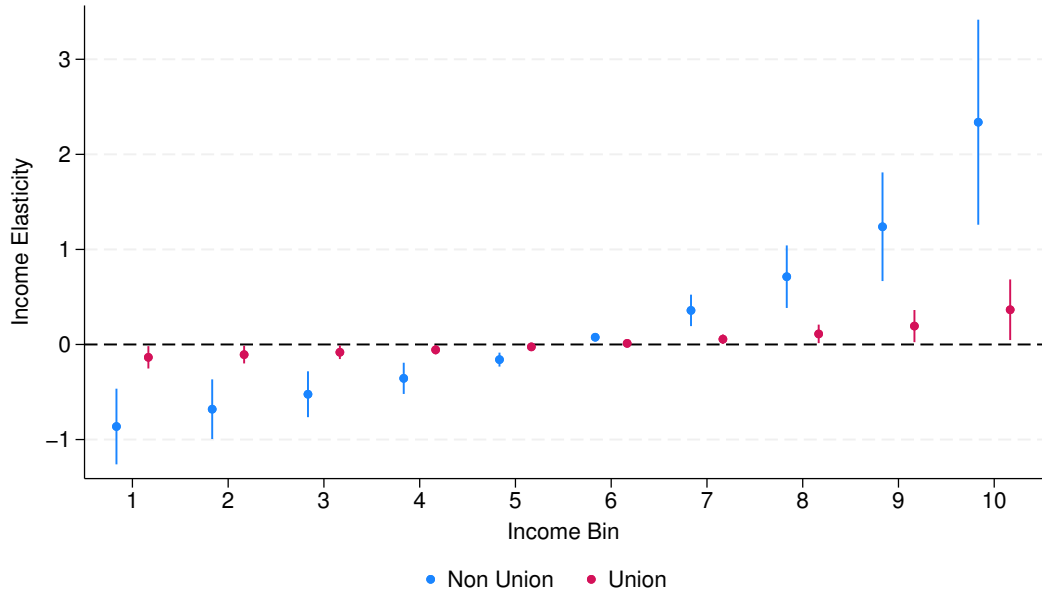
Figure 4.5 shows the implied income elasticities for a 1% currency change, differentially for union and non-union members, from estimated coefficients shown in Table A.9. Our analysis shows that union membership does not significantly explain income inequality changes following currency devaluation or appreciation. Contrary to earlier studies (such as those by Blanco et al. (2024)), we find that low income non-union workers tend to benefit more after devaluations. In fact, the decline in income inequality after devaluation is mostly driven by improvements in income for non-union workers, not union members. A similar pattern is observed with currency appreciation, where non-union workers show a stronger response in terms of income changes. In both cases, there is little differential effect along the income distribution for union members.

In conclusion, union membership does not appear to be the main factor driving income inequality reductions after economic shocks in Europe. Instead, non-union members play a larger role in this process, which contrasts with findings from developing countries like Argentina, where unions have a more significant impact on income inequality.

Figure 4.5: Union Membership



(a) Devaluations



(b) Appreciations

Notes. This figure shows estimated income elasticities by income deciles after a 1% currency change by union membership (devaluations for Panel a and appreciations for Panel b). Fixed effects are included at the region-year levels. Standard errors are clustered at the region level (NUTS-1). Income is measured as real income pre-tax.

4.3 Labor Mobility

Labor mobility was identified as main driver of inequality changes after currency swings in the literature. In this section we asses the contribution of labor mobility to explain our empirical findings. In a nutshell, household in EU-SILC report if they changed their employer compared to previous year or if they changed their employment status compared to previous year (e.g. unemployed to employed). We can then estimate the baseline model including these two indicator variables. Our results show that most of the income changes are driven by households that either change employer or status.

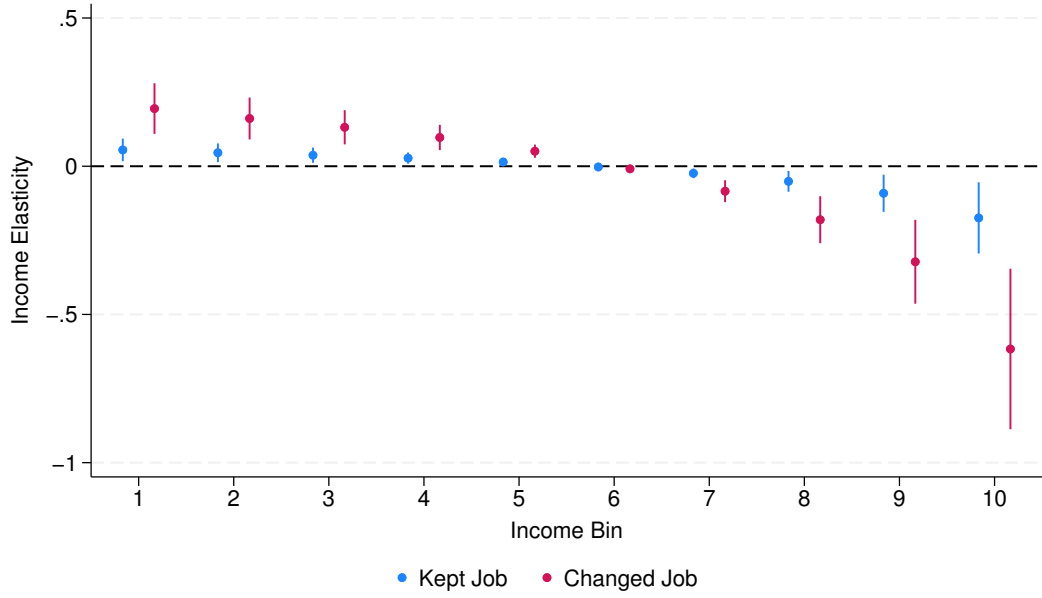
Job Changes. Households report if they switched jobs compared to last year.⁷ This allows us to create an indicator variable to divide households in two groups and estimate the baseline model including an interaction term that captures the correlation between real income and exchange rates for these two groups. The empirical model is

$$\begin{aligned}
 \text{dlog Real Pre-Tax Income}_{hct} = & \alpha \\
 & + \beta_D^{Kept Job} \times \mathbb{I}(D)_{ct} \times \text{dlog NER}_{ct} \times (\text{N. Pre-Tax Inc.}_{h,t-1} - \text{Med. Pre-Tax N.Inc.}_{h,t-1}) \\
 & + \beta_D^{Changed Job} \times \mathbb{I}(D)_{ct} \times \text{dlog NER}_{ct} \times (\text{N. Pre-Tax Inc.}_{h,t-1} - \text{Med. Pre-Tax N.Inc.}_{h,t-1}) \times \mathbb{I}(h \text{ had Employer Change}) \\
 & + \beta_A^{Kept Job} \times \mathbb{I}(A)_{ct} \times \text{dlog NER}_{ct} \times (\text{N. Pre-Tax Inc.}_{h,t-1} - \text{Med. Pre-Tax N.Inc.}_{h,t-1}) \\
 & + \beta_A^{Changed Job} \times \mathbb{I}(A)_{ct} \times \text{dlog NER}_{ct} \times (\text{N. Pre-Tax Inc.}_{h,t-1} - \text{Med. Pre-Tax N.Inc.}_{h,t-1}) \times \mathbb{I}(h \text{ had Employer Change}) \\
 & + \text{Controls}_{h,t-1} + \lambda_{r,t} + e_{ht}
 \end{aligned} \tag{7}$$

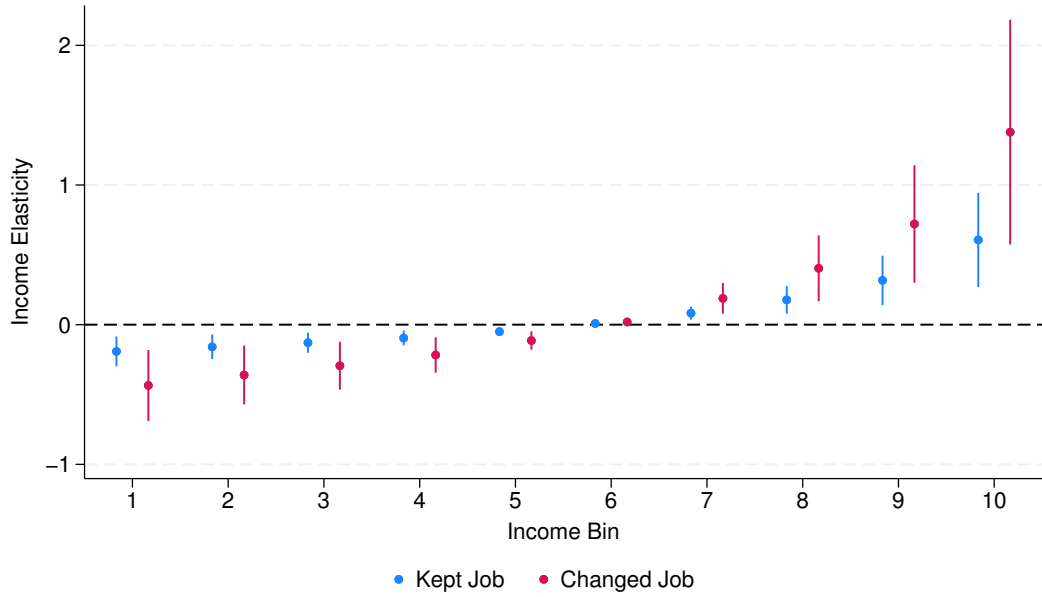
The idea is that $\beta_D^{Changed Job}$ and $\beta_A^{Changed Job}$ capture the differential effect of currency changes and real income for the group of households that changed jobs after the currency swing along the income distribution (one parameter for devaluations and one for appreciations). Figure 4.6 computes the implied elasticities for devaluations and appreciations along the income distribution, based on estimates from Table A.10.

⁷Figure A.4 in Appendix shows shares of changes over time accross the whole sample.

Figure 4.6: Job Change



(a) Devaluations



(b) Appreciations

Notes. This figure shows estimated income elasticities by income deciles after a 1% currency change depending on job change indicator (devaluations for Panel a and appreciations for Panel b). Fixed effects are included at the region-year levels. Standard errors are clustered at the region level (NUTS-1). Income is measured as real income pre-tax.

The findings show that households who kept their jobs after the evaluation exhibit a small effect on income, with a positive but small effect for middle-income households and a negative small effect for high-income households. However, a more substantial change is observed in households that changed employers. Workers who found a new employer after the evaluation saw the largest increase in real income, particularly among low-income households, while the effect was negative for high-income households. All these results are reversed for appreciations.

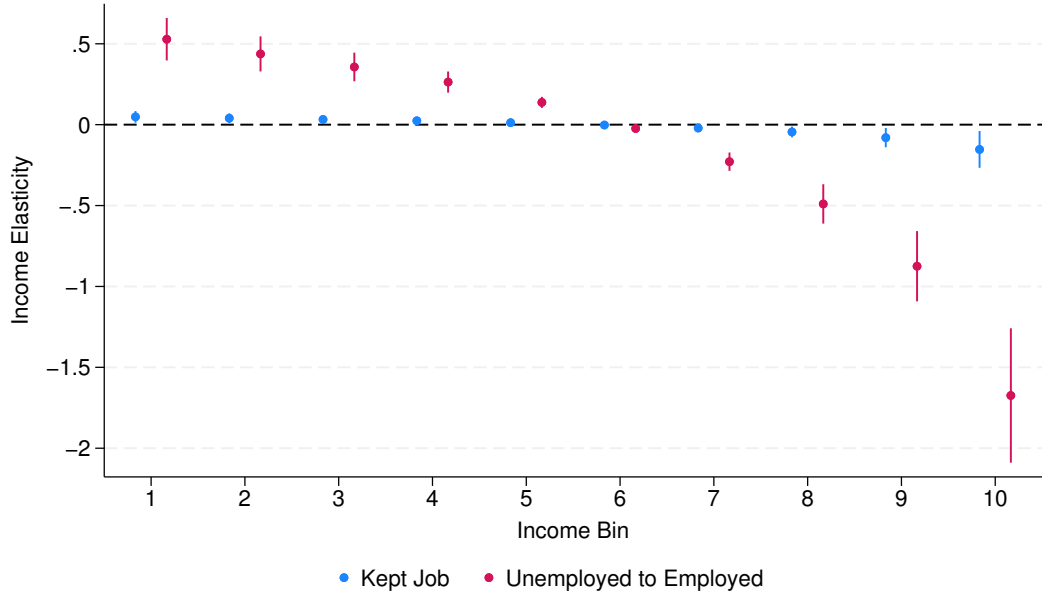
Employment Status Change. Households also report if they had an employment status change compared to last year.⁸ We construct an indicator that takes value of one if a household switched from unemployed to employed the year of the currency change. We repeat the baseline regression including an additional term to differentiate the income change for households not changing status versus transitioning from unemployed to employed. The empirical model results

$$\begin{aligned}
\text{dlog Real Pre-Tax Income}_{hct} = & \alpha \\
& + \beta_D^{Kept Job} \times \mathbb{I}(D)_{ct} \times \text{dlog NER}_{ct} \times (\text{N. Pre-Tax Inc.}_{h,t-1} - \text{Med. N. Pre-Tax Inc.}_{h,t-1}) \\
& + \beta_D^{U to E} \times \mathbb{I}(D)_{ct} \times \text{dlog NER}_{ct} \times (\text{N. Pre-Tax Inc.}_{h,t-1} - \text{Med. N. Pre-Tax Inc.}_{h,t-1}) \times \mathbb{I}(h \text{ Unemployment to Employment}) \\
& + \beta_A^{Kept Job} \times \mathbb{I}(A)_{ct} \times \text{dlog NER}_{ct} \times (\text{N. Pre-Tax Inc.}_{h,t-1} - \text{Med. N. Pre-Tax Inc.}_{h,t-1}) \\
& + \beta_A^{U to E} \times \mathbb{I}(A)_{ct} \times \text{dlog NER}_{ct} \times (\text{N. Pre-Tax Inc.}_{h,t-1} - \text{Med. N. Pre-Tax Inc.}_{h,t-1}) \times \mathbb{I}(h \text{ Unemployment to Employment}) \\
& + \text{Controls}_{h,t-1} + \lambda_{r,t} + e_{ht}
\end{aligned}$$

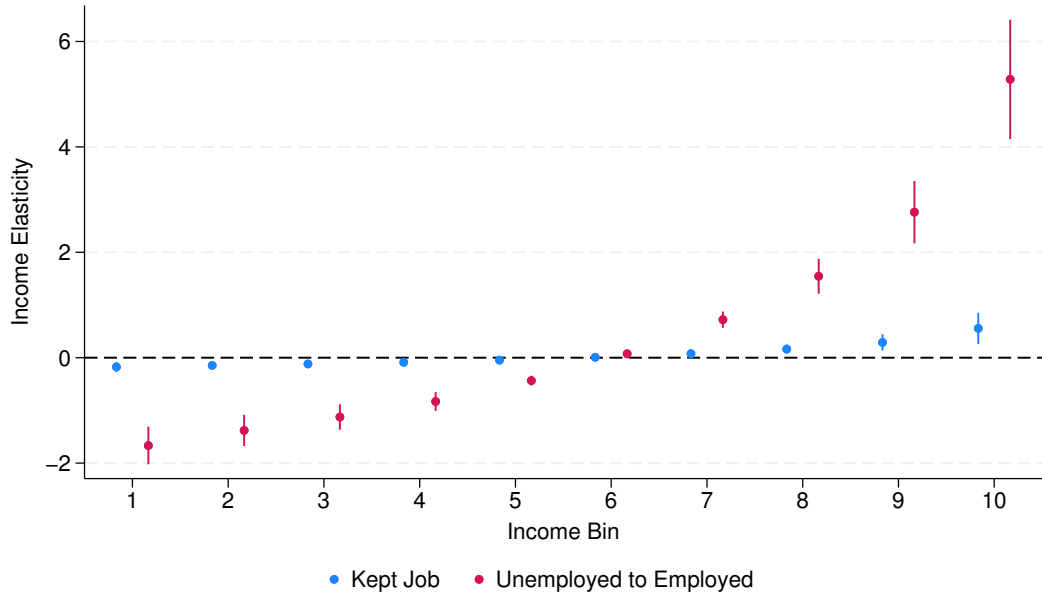
Figure 4.7 shows the implied income elasticity for a 1% currency change between the two relevant groups, using estimated coefficients from Table A.11.

⁸Figure A.5 in Appendix shows shares of changes over time across the whole sample.

Figure 4.7: Employment Status Change



(a) Devaluations



(b) Appreciations

Notes. This figure shows estimated income elasticities by income deciles after a 1% currency change depending on employment status indicator (devaluations for Panel a and appreciations for Panel b). Fixed effects are included at the region-year levels. Standard errors are clustered at the region level (NUTS-1). Income is measured as real income pre-tax.

In both cases, households that report either changing employer or status display the largest effect. For instance, after a currency devaluation, the improvement in income inequality is mostly driven by households that found another employer (see Figure 4.6a) or households that were unemployed and switched to employed after the devaluation (see Figure 4.7a).

5 Concluding Remarks

This paper investigates the relationship between foreign exchange (FX) shocks and income inequality in Europe, offering a nuanced understanding of how currency devaluations and appreciations impact income distribution. Using a robust dataset that spans 31 European countries over 19 years, we demonstrate that currency devaluations reduce income inequality, while appreciations have the opposite effect. These findings extend existing literature, highlighting labor mobility as the key mechanism driving these outcomes in Europe, in contrast to union dynamics observed in other regions like Latin America.

The policy implications of these findings are clear: managing exchange rate volatility and fostering labor mobility are crucial for addressing income inequality in Europe. Policymakers should also consider the role of fiscal instruments and labor market policies to amplify the redistributive effects of devaluations while mitigating the adverse impacts of appreciations.

Future research could build on this work by exploring the heterogeneity of FX impacts across different socioeconomic groups and industries, as well as examining the long-term consequences of repeated currency shocks. Understanding these dynamics will be essential for crafting targeted and effective policies in an increasingly interconnected global economy.

Data Disclaimer

This study is based on data from Eurostat:

1. European Statistics on Income and Living Conditions (EU-SILC)

- Reference years: 2004-2021
- Release date: 5 October 2023
- Version: EU-SILC release 2 in 2023 (autumn release)
- DOI: <https://doi.org/10.2907/EUSILC2004-2022V1>

2. Structure of Earnings Survey (SES)

- Reference years: 2002-2018
- Release date: July 2021
- Version: July 2021

The responsibility for all conclusions drawn from the data lies entirely with the authors.

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A Additional Tables and Figures

Figure A.1: Datasets Availability EU-SILC

		AT	BE	BG	CY	CZ	DE	DK	EE	EL	ES	FI	FR	HR	HU	IE	IT	LT	LU	LV	MT	NL	PL	PT	RO	SE	SI	SK	CH	IS	NO	RS	UK	
EU-SILC 2022	Longitudinal																																	
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
EU-SILC 2021	Longitudinal	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2020	Longitudinal	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2019	Longitudinal	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2018	Longitudinal	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2017	Longitudinal	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2016	Longitudinal	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2015	Longitudinal	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2014	Longitudinal	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2013	Longitudinal	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2012	Longitudinal	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2011	Longitudinal	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2010	Longitudinal	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2009	Longitudinal	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2008	Longitudinal	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2007	Longitudinal	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2006	Longitudinal	x	x		x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2005	Longitudinal	x	x																															
	Cross-sectional	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
EU-SILC 2004	Cross-sectional	x	x																															

Comment

SUF: scientific use files, available for download

Comment

EU-SILC data (cross-sectional and longitudinal) are available as scientific use files (SUFs)

x - data available

Comment
SUF: scientific use files, available for download

Comment

EU-SILC data
(cross-sectional and longitudinal)
are available
as scientific use files (SUFs)

x - data available

Version 08-05-2024

Notes. This figure shows the data availability for EU-SILC accross countries and years.

Source: <https://ec.europa.eu/eurostat/documents/203647/771732/Datasets-availability-table.pdf>

Figure A.2: Regions in Europe



Notes. This figure shows the regions definition for the dataset (NUTS-1 2021 Level 1).

Source: <https://ec.europa.eu/eurostat/documents/345175/17779945/2021-NUTS-1-map.pdf>

Table A.1: Euro Area vs Non Euro Area

	(1) All Sample	(2) Euro Area vs Non Euro Area
lag Relative Income * dlog NER (Appreciations)	0.0139*** (0.00265)	
lag Relative Income * dlog NER (Devaluations)	-0.00222** (0.00108)	
lag Relative Income * dlog NER (Appreciations) * Euro		0.0193*** (0.00135)
lag Relative Income * dlog NER (Appreciations) * Non Euro		0.0102*** (0.00131)
lag Relative Income * dlog NER (Devaluations) * Euro		-0.00339*** (0.000665)
lag Relative Income * dlog NER (Devaluations) * Non Euro		-0.00135** (0.000628)
lag Relative Income	-0.00337*** (0.000215)	-0.00339*** (0.0000429)
lag Occupation	-0.00830*** (0.00102)	-0.00833*** (0.000279)
lag Education	0.0000889*** (0.0000168)	0.0000878*** (0.00000858)
lag Sex	-0.00737*** (0.00231)	-0.00749*** (0.00133)
lag Age	-0.000183 (0.000150)	-0.000190*** (0.0000580)
Constant	0.105*** (0.00836)	0.106*** (0.00403)
Adjusted R^2	0.087	0.087
Observations	1,072,171	1,072,171
FE	Region-Year	Region-Year
Standard Errors	Cluster Region	Robust

Table A.2: By FX Regime

	(1) All Sample	(2) Euro/Euro Pegged vs Non Euro/Flexible
lag Relative Income * dlog NER (Appreciations)	0.0139*** (0.00265)	
lag Relative Income * dlog NER (Devaluations)	-0.00222** (0.00108)	
lag Relative Income * dlog NER (Appreciations) * Euro/Euro Pegged		0.0195*** (0.00153)
lag Relative Income * dlog NER (Appreciations) * Non Euro/Flexible		0.0110*** (0.00123)
lag Relative Income * dlog NER (Devaluations) * Euro/Euro Pegged		-0.00262*** (0.000679)
lag Relative Income * dlog NER (Devaluations) * Non Euro/Flexible		-0.00185*** (0.000621)
lag Relative Income	-0.00337*** (0.000215)	-0.00338*** (0.0000428)
lag Occupation	-0.00830*** (0.00102)	-0.00832*** (0.000279)
lag Education	0.0000889*** (0.0000168)	0.0000883*** (0.00000858)
lag Sex	-0.00737*** (0.00231)	-0.00745*** (0.00132)
lag Age	-0.000183 (0.000150)	-0.000187*** (0.0000580)
Constant	0.105*** (0.00836)	0.106*** (0.00403)
Adjusted R^2	0.087	0.087
Observations	1,072,171	1,072,171
FE	Region-Year	Region-Year
Standard Errors	Cluster Region	Robust

Table A.3: Post-Tax Real Income

	(1) Pre-Tax dlog Real Income	(2) Post-Tax dlog Real Income
lag Relative Income (Pre-Tax) * dlog NER (Appreciations)	0.0139*** (0.00265)	0.0131*** (0.00246)
lag Relative Income (Pre-Tax) * dlog NER (Devaluations)	-0.00222** (0.00108)	-0.00201* (0.00103)
lag Relative Income (Pre-Tax)	-0.00337*** (0.000215)	-0.00321*** (0.000211)
lag Occupation	-0.00830*** (0.00102)	-0.00813*** (0.000871)
lag Education	0.0000889*** (0.0000168)	0.0000799*** (0.0000148)
lag Sex	-0.00737*** (0.00231)	-0.00912*** (0.00220)
lag Age	-0.000183 (0.000150)	-0.0000285 (0.000149)
Constant	0.105*** (0.00836)	0.0983*** (0.00830)
Adjusted R^2	0.087	0.082
Observations	1,072,171	1,069,903
FE	Region-Year	Region-Year
Standard Errors	Cluster Region	Cluster Region

Table A.4: Thresholds

	(1) All Sample
lag Relative Income * dlog NER (Appreciations < 5%)	0.0111*** (0.00358)
lag Relative Income * dlog NER (Appreciations 5% – 10%)	0.0156*** (0.00344)
lag Relative Income * dlog NER (Appreciations > 10%)	0.0306*** (0.0101)
lag Relative Income * dlog NER (Devaluations < 5%)	-0.00667 (0.00729)
lag Relative Income * dlog NER (Devaluations 5% – 10%)	-0.00843*** (0.00263)
lag Relative Income * dlog NER (Devaluations > 10%)	-0.00125 (0.00104)
lag Relative Income	-0.00331*** (0.000220)
lag Occupation	-0.00840*** (0.00101)
lag Education	0.0000832*** (0.0000166)
lag Sex	-0.00739*** (0.00230)
lag Age	-0.000184 (0.000150)
Constant	0.107*** (0.00822)
Adjusted R^2	0.087
Observations	1072171
FE	Region-Year
Standard Errors	Cluster Region

Table A.5: Active vs Inactive

	(1) Active	(2) Inactive	(3) All Sample
lag Relative Income * dlog NER (Appreciations)	0.0139*** (0.00265)	-0.00551 (0.00365)	0.00922*** (0.00213)
lag Relative Income * dlog NER (Devaluations)	-0.00222** (0.00108)	0.00219** (0.00105)	-0.00146 (0.000901)
lag Relative Income	-0.00337*** (0.000215)	-0.00412*** (0.000187)	-0.00337*** (0.000196)
lag Occupation	-0.00830*** (0.00102)	-0.00535*** (0.000585)	-0.00723*** (0.00103)
lag Education	0.0000889*** (0.0000168)	0.0000768*** (0.0000106)	0.0000837*** (0.0000159)
lag Sex	-0.00737*** (0.00231)	-0.0101*** (0.00238)	-0.00841*** (0.00202)
lag Age	-0.000183 (0.000150)	-0.0000803 (0.000185)	-0.00108*** (0.000138)
Constant	0.105*** (0.00836)	0.00466 (0.0138)	0.120*** (0.00977)
Adjusted R^2	0.087	0.093	0.077
Observations	1,072,171	315,830	1,514,942
FE	Region-Year	Region-Year	Region-Year
Standard Errors	Cluster Region	Cluster Region	Cluster Region

Table A.6: Adding Macroeconomic Controls

	(1) Baseline	(2) Macro Controls
lag Relative Income * dlog NER (Appreciations)	0.0139*** (0.00265)	0.00718** (0.00288)
lag Relative Income * dlog NER (Devaluations)	-0.00222** (0.00108)	-0.00228** (0.000887)
lag Relative Income	-0.00337*** (0.000215)	-0.00235*** (0.000271)
lag Occupation	-0.00830*** (0.00102)	-0.00868*** (0.000979)
lag Education	0.0000889*** (0.0000168)	0.0000784*** (0.0000158)
lag Sex	-0.00737*** (0.00231)	-0.00729*** (0.00228)
lag Age	-0.000183 (0.000150)	-0.000183 (0.000150)
GDP growth * lag Relative Income (Appreciations)		-0.00648** (0.00305)
GDP growth * lag Relative Income (Devaluations)		0.00498 (0.00317)
Inflation * lag Relative Income (Appreciations)		-0.0330*** (0.00772)
Inflation * lag Relative Income (Devaluations)		-0.0348*** (0.00622)
lag Unemployment rate * lag Relative Income (Appreciations)		-0.0000709** (0.0000285)
lag Unemployment rate * lag Relative Income (Devaluations)		-0.0000705*** (0.0000244)
Constant	0.105*** (0.00836)	0.109*** (0.00878)
Adjusted R^2	0.087	0.088
Observations	1,072,171	1,072,171
FE	Region-Year	Region-Year
Standard Errors	Cluster Region	Cluster Region

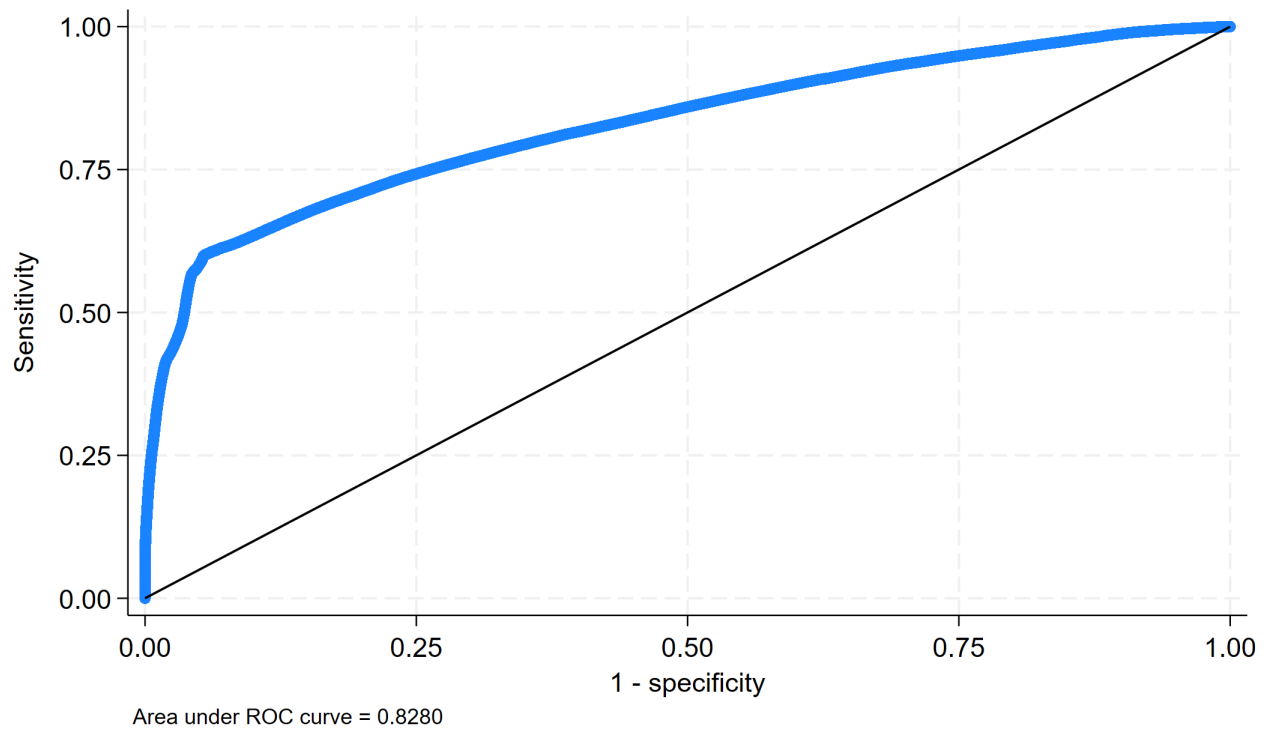
Table A.7: Quadratic Income

	(1)	(2)
lag Relative Income * dlog NER (Appreciations)	0.0139*** (0.00265)	0.0185*** (0.00372)
lag Relative Income * dlog NER (Devaluations)	-0.00222** (0.00108)	-0.00357** (0.00165)
lag Relative Income Squared* dlog NER (Appreciations)		-0.0000586*** (0.0000201)
lag Relative Income Squared* dlog NER (Devaluations)		0.0000158 (0.0000133)
lag Relative Income	-0.00337*** (0.000215)	-0.00381*** (0.000318)
lag Occupation	-0.00830*** (0.00102)	-0.00894*** (0.000947)
lag Education	0.0000889*** (0.0000168)	0.0000964*** (0.0000163)
lag Sex	-0.00737*** (0.00231)	-0.00972*** (0.00216)
lag Age	-0.000183 (0.000150)	-0.000150 (0.000152)
lag Relative Income Squared		0.00000487*** (0.00000157)
Constant	0.105*** (0.00836)	0.110*** (0.00793)
Adjusted R^2	0.087	0.089
Observations		
FE	Region-Year	Region-Year
Standard Errors	Cluster Region	Cluster Region

Table A.8: Employment and Income

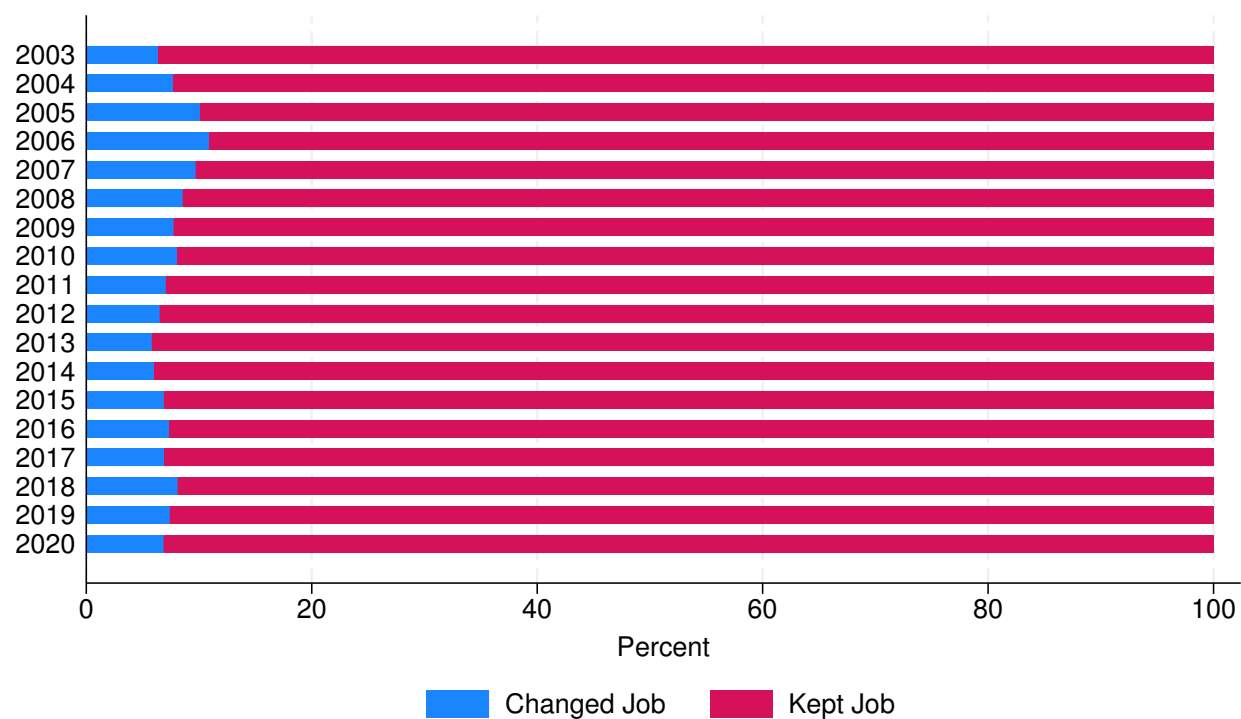
	(1) Baseline	(2) Controlling for Hours Worked
lag Relative Income * dlog NER (Appreciations)	0.0139*** (0.00265)	0.0146*** (0.00107)
lag Relative Income * dlog NER (Devaluations)	-0.00222** (0.00108)	-0.00207*** (0.000522)
lag Relative Income	-0.00337*** (0.000215)	-0.00404*** (0.0000441)
lag Occupation	-0.00830*** (0.00102)	-0.00827*** (0.000273)
lag Education	0.0000889*** (0.0000168)	0.0000926*** (0.00000842)
lag Sex	-0.00737*** (0.00231)	-0.000660 (0.00129)
lag Age	-0.000183 (0.000150)	0.000220*** (0.0000565)
lag Hours Worked (weekly)		-0.00179*** (0.0000362)
Hours Worked (weekly)		0.00361*** (0.0000354)
Constant	0.105*** (0.00836)	-0.0214*** (0.00423)
Adjusted R^2	0.087	0.140
Observations	1,072,171	1,072,171
FE	Region-Year	Region-Year
Standard Errors	Cluster Region	Cluster Region

Figure A.3: Area Under ROC - Union Logit Model



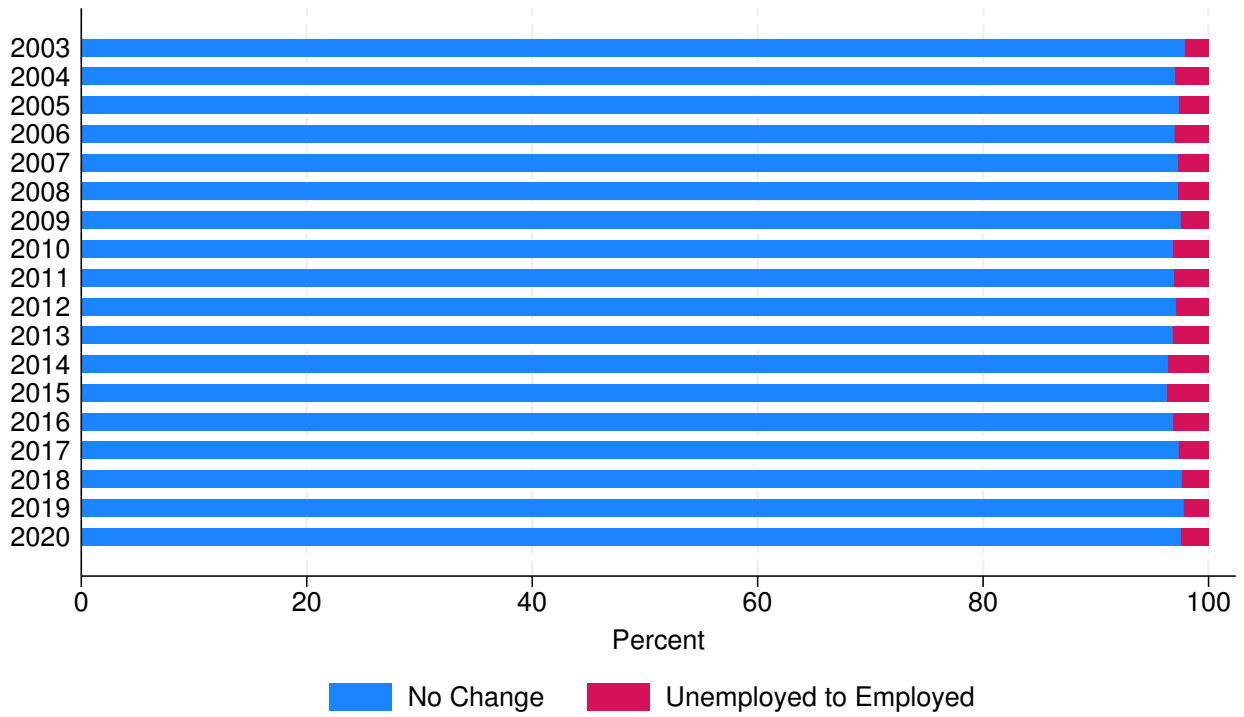
Notes. This figure show the area under the curve using logit predicted probabilities of union membership.

Figure A.4: Changed Jobs - Shares



Notes. This figures shows the share of observations per year where households reported an employer change.

Figure A.5: Unemployed to Employed - Shares



Notes. This figures shows the share of observations per year where households reported an employment status change (from unemployed to employed).

Table A.9: Logit Union

	(1) Logit Model
lag Relative Income * dlog NER (Appreciations)	0.0425*** (0.0118)
lag Relative Income * dlog NER (Devaluations)	-0.0138*** (0.00271)
lag Relative Income * dlog NER (Appreciations) * Logit Union Prob.	-0.0359** (0.0137)
lag Relative Income * dlog NER (Devaluations) * Logit Union Prob.	0.0140*** (0.00307)
lag Relative Income	-0.00327*** (0.000212)
lag Occupation	-0.00547*** (0.00161)
lag Education	0.000111*** (0.0000146)
lag Sex	-0.00610** (0.00269)
lag Age	-0.000250 (0.000160)
lag Logit Union Prob.	-0.593*** (0.125)
Constant	0.558*** (0.0915)
Adjusted R^2	0.091
Observations	903,877
FE	Region-Bin Income, Year
Standard Errors	Cluster Region-Bin Income

Table A.10: Job Changes

	(1) Changed Job
lag Relative Income * dlog NER (Appreciations)	0.0116*** (0.00389)
lag Relative Income * dlog NER (Devaluations)	-0.00333** (0.00138)
lag Relative Income * dlog NER (Appreciations) * Changed Job	0.0147 (0.00916)
lag Relative Income * dlog NER (Devaluations) * Changed Job	-0.00845*** (0.00296)
lag Relative Income	-0.00153*** (0.000252)
lag Occupation	-0.00386*** (0.00124)
lag Education	0.0000386** (0.0000170)
lag Sex	0.00313 (0.00220)
lag Age	-0.000422*** (0.000151)
Constant	0.0772*** (0.00873)
Adjusted R^2	0.058
Observations	935,678
FE	Region-Bin Income, Year
Standard Errors	Cluster Region-Bin Income

Table A.11: Unemployment to Employment

	(1) Changed Job
lag Relative Income * dlog NER (Appreciations)	0.0106*** (0.00342)
lag Relative Income * dlog NER (Devaluations)	-0.00293** (0.00131)
lag Relative Income * dlog NER (Appreciations) * U to E	0.0903*** (0.0125)
lag Relative Income * dlog NER (Devaluations) * U to E	-0.0291*** (0.00466)
lag Relative Income	-0.00152*** (0.000238)
lag Occupation	-0.00397*** (0.00118)
lag Education	0.0000379** (0.0000176)
lag Sex	0.00378* (0.00205)
lag Age	-0.000500*** (0.000153)
Constant	0.0809*** (0.00864)
Adjusted R^2	0.059
Observations	1,035,607
FE	Region-Bin Income, Year
Standard Errors	Cluster Region-Bin Income