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Abstract*

This paper studies the dynamics of vulnerable non-poor households in Latin America, focusing on how they compare with the poor and how both groups respond to macroeconomic fluctuations. Using harmonized household survey microdata from 15 countries over more than three decades (1992–2024), complemented with longitudinal data for four of the region's largest economies, we examine how the size of socioeconomic groups evolves with long-run economic growth and cyclical fluctuations and whether labor market responses to macroeconomic conditions differ systematically between poor and vulnerable individuals. We find that the share of vulnerable non-poor individuals has risen modestly, reflecting higher inflows from poverty than outflows to richer groups. While labor market outcomes are strongly procyclical for both poor and vulnerable individuals, a striking pattern emerges across countries: In less developed economies, vulnerable individuals experience significantly stronger cyclical changes in labor market outcomes than the poor, whereas the opposite pattern arises in more developed economies, particularly along employment margins. Exploiting longitudinal data, we further show that transitions into and out of vulnerability are driven primarily by changes in labor income, especially through employment and hourly earnings adjustments. Overall, the results highlight that the relationship between vulnerability and macroeconomic fluctuations depends critically on labor market structure, which shapes the adjustment margins available to different groups of workers

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1 Introduction

Over the last three decades, Latin America has experienced a substantial decline in poverty (Chang et al., 2025; Gasparini et al., 2023), yet a large share of the population remains concentrated just above the poverty line. These vulnerable non-poor households are not classified as poor under conventional definitions, but they still face a substantial risk of falling into poverty in the face of adverse shocks. Understanding the dynamics of this group is particularly relevant in a region characterized by recurrent macroeconomic instability, widespread labor market informality, and limited social protection systems (Levy and Schady, 2013; OECD, 2025).

While a large literature has examined poverty dynamics and labor market adjustment over the business cycle, much less is known about how vulnerable non-poor households respond to macroeconomic fluctuations and whether their responses differ systematically from those of the poor. This distinction is potentially important. Although both groups face economic insecurity, they may occupy different positions within the labor market, differ in their attachment to employment margins, and therefore adjust differently to changes in aggregate economic conditions. Understanding these heterogeneous responses is key to characterizing the nature of vulnerability in Latin America and the mechanisms through which macroeconomic fluctuations translate into changes in socioeconomic status.

This paper studies the dynamics of poor and vulnerable non-poor groups in Latin America, with a particular focus on their relationship with macroeconomic fluctuations. To this end, we draw on the Socio-Economic Database for Latin America and the Caribbean (SEDLAC, 2024), a large database of harmonized household surveys developed by CEDLAS and the World Bank, covering 15 Latin American countries over the period 1992–2024. Throughout the paper, we classify individuals into three groups based on daily household per capita income measured in 2017 PPP US dollars: the poor, with incomes below USD 6.85; the vulnerable non-poor, with incomes between USD 6.85 and USD 14; and the non-vulnerable, with incomes above USD 14. The analysis combines repeated cross-sectional information for the full sample of countries with longitudinal data for four of the region's largest economies—Argentina, Brazil, Chile, and Peru—allowing us to examine both aggregate changes in the size of socioeconomic groups and individual labor market responses over the business cycle.

We first examine how the size of these groups evolved over the last three decades and how these changes correlate with long-run economic growth and cyclical economic fluctuations. To distinguish between long-run and cyclical movements, we decompose GDP per capita into trend and cyclical components using a Hodrick-Prescott filter (Hodrick and Prescott, 1997). We document two main patterns. First, the share of vulnerable non-poor individuals increased, driven by a greater incidence of transitions from poverty into vulnerability than from vulnerability into the non-vulnerable. This increase reinforces the view of vulnerability as a quantitatively important and persistent socioeconomic condition in Latin America. Second, while long-run economic growth is associated with a moderate expansion of the vulnerable group, negative cyclical fluctuations tend to increase its size, suggesting that macroeconomic conditions induce substantial movements across socioeconomic groups. These patterns are consistent with the idea that the vulnerable non-poor function as a transition group within the region's income distribution.

We then examine whether labor market outcomes of the poor and the vulnerable non-poor respond differently to macroeconomic conditions. A central empirical challenge is that labor market outcomes and socioeconomic status may be jointly determined by contemporaneous economic conditions. To address this issue, we implement two complementary strategies. First, for a subset of countries with longitudinal data, we classify individuals into socioeconomic groups based on lagged household income and examine how subsequent labor market outcomes evolve with macroeconomic conditions. Second, using repeated cross sections for the full sample of countries, we classify individuals according to predicted household income constructed from predetermined characteristics. Both approaches yield similar patterns. Across all countries, labor market outcomes are strongly procyclical for both groups: Periods of above-trend economic activity are associated with higher employment, lower unemployment and informality, and higher wages and earnings. However, the relative magnitude of these responses differs systematically across countries with different labor market structures.

In economies with higher levels of poverty, informality, and rurality, vulnerable individuals tend to experience stronger labor market improvements during economic expansions than the poor. In contrast, in more developed economies, the poor often exhibit larger cyclical responses, particularly along employment margins. These patterns suggest that the relationship between vulnerability and macroeconomic fluctuations depends critically on the structure of labor markets. In less developed economies, poor individuals are more likely to be concentrated in low-productivity activities with limited scope for cyclical adjustment, while vulnerable individuals appear better positioned to benefit from economic expansions. By contrast, in more developed economies, poor individuals exhibit stronger attachment to the employment and unemployment margins, making their labor market outcomes more responsive to cyclical fluctuations.

Finally, exploiting the longitudinal data available for a subset of countries, we examine transitions into and out of vulnerability, thereby linking the cyclical labor market responses with changes in socioeconomic status. We document substantial movement into and out of vulnerability over the economic cycle and show that transitions are driven primarily by changes in labor income rather than other income sources or household composition. We further show that, within labor income, both the employment and earnings margins matter, with changes in hourly labor income playing a particularly important role in transitions into and out of vulnerability.

This paper relates to several strands of the literature. First, it contributes to work on vulnerability and the vulnerable non-poor in developing countries, which emphasizes that a large share of households above the poverty line remain exposed to adverse shocks and cannot be considered economically secure (Banerjee and Duflo, 2008; Birdsall et al., 2014; López-Calva and Ortiz-Juarez, 2014; OECD, 2019). Second, it relates to the literature examining labor market adjustment over the business cycle in Latin America, particularly the role of the informality and employment margins in shaping responses to macroeconomic fluctuations (Bosch and Maloney, 2010; Fernández and Meza, 2015; Coşkun, 2022). Our contribution is to bring these strands of the literature together by examining how labor market responses to cyclical fluctuations differ between poor and vulnerable non-poor individuals, how these differences vary across labor market structures in the region, and how they translate into transitions across socioeconomic groups over the cycle.

The rest of the paper is organized as follows. Section 2 describes the main data sources and the construction of the harmonized database used throughout the analysis. Section 3 discusses the definition and operationalization of the vulnerable non-poor group and presents its main demographic, educational, and labor market characteristics. Section 4 examines the evolution of socioeconomic groups and their relationship with long-run economic growth and cyclical fluctuations. Section 5 analyzes how labor market outcomes of poor and vulnerable individuals respond to macroeconomic conditions and whether these responses differ systematically across socioeconomic groups and countries. Section 6 exploits longitudinal data to study transitions across socioeconomic groups over the economic cycle and the labor market mechanisms underlying those transitions. Section 7 concludes.

2 Data

We mainly rely on microdata drawn from national household surveys compiled in the Socioeconomic Database for Latin America and the Caribbean (SEDLAC), a long-standing collaboration between CEDLAS at Universidad Nacional de La Plata and the World Bank. Despite well-known limitations—such as measurement errors, non-response biases, and variations in survey quality—household surveys remain the most comprehensive and reliable source of socioeconomic information on Latin American populations. Once harmonized, they allow researchers to classify individuals into socioeconomic groups and construct comparable indicators at both the national and regional levels. Importantly, they also make it possible to analyze long-term dynamics for the whole region: The dataset used in this study spans more than three decades (1992–2024) and is based on nationally representative information from 15 Latin American countries. We include countries for which recent household survey microdata spanning at least two decades are available, enabling us to study labor market outcomes. Specifically, we use data from Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, the Dominican Republic, Ecuador, El Salvador, Honduras, Mexico, Panama, Paraguay, Peru, and Uruguay. Table A.1 in the Appendix lists the surveys used in this study.[1]

These surveys are harmonized following the protocol of SEDLAC (2024). Given that household surveys in Latin America differ in structure, questionnaire design, and methodological approaches—not only across countries but sometimes also over time within the same country—ensuring the surveys are comparable is a key challenge. SEDLAC addresses this issue by applying a standardized and common methodology across countries in the region, enabling construction of consistent and comparable labor, distributional, and other socioeconomic variables. In line with this approach, we apply uniform definitions and data processing procedures to facilitate cross-country comparison of the indicators used throughout our analysis.

We conduct the analysis using all available surveys since 1992 (see Table A.2 in the Appendix). The dataset comprises 386 national household surveys from 15 countries, covering nearly 50 million individuals.[2] This extensive sample ensures broad representation of the Latin American population and labor force while providing high statistical power to analyze cross-country and group-level heterogeneity. However, for expositional simplicity, the paper focuses primarily on regional averages. Throughout the paper, unless otherwise noted, all reported means are unweighted. In particular, the Latin American average is computed as a simple average across the 15 countries, assigning equal weight to each country and thus better capturing the situation of a typical country in the region, rather than being driven by the largest economies, such as Brazil and Mexico.

In addition to the repeated cross-sectional data, we construct short panel datasets for four countries over the following periods: Argentina (2003–24), Brazil (2005–22), Chile (2011–22), and Peru (2005–23). The data are drawn from household or employment surveys, depending on the country and period. Although survey designs differ across countries—in terms of rotation schemes, interview frequency, and the number of times individuals are observed—all datasets allow individuals to be followed over time within households, making it possible to construct short panels. For the purposes of this analysis, we harmonize the panel structure across countries by focusing on pairs of observations for the same individual observed one year apart. Additional details on the construction of these panels are provided in Section 5.1.

[1] The Argentinean survey (EPH) only covers urban areas, which may introduce some bias into the estimations. However, given that over 93% of Argentina's population resides in urban areas, the potential bias is likely to be limited.

[2] For the cross-country analysis, we use a 10% country–year sample to keep processing times manageable. Reassuringly, for a subset of key outcomes, estimating our main specifications on both the 10% sample and the full sample yields only minor differences in magnitudes and statistical significance, leaving the core conclusions unchanged. For the panel data analysis, we rely on the full sample.

3 The vulnerable non-poor

This paper primarily focuses on comparing two groups: the poor and the vulnerable non-poor. Intuitively, the distinction is clear. The poor are those whose resources are insufficient to meet basic needs, a condition marked by deprivation and urgency. The vulnerable non-poor, by contrast, are not classified as poor under standard definitions, yet their living standards remain precarious. They thus have limited protection against adverse shocks and therefore face substantial risk of falling into poverty.

Translating this intuition into operational measures has proved highly challenging. In this section, we first provide an operational definition of the poor and the vulnerable non-poor, then characterize these groups along a range of socioeconomic and labor market dimensions.

3.1 Defining the vulnerable

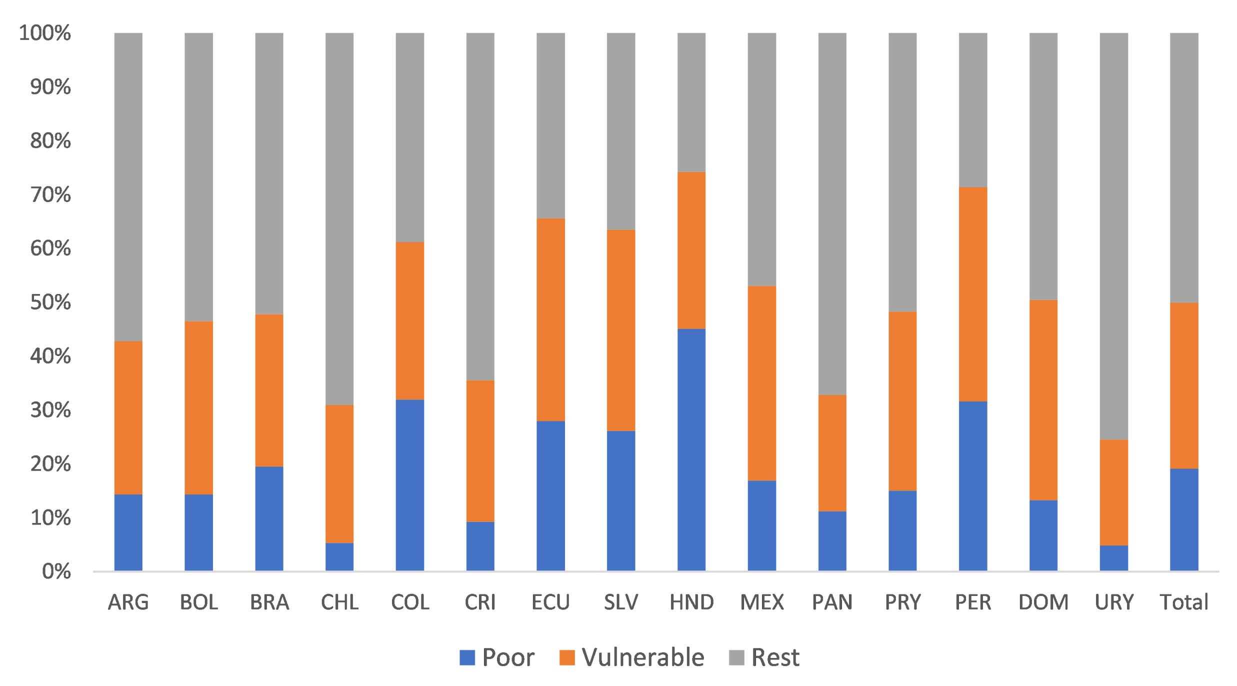
Two difficulties stand out in the vast literature that seeks to divide the population into socioeconomic groups—including the extensive literature on poverty measurement, as well as work on social classes, polarization, and vulnerability (Atkinson, 1987; Esteban and Ray, 1994; Sen, 1976): (i) Individual well-being is inherently multidimensional, and (ii) each dimension is continuous. To address the first challenge, researchers typically select a limited set of welfare dimensions—most often a monetary indicator, such as income or expenditures—as a proxy for the others. To address the second, they apply somewhat arbitrary thresholds to define the groups.

In light of these challenges, we make two methodological decisions. First, we use household per capita income as the measure of individual well-being. While this choice has well-known limitations, it is widely accepted, serving as a standard proxy for well-being in both academic research and official national estimates of poverty and inequality. Second, based on their incomes, individuals are classified into three groups using daily income thresholds expressed in 2017 PPP US dollars (USD): (i) the poor (P), with incomes below USD 6.85 per day; (ii) the vulnerable non-poor (V), with incomes between USD 6.85 and USD 14 per day; and (iii) the rest (R), with incomes above USD 14 per day.

The choice of USD 6.85 and USD 14 as thresholds follows conventions established in the literature. The value of USD 6.85 corresponds to the World Bank's upper-middle-income poverty line, which is widely applied to countries in Latin America and captures individuals who still face clear material deprivations. The upper bound of USD 14 has been proposed in studies of the region as a reasonable cutoff for distinguishing the vulnerable from the middle class since households below this level continue to face a substantial risk of falling into poverty when exposed to adverse shocks (e.g., López-Calva and Ortiz-Juarez, 2014). Using these thresholds thus ensures comparability with existing studies and provides a pragmatic way of separating groups that differ in their degree of economic security. Under these thresholds, the average income among the vulnerable was USD 10.3 per day in 2024, 2.4 times that of the poor and around one-third of the average of the rest of the population. This value is remarkably similar across countries, ranging from USD 9.8 in Honduras to USD 10.9 in Uruguay (see Table A.3 in the Appendix).

Figure 1 reports the share of individuals in each socioeconomic group by country in 2024 (or the closest available year for countries without a survey in that year). Under our benchmark definition, the vulnerable account for an average of 30.8% of the population across Latin American countries. While this share ranges from about 20% in Uruguay to nearly 40% in Peru, most countries cluster around the regional average: In 9 out of 15 countries, the deviation from the regional mean is less than 5 percentage points.

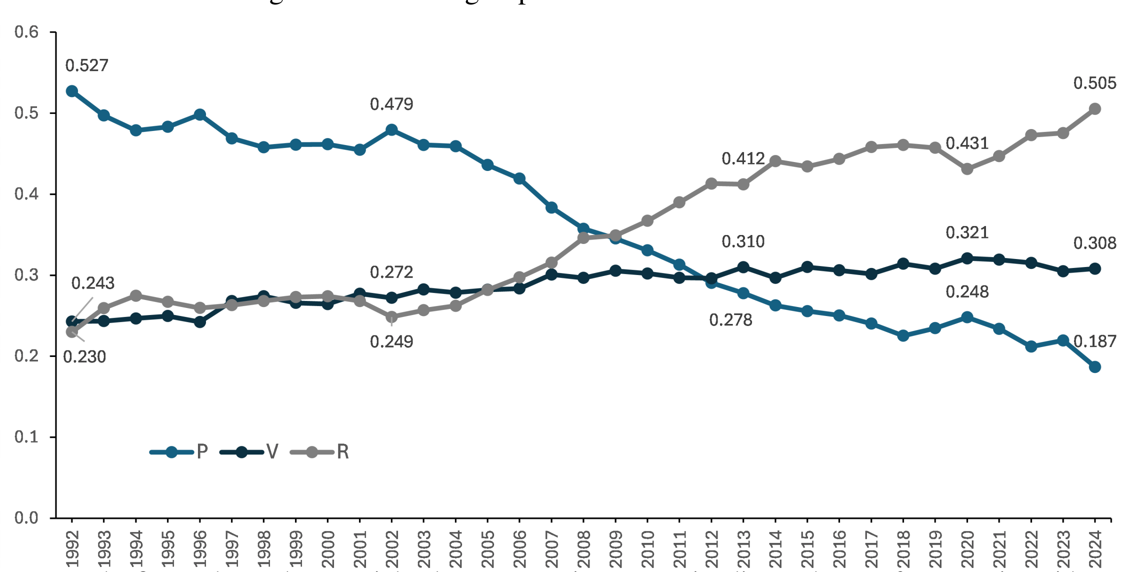
Figure 1: Groups of vulnerability by country - 2024



Source: Authors' own calculations based on microdata from national household surveys.

Figure 2 reveals an increase in the share of the vulnerable group V in Latin America over time. The increase was modest: The mean share rose from 24% in 1992 to 31% by 2013 and remained close to that level in the following decade. In contrast, these three decades witnessed an extraordinary reduction in poverty and a marked expansion of the non-vulnerable group. In the early 1990s, the mean share of Latin American people living in poverty was 52.7%. By 2024, that share had declined to 18.7%. The mirror image of this decline is the marked expansion of the non-vulnerable group (R), whose mean share rose from 23% in 1992 to 50.5% in 2024.[3] In Section 4, we revisit these dynamics and examine how movements across socioeconomic groups—particularly into and out of vulnerability—are shaped by the business cycle.

Figure 2: Share of groups over time - 1992-2024. Latin America.



Notes: The figure shows the unweighted mean over time, assuming linear changes for countries with no information in a given year.
Source: Authors' own calculations based on microdata from national household surveys.

3.2 Characterizing the vulnerable

Table 1 characterizes the vulnerable non-poor (V), the poor (P), and the non-vulnerable (R) by reporting key demographic, educational, and labor market indicators for the Latin American average in 2024. Country-level statistics are presented in Tables B.1 to B.3 in Appendix B .

Demographics

Panel (b) of Table 1 summarizes demographic differences across socioeconomic groups.[4] The vulnerable population occupies an intermediate position between the poor and the non-vulnerable, with a clear demographic gradient across these groups. On average, the vulnerable are 31 years old and older than the poor, and children represent a smaller share of the group (34%) while prime-age (55%) and elderly adults (11%) represent larger shares. Gender composition follows

[3]These general results do not significantly change for reasonably small changes in the thresholds. For instance, while the share of V increases by 6.5 percentage points over the full period (1992–2024) under our benchmark definitions, the increase rises to 9 percentage points when both thresholds are raised by 10% and falls to 2 percentage points when they are lowered by 10%. In both exercises, the share of V barely changes between 2013 and 2024.

[4]Table B.4 in Appendix B reports similar results based on regressions with country fixed effects, along with their corresponding standard errors. Country-level descriptive statistics are presented in Table B.1.

Table 1: Descriptive statistics by income group. Latin American average, 2024

	P	V	R	Total	V-P	V-R
(a) Group share	18.7	30.8	50.5	100	12.1	-19.7
(b) Demographics						
Mean age	26.6	31.2	39.4	34.7	4.6	-8.2
Share [0,14]	45.7	34.4	17.2	27.5	-11.3	17.2
Share [65+]	7.2	10.7	17.3	13.8	3.5	-6.6
Share [25,64]	47.1	54.9	65.5	58.7	7.8	-10.6
Share women [25,64]	57.1	55.0	50.2	52.6	-2.1	4.8
Household size	4.1	3.6	2.7	3.1	-0.5	0.9
Number of children	1.8	1.3	0.6	1.1	-0.5	0.7
Dependency rate	2.4	1.9	1.4	1.7	-0.5	0.5
Share urban	61.0	72.7	83.2	76.3	11.7	-10.5
(c) Education						
Years of education [25–65]	7.7	8.9	11.6	10.2	1.2	-2.7
Years of education [25–35]	9.1	10.5	13.0	11.6	1.4	-2.5
Years of education [36–45]	8.0	9.4	12.1	10.5	1.4	-2.7
Years of education [46–65]	6.2	7.3	10.4	9.0	1.1	-3.1
Share low education [25–65]	64.4	55.3	35.3	47.0	-9.1	20.0
Share medium education [25–65]	27.7	34.7	37.1	34.5	7.0	-2.4
Share high education [25–65]	7.9	10.0	27.6	18.6	2.1	-17.6
Gross enrollment rates [13–17]	86.4	90.6	92.2	90.0	4.2	-1.6
Gross enrollment rates [18–23]	29.5	38.6	51.4	43.2	9.1	-12.8
(d) Labor market						
Labor force participation	64.4	72.9	83.1	77.2	8.5	-10.2
Female labor force participation	48.9	59.6	73.9	65.3	10.7	-14.3
Employment	55.7	67.3	80.7	73.4	11.6	-13.4
Unemployment	14.0	7.8	2.9	5.0	-6.2	4.9
Duration of unemployment	3.8	5.6	5.1	4.9	1.8	0.5
Informality productive	77.6	59.4	35.9	46.9	-18.2	23.5
Informality social protection	81.6	65.6	40.6	51.6	-16.0	25.0
Hourly wages	2.3	3.6	7.4	5.9	1.3	-3.8
Hours of work	36.2	40.3	43.3	41.7	4.1	-3.0
Earnings	310.6	568.8	1254.5	983.2	258.2	-685.7

Notes: *P* (Poor), *V* (Vulnerable), and *R* (Rest) are defined as in Section 3. All *Share* variables are expressed as percentages (multiplied by 100). *Children [0,14]* is a dummy variable equal to 1 if the individual is aged between 0 and 14; similar definitions apply to *Share [65+]* and *Share [25,64]*. *Woman [25,64]* is a dummy equal to 1 if the individual is female and within the 25–64 age range. *Household size* indicates the total number of household members. *Number of children* counts household members aged 0–14. *Dependency rate* is computed as household size divided by the number of income earners in the household. *Share urban* indicates residence in urban areas. *Years of education* measures completed years of formal schooling for the specified age ranges. Low, medium, and high education refer to 0–8, 9–13, and 14+ years of education, respectively. *Gross enrollment rates* measure school attendance for the specified age ranges. *Labor force participation*, *Employment*, and *Unemployment* follow standard ILO definitions. *Female labor force participation* is restricted to women aged 25–64. *Duration of unemployment* is measured in months. *Informality productive* classifies salaried workers based on firm size, while *Informality social protection* uses access to social security or pension contributions; in both measures, employers are formal, unpaid workers are informal, and self-employed are formal if they are professionals. *Hourly wages* is labor earnings divided by hours worked; *Hours of work* refers to weekly hours in the main occupation; *Earnings* refers to monthly total labor income. All monetary variables are in PPP-adjusted 2017 USD.
Source: Own calculations based on microdata from national household surveys.

a similar pattern, with women accounting for 55% of prime-age individuals. Household characteristics reinforce this gradient. Vulnerable households average 3.6 members and 1.3 children, implying a dependency rate of 1.9, and are thus substantially less burdened than poor households, whose dependency rate is 2.4. Finally, residential patterns also vary systematically: About 73% of the vulnerable reside in urban areas, consistent with a steady increase in urbanization along the income distribution.

Overall, the vulnerable lie closer to the poor than to the non-vulnerable, as reflected in larger gaps between V and R than between V and P across most indicators. Table B.5 and Figure B.1 in Appendix B show that these patterns display meaningful dynamics. Age structure and gender composition increasingly differentiate the three groups over time, with the vulnerable drifting away from both the poor and the non-vulnerable, but particularly the latter, whereas, in terms of household structure and location, they converge toward the poor and diverge from the non-vulnerable.

Education

Panel (c) of Table 1 reports educational indicators.[5] As expected, education exhibits a strong socioeconomic gradient, with the vulnerable occupying an intermediate position across all indicators. Average schooling among vulnerable adults aged 25–65 reaches 8.9 years and rises markedly for younger cohorts (10.5 years among those aged 25–35, compared to 7.3 among those aged 46–65), reflecting substantial educational progress. At the same time, differences across income groups have narrowed across cohorts, although sizable socioeconomic disparities persist. This pattern is mirrored in the distribution of educational attainment. The share of adults with low education remains strikingly high among the vulnerable (55%), much closer to the poor than to the non-vulnerable. Consistent with this pattern, school enrollment among young adults is only 39% for the vulnerable, well below the 51% observed among the non-vulnerable. By contrast, enrollment among adolescents aged 13–17 exceeds 90% for both the vulnerable and the non-vulnerable, with almost no difference between the two groups, while the gap with the poor remains sizable. This suggests that near-universal access to lower-secondary schooling largely equalizes enrollment between V and R, but not fully for P.

Table B.7 and Figure B.2 in Appendix B document a dual dynamic. While the expansion of basic and secondary education has narrowed gaps at lower levels—particularly among younger cohorts—differences remain pronounced and increasingly concentrated at the upper end of the income distribution, driven by faster gains in tertiary attainment among the non-vulnerable.

[5] Table B.6 in Appendix B reports similar results based on regressions with country fixed effects. Country-level descriptive statistics are presented in Table B.2

Labor market

We next examine the labor market outcomes reported in Panel (d) of Table 1.[6] As with previous dimensions, a clear socioeconomic gradient emerges, with the vulnerable occupying an intermediate position across all indicators. The vulnerable exhibit relatively strong labor market attachment: Labor force participation reaches 73%, employment 67%, and average hours worked 40 per week. At the same time, unemployment (7.8%) and informality rates (60%, taking the productive definition) remain substantial, although markedly lower than among the poor. Part of the gradient is mechanical, however, as socioeconomic status is defined based on current income: Individuals experiencing job loss are more likely to fall into poverty. Notably, unemployment duration is longer among the vulnerable (5.6 months) than among the poor. This may reflect selection, as individuals exiting unemployment are also more likely to exit poverty, or differences in search behavior, with more resources allowing the vulnerable to sustain longer job searches. Earnings-related indicators reinforce the gradient. Hourly wages among the vulnerable average USD 3.6 (PPP 2017) and, combined with higher employment and longer working hours, translate into substantially higher monthly earnings than among the poor—around 45% higher—yet still far below those of the non-vulnerable, whose earnings are more than twice as high.

Table B.9 and Figure B.3 in Appendix B reveal different dynamics. While between-group gaps in participation, employment, unemployment, and informality have widened, gaps in wages and earnings have narrowed, pointing to convergence in income-related dimensions despite persistent disparities in labor market attachment.

4 The size of income groups over the economic cycle

As discussed in Section 3, the size of the vulnerable non-poor group (V) has increased modestly over the past three decades, rising on average from 24.3% to 30.8% across Latin American countries, in contrast to a sharp contraction of the poor (P) and a marked expansion of the non-vulnerable population (R), which highlights the distinct position of V as a transition group and motivates a closer examination of how the sizes of all three groups respond to economic growth and cyclical fluctuations.

4.1 Accounting for changes in the size of the vulnerable group

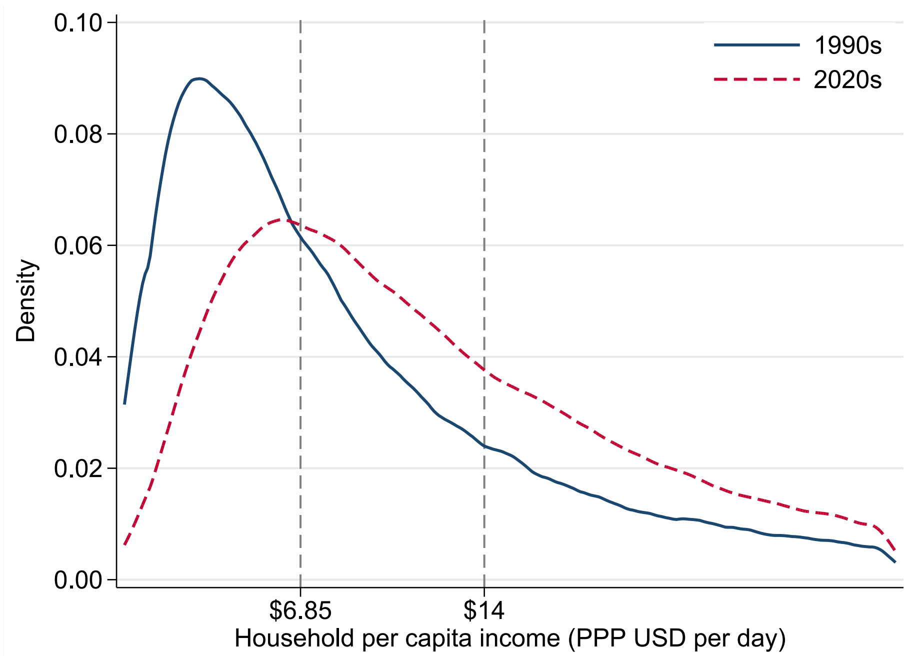
We begin by examining two statistical factors that may account for the slow gradual rise in the share of the vulnerable non-poor in Latin America: (i) the position of the thresholds defining group V

[6]Table B.8 in Appendix B reports similar results based on regressions with country fixed effects. Country-level descriptive statistics are presented in Table B.3.

within the income distribution, and (ii) non-uniform income changes along the distribution.

Consider a small horizontal shift in the (log) income distribution. The share of group V in the population will increase if the density around its lower threshold (USD 6.85) is higher than around its upper threshold (USD 14). To illustrate this point, Figure 3 presents a non-parametric estimation of the income distribution density for our pooled sample of Latin American countries. The figure shows estimated densities for two periods—the 1990s and the 2020s. Although the distributions have shifted over time, the pattern remains similar: The density around the lower threshold is substantially higher than around the upper threshold. This asymmetry helps explain, at least in part, the observed increase in the share of group V.[7]

Figure 3: Density household per capita income - Latin America



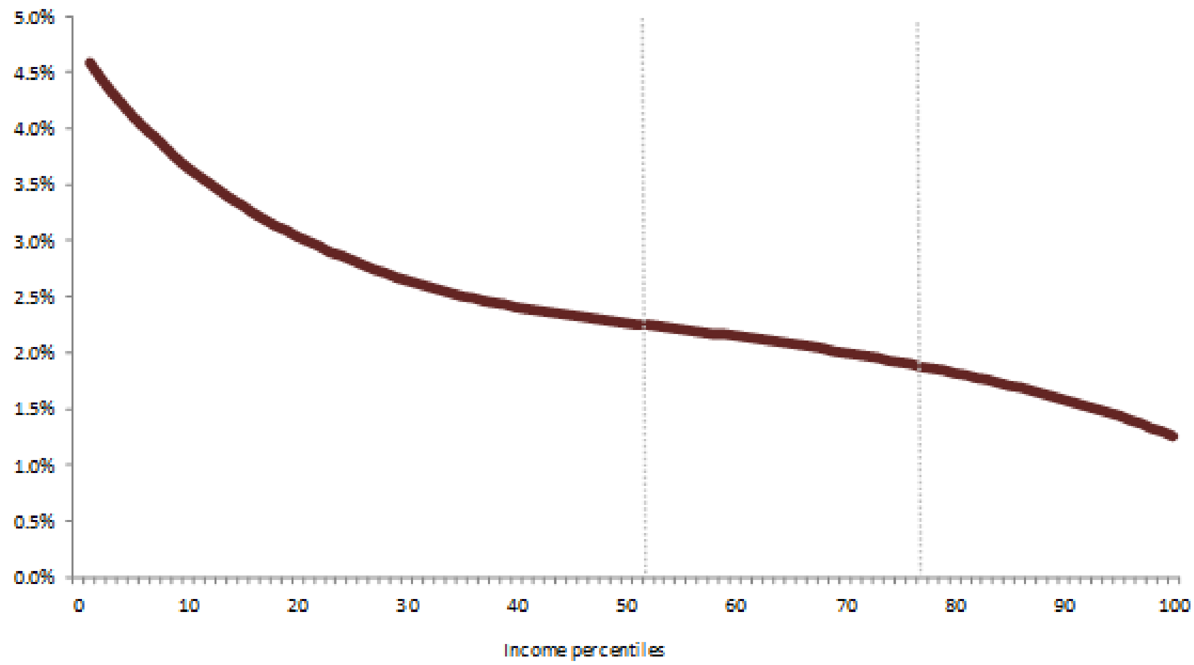
Notes: The figure shows a non-parametric estimation of the density function of the household income distribution in the pooled sample of Latin American countries.
Source: Authors' own calculations based on microdata from national household surveys. The figure shows a non-parametric estimation of the density function of the household income distribution in the pooled sample of Latin American countries.

A second factor that may contribute to the increase in the share of group V is non-uniform income growth along the distribution. In particular, if income growth rates are higher around the lower threshold of group V than around its upper threshold, this asymmetry may generate more entries into vulnerability than exits from it. Figure 4 presents the unweighted mean growth

[7] Naturally, this result depends on the thresholds used to define the groups. However, the difference between the densities at the two thresholds is sufficiently large that the results discussed in this paragraph are robust to substantial changes in those thresholds.

incidence curve for Latin America over the period 1992–2024.[8] The curve is clearly decreasing in income, implying that for any selected thresholds, income growth has been stronger at lower income levels. This pattern is consistent with an increase in the size of group V over time.

Figure 4: Growth incidence curve - Latin America 1992-2024



Notes: The figure shows the unweighted growth incidence curves for 15 Latin American countries. The vertical lines show the percentiles that define group V in the initial year (1992).
Source: Bracco et al. (2025).

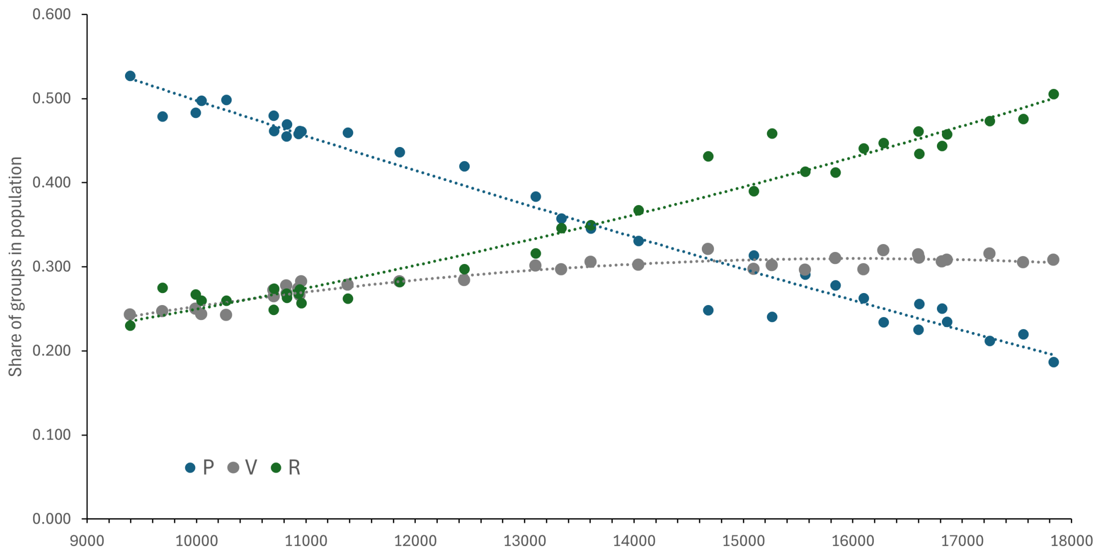
4.2 Elasticities of income group shares with respect to GDP

We now turn to a closer examination of the relationship between economic growth and the size of income groups. Figure 5 provides a first descriptive look at how group sizes relate to aggregate economic conditions, plotting the population share of each income group against per capita GDP—measured in constant 2017 PPP US dollars and sourced from the International Monetary Fund—for the Latin American average. As expected, the share of the poor is highly sensitive to economic growth, with an arc elasticity of -1.5 over the entire period. This implies that if past trends were to continue, a country growing at about 2% per year over three decades could reduce poverty from above 50% to below 20%. The elasticity for the non-vulnerable group is also large, at 1.2. By contrast, the elasticity for the vulnerable non-poor group is considerably smaller, around 0.4,

[8] See Bracco et al. (2025) for a discussion on the calculations of growth incidence curves in Latin America.

indicating that its size has increased with economic growth only modestly on average.[9]

Figure 5: Scatterplot share of each group and per capita GDP



Notes: The figure shows the unweighted mean over time, assuming linear changes in the share of each group for countries with no information in a given year.
Source: Authors' own calculations based on microdata from national household surveys.

Similar patterns emerge from country-level data. Table 2 reports the results from estimating simple models of the (log) share of each socioeconomic group as a function of (log) GDP per capita, including country fixed effects. The estimates in the first row confirm a pronounced decline in poverty as economies grow, mirrored by a substantial expansion of the non-vulnerable group, alongside a more modest but statistically significant increase in the share of the vulnerable non-poor.[10]

These results reflect average responses of group sizes to long-run economic growth, without distinguishing between trend-driven changes and short-run fluctuations around the trend. To explore how group shares shift over the business cycle, we decompose log GDP per capita into its

[9]Figure A.1 in the Appendix shows that as log GDP per capita rises, every country records a lower poverty share. At the same time, the share of the vulnerable non-poor generally rises, indicating movement out of poverty without a proportional escape from vulnerability.

[10]The resulting semi-elasticities—where the left-hand-side variable is the group share—are -0.447 for P, 0.068 for V, and 0.378 for R.

cyclical and trend components using a Hodrick-Prescott filter (Hodrick and Prescott, 1997).[11] A positive value of the cyclical component indicates that GDP per capita is above its long-run trend (economic expansion), while a negative value indicates that GDP per capita is below trend (economic contraction). Figure 6 depicts the evolution of log GDP per capita for the Latin American average together with its estimated trend and cyclical components. The trend component indicates sustained long-run growth in the region, while the cyclical component highlights recurrent fluctuations around that path. In particular, the slowdown in the early 2000s, the contraction associated with the Global Financial Crisis of 2009, and the sharp decline during the COVID-19 pandemic emerge as the most pronounced cyclical downturns in the period.[12] The correlation between total GDP per capita growth and its cyclical component is very high (0.972), suggesting that the cyclical fluctuations identified here largely overlap with the broad phases of aggregate economic activity. As a result, interpretations associated with positive and negative cyclical movements can be extended to economic expansions and contractions, respectively.

Table 2: Elasticities of group shares with respect to (log) GDP per capita, and their cycle and trend components

	P	V	R
GDP pc	-1.530***	0.230**	1.127***
	(0.0503)	(0.0340)	(0.0125)
Components of GDP pc			
Cycle	-1.376***	-0.474**	1.173***
	(0.3327)	(0.2224)	(0.2811)
Trend	-1.535***	0.253***	1.126***
	(0.0501)	(0.0341)	(0.0135)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' own calculations based on microdata from national household surveys.

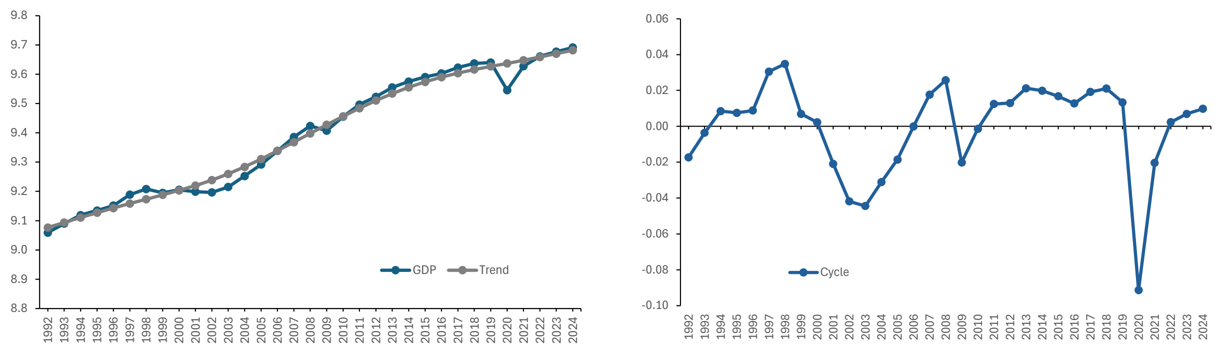
[11] The Hodrick-Prescott filter decomposes a time series y_t into a trend component τ_t and a cyclical component c_t such that $y_t = \tau_t + c_t$. The trend is obtained by solving a penalized least squares problem that minimizes the sum of squared deviations of the series from the trend, subject to a smoothness penalty on the second difference of the trend component. We set the smoothing parameter to $\lambda = 100$, a conventional choice for annual data. We assess the sensitivity of our results to changes in the smoothing parameter of the Hodrick-Prescott filter and to the use of three alternative filters: the Baxter-King band-pass filter (Baxter and King, 1999), the Christiano–Fitzgerald band-pass filter (Christiano and Fitzgerald, 2003), and a Butterworth filter (Gomez, 2001). Our results are robust across all specifications. They also hold when we instead include log GDP per capita and control for a linear trend. Additional results are available upon request.

[12] Results are broadly similar across countries. Appendix Figure A.2 illustrates the cases of three large countries (Brazil, Chile, and Peru), which are examined in greater detail in the following sections.

Figure 6: Average GDP per capita in Latin America: Trend and cycle components from a Hodrick-Prescott decomposition

(a) Log GDP and trend component

(b) Cycle component



Notes: Values in logs. GDP cyclical component in percent deviations from trend.
Source: Authors' own calculations based on GDP values from International Monetary Fund.

The decomposition allows us to estimate models of the (log) share of each socioeconomic group as a function of the cycle and trend components, based on the pooled sample, including country fixed effects. The second panel in Table 2 presents the results. As in the first row, the elasticities of V are smaller in absolute value than those of P and R, with respect to both the trend and cyclical components of GDP per capita. Interestingly, V is the only group for which the elasticity with respect to the cyclical component changes sign relative to the trend. While the trend elasticity is positive—consistent with the long-run forces discussed above—the cyclical elasticity is negative. An implication is that temporary contractions lead to net inflows into group V, with more individuals entering vulnerability—likely from the non-vulnerable group (R)—than exiting it, most plausibly toward the poor (P). One interpretation is that vulnerable households are able to cope relatively well during short downturns, avoiding a large-scale slide into poverty. If so, the vulnerable may be less vulnerable than the label suggests.

5 Labor responses over the economic cycle

In this section, we shift the focus from changes in group sizes to the labor market mechanisms underlying those changes. Specifically, we analyze how labor market outcomes are associated with macroeconomic fluctuations, and whether these patterns differ systematically between poor and vulnerable non-poor individuals. To this end, we estimate the following specification:

$$\begin{aligned} L_{ict} = {} & \alpha + \beta V_{ict} + \gamma_1\, cycle_{ct} + \gamma_2 (cycle_{ct} \cdot V_{ict}) \\ & + \delta_1\, trend_{ct} + \delta_2 (trend_{ct} \cdot V_{ict}) + X'_{ict}\theta + \lambda_c + \varepsilon_{ict} \end{aligned} \quad (1)$$

Here, L_{ict} denotes labor market outcomes of individual i in country c and year t, including labor force participation, employment, unemployment, informality, hourly wages, and earnings.[13] The variable V_{ict} is an indicator equal to 1 if the individual belongs to the vulnerable non-poor group, with the poor (P) as the reference category. The variables $cycle_{ct}$ and $trend_{ct}$ correspond to the cyclical and trend components of log real GDP per capita, respectively, obtained from the Hodrick-Prescott decomposition discussed in the previous section. This decomposition allows us to distinguish between short-run macroeconomic fluctuations and longer-run changes in economic conditions. The interaction terms with V_{ict} allow these associations to differ between poor and vulnerable individuals. The vector X_{ict} includes individual and household characteristics—such as gender, age, and education—as well as country fixed effects (λ_c) and a dummy variable capturing the effects of the COVID-19 pandemic.[14]

Our main parameters of interest are γ_1 and γ_2, which capture how labor market outcomes are associated with short-run macroeconomic fluctuations. Specifically, the coefficient γ_1 reflects how outcomes for the poor vary with the cyclical component of GDP, while γ_2 captures the differential association for vulnerable non-poor individuals. The total effect for individuals in V is thus given by $\gamma_1 + \gamma_2$.

A central empirical challenge is that both labor market outcomes and socioeconomic status may be jointly determined by contemporaneous economic conditions. In particular, when individuals are classified into groups based on current income, transitory shocks to labor market outcomes may mechanically affect group membership, potentially biasing the estimated differential responses.

To mitigate this concern, we implement two alternative empirical strategies. First, for a subset of countries with available longitudinal data, we construct a panel dataset that allows us to define socioeconomic group membership of individuals observed at time t based on their lagged per capita household income observed at time $t-1$. This approach weakens the mechanical link between current labor outcomes and group classification but comes at the cost of reduced sample size and limited country coverage. The results are presented in Section 5.1.

Second, we classify individuals observed at time t into socioeconomic groups using predicted per capita household income constructed from predetermined characteristics. We estimate income equations using cross-sectional data from year $t-1$ and apply the resulting coefficients to indi-

[13]Serrano et al. (2019) use a similar model to examine gender differences in labor force participation responses over the economic cycle in Latin America.

[14]We normalize survey weights within each country–year cell so that each country–year contributes equally to the analysis, regardless of population size. This normalization prevents large countries such as Brazil or Mexico from dominating the regional estimates and allows us to interpret the estimates as reflecting patterns that are representative of the average country–year in the region. In practice, the individual weights are divided by the sum of weights within each country–year, and the resulting normalized weights are used as probability weights in the regressions. As robustness checks, we also estimate models using unadjusted population weights, so that the results reflect the average individual in the region, and specifications in which normalization is carried out at the country rather than the country–year level. The results are highly consistent across these alternative weighting schemes.

viduals observed in year t to predict their income. Individuals are then assigned to socioeconomic groups based on these predictions. Because this approach relies on cross-sectional data, it can be applied to the full set of countries in our sample, substantially expanding coverage. However, it may introduce measurement error if unobserved determinants of income are quantitatively important. These results are presented in Section 5.2.

Taken together, these two approaches allow us to assess the robustness of the results to alternative definitions of socioeconomic status while balancing concerns related to endogeneity, measurement error, and external validity.

While pooling all four countries provides a useful benchmark, we do not find the resulting patterns very informative, as they mask substantial cross-country heterogeneity. To characterize this heterogeneity, we conduct a principal component analysis using the full sample of 15 Latin American countries, based on three key structural indicators: informality, poverty, and rurality. Countries are then classified into two groups according to their position in the resulting component space. Group 1 comprises economies with higher informality, poverty, and rurality, whereas Group 2 includes more developed economies with lower levels of these indicators.[15] Table A.5 in the Appendix reports descriptive statistics for both groups. This classification helps reveal more consistent patterns in the relationship between labor market outcomes and macroeconomic fluctuations.

5.1 Classification of groups based on lagged income from panel data

We begin with the panel-based approach, in which we observe the same individuals at times $t-1$ and t. This allows us to classify individuals into socioeconomic groups using observed household income at time $t-1$, thereby treating group membership as predetermined with respect to labor market outcomes at time t. We then examine how those outcomes are associated with macroeconomic shocks. Details on the construction of these short panels are provided below.

We rely on longitudinal information constructed from nationally representative household and labor force surveys for four of the largest economies in Latin America—Argentina, Brazil, Chile, and Peru—which together account for more than 50% of the region's population. The periods covered and corresponding surveys are listed in Appendix Table A.6. Data come from household surveys or employment surveys, depending on the country. While survey designs differ across countries—in terms of rotation schemes, interview frequency, and the total number of times individuals are observed—all datasets allow individuals to be followed for at least one year, making it possible to construct short panels. We harmonize the panel structure across countries by focus-

[15] Appendix Table A.4 presents the first principal component of all countries. Group 1 comprises Bolivia, Colombia, Ecuador, El Salvador, Honduras, Mexico, Peru, and Paraguay, while Group 2 includes Argentina, Brazil, Chile, Costa Rica, the Dominican Republic, Panama, and Uruguay.

ing exclusively on pairs of observations for the same individual observed one year apart. That is, regardless of the original survey frequency, we retain only interannual observations for each individual.[16] This approach ensures the results are comparable across countries and surveys, despite differences in their original panel designs.

As a result, the panels used in the analysis consist of annual transitions constructed from short panels. The total number of observations varies by country and outcome, but pooling across years yields large samples, typically on the order of tens of thousands of observations per country for most labor market outcomes. This harmonized panel structure allows us to consistently define socioeconomic groups based on lagged household income and to analyze labor market dynamics over the economic cycle in a comparable manner across countries.

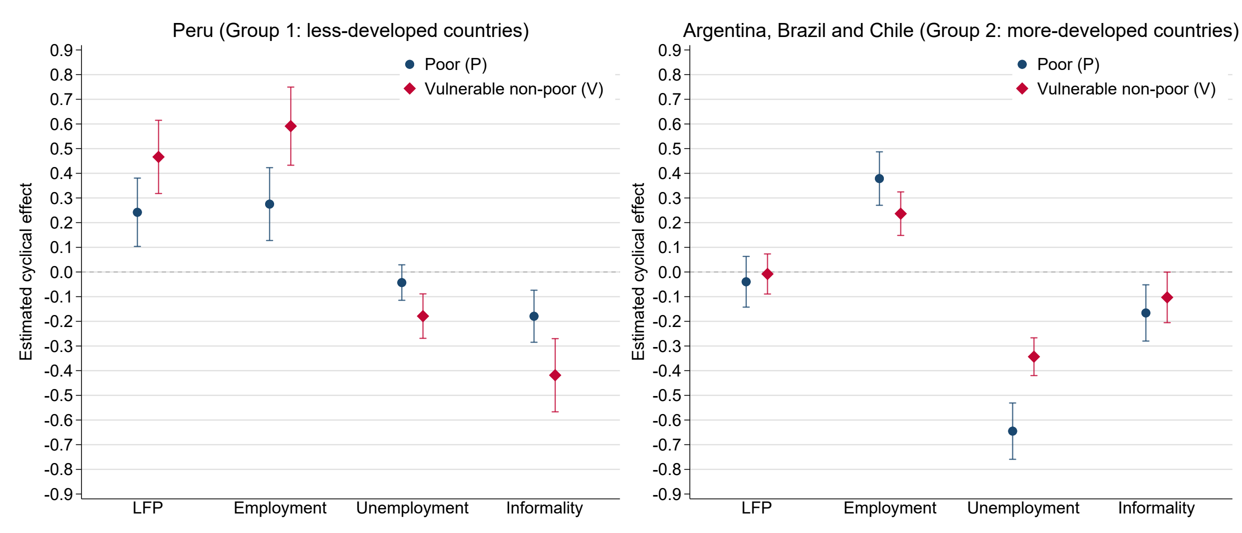
Using these data, we estimate Equation 1, defining socioeconomic groups based on per capita household income in period $t-1$. In particular, individuals are classified as poor or vulnerable according to the same income thresholds used in the cross-sectional analysis but applied to lagged income in order to weaken the mechanical link between current labor market outcomes and group assignment. As discussed above, we report the results separately for two groups of countries, differentiated by their level of development. Among the four countries examined in this section, Peru belongs to Group 1, while Argentina, Brazil, and Chile belong to Group 2.

Figure 7 reports the coefficients of the cyclical component of (log) per capita GDP from Equation 1 for a range of labor market outcomes for poor and vulnerable individuals in each country group. The left panels report the results for Peru (see also Appendix Table A.7). Periods in which GDP is above trend—that is, cyclical fluctuations are positive—are associated with improvements across all labor market outcomes for both groups, P and V. In particular, above-trend economic activity is linked to higher employment rates and labor force participation, lower unemployment and informality, and increased hourly wages and total earnings. Although all effects are positive for both groups, they are larger for the vulnerable, although the differences are not always statistically significant. During economic upturns in Peru, group V experiences larger increases in employment, wages, and earnings, as well as more pronounced declines in unemployment and labor informality. For instance, a 1% increase in GDP per capita relative to its trend is associated with an increase in employment of roughly 0.6 percentage points for the vulnerable, compared to about 0.3 percentage points for the poor.

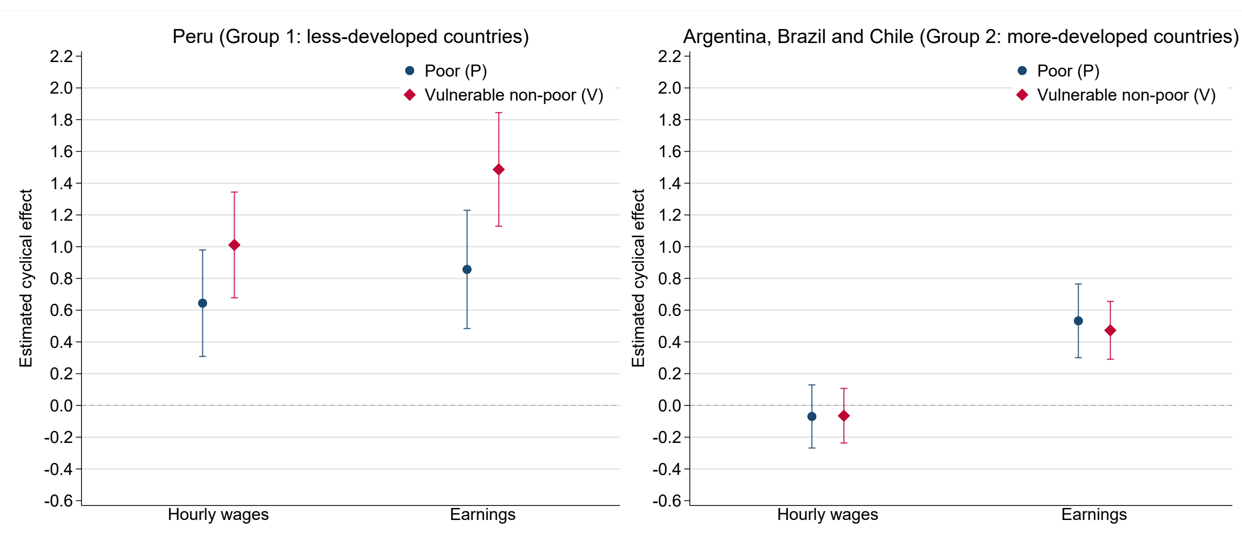
[16] For example, in quarterly surveys, individuals interviewed in 2008Q1 are linked to their observation in 2009Q1; analogous matching is applied in surveys with different fieldwork structures.

Figure 7: Cyclical effects on labor market outcomes for poor and vulnerable non-poor individuals (classification based on income in $t-1$)

a. Labor market status indicators



b. Wages and earnings



Notes: The figure portrays the estimated effects of economic fluctuations on labor market outcomes for poor individuals (P) and vulnerable non-poor individuals (V). Poverty and vulnerability are defined using household income in period $t-1$, following the thresholds described in Section 3. The business-cycle indicator is the cyclical component of log GDP per capita obtained from a Hodrick-Prescott decomposition. Positive values correspond to years in which GDP per capita is above its long-run trend (economic expansions), while negative values indicate economic downturns. Each marker shows the estimated coefficient from Equation 1: γ_1 for P and $\gamma_1 + \gamma_2$ for V, measuring the effect of a one-unit increase in the cyclical component on the corresponding outcome; vertical bars denote 95% confidence intervals based on robust standard errors. All specifications include country fixed effects and individual-level controls. Estimates are reported separately for two groups of countries identified through a principal component analysis based on informality, poverty, and rurality indicators. Group 1 includes economies with higher levels of informality, poverty, and rurality (Peru), whereas Group 2 includes more developed economies with lower levels of these characteristics (Argentina, Brazil, and Chile).
Source: Own calculations.

The right panels in Figure 7 report the results for the pooled sample of Argentina, Brazil, and Chile, the three countries belonging to Group 2 (see also Table A.8).[17] As in the case of Peru, increased economic activity is associated with improved labor market outcomes for both the poor and the vulnerable. This pattern holds across most outcomes, with the exception of labor force participation and hourly wages, for which the estimated effects are very close to zero and statistically nonsignificant. However, in contrast to the Peruvian case, economic upturns in Group 2 countries benefit the poor the most, rather than the vulnerable. Economic growth above the long-run trend is associated with improved labor market outcomes for V, but these effects are smaller than those observed for P. For example, a 1% increase in GDP per capita relative to trend is associated with employment gains of around 0.4 percentage points for the poor, compared to roughly 0.25 percentage points for the vulnerable. These differences, however, are generally not statistically significant, except in the case of unemployment.

While these effects may appear modest at an annual frequency, they accumulate over the course of typical business cycles and become economically meaningful. For instance, an average expansion in the region—characterized by cyclical growth of about 1.5% per year over roughly three years—is associated with cumulative employment gains of close to 2 percentage points for the vulnerable and about 1 percentage point for the poor in Peru. In contrast, in Argentina, Brazil, and Chile, the pattern is reversed: Employment gains for the poor reach around 1.8 percentage points—almost twice as large as in Peru—while gains for the vulnerable are closer to 1.2 percentage points, substantially smaller than those observed for their counterparts in Peru.

These magnitudes are comparable to those implied by more extreme cyclical fluctuations, such as the strong expansion observed in Argentina around 2010 or the downturns in Mexico in 1995, Uruguay in 2002, and Argentina in 2001, in which the cyclical component reached around 3% in a single year. In such cases, the estimated coefficients imply employment changes of roughly 1.5 to 2 percentage points for the most responsive group in each country set (with effects of the opposite sign during downturns) and about 0.8 to 1.2 percentage points for the less responsive group.

In sum, for this small group of countries with panel data, the results suggest that positive cyclical fluctuations above the long-run trend are beneficial for both groups, P and V, across a broad set of labor market outcomes. However, the relative magnitude of these effects differs. In particular, in Peru, the estimated responses are stronger for group V, but for the other three countries—Argentina, Brazil, and Chile—the coefficients tend to be larger for the poor.[18] Next, we assess our results' robustness using an alternative approach that allows us to extend the analysis to the full set of countries in our sample.

[17] Appendix Tables A.9 through A.11 report the results for each country separately. The overall patterns are largely robust, although they are clearer in the case of Brazil.

[18] The exception is Chile, where the estimates for wages and earnings are not statistically significant.

5.2 Classification of groups based on predicted income

In this section we classify individuals observed at time t into socioeconomic groups based on their expected per capita household income constructed from predetermined characteristics. In general terms, we estimate Mincer-type regressions using cross-sectional data from year $t-1$ and apply the resulting coefficients to individuals observed in year t to predict their income. The predicted income captures the expected income given the household's observable characteristics and structural context at the beginning of year t, which we denote as $\hat{y}_{ict-1}$.

In the first of four stages, we estimate the following model of household income in year $t-1$ for each country c:

$$\ln y_{ict-1} = \psi_{ct-1} X_{ict-1} + \varepsilon_{ict-1} \tag{2}$$

Here, y_{ict-1} is the observed income of household i in country c at time $t-1$, and X_{ict-1} includes household characteristics such as education, demographics, and location.

In the second stage, we compute predicted per capita incomes $\hat{y}_{ict-1}$ of households at the beginning of year t, combining the coefficients in Equation 2 (estimated from data in $t-1$) with the observed characteristics of households in year t:

$$\hat{y}_{ict-1} = exp(\hat{\psi}_{ct-1} X_{ict}) \tag{3}$$

In the third stage, we classify households observed in t into groups P, V, and R according to $\hat{y}_{ict-1}$ so as to replicate the shares of each group in country c in year $t-1$.

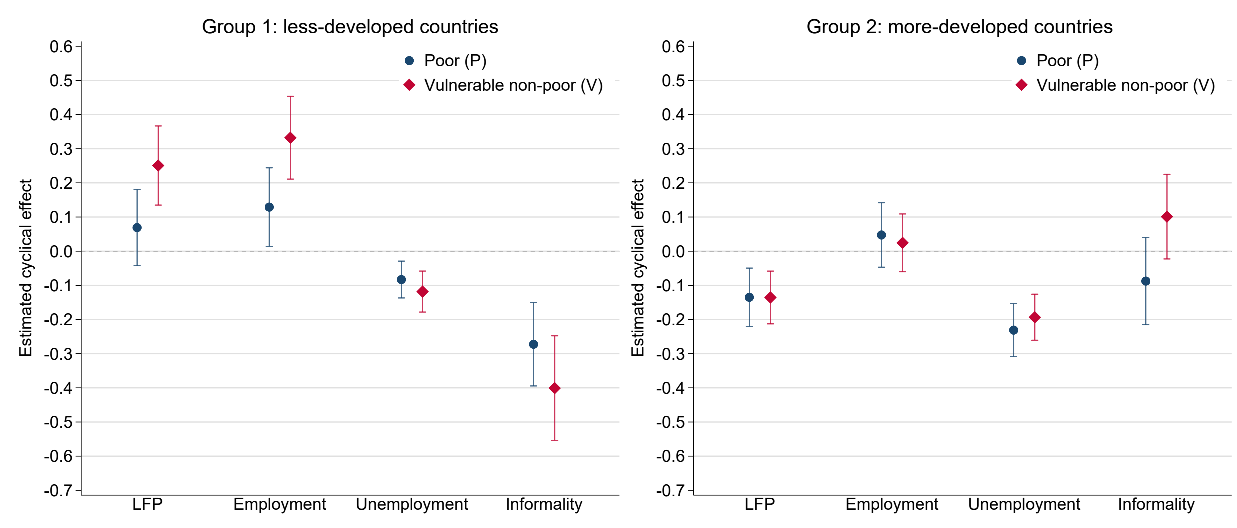
Finally, in the fourth stage, we estimate Equation 1 using the dummy variable V_{ict} constructed in step 3 to analyze how labor market outcomes respond to changes in the macroeconomic environment. The results shed light on whether and how labor market outcomes respond differently to changes in economic conditions for individuals with observable characteristics associated with being poor (P) versus those associated with being vulnerable (V).

First, we verify that the results obtained using this approach are consistent with those reported in the previous subsection for the four countries with panel data. We next extend the analysis to the full sample of 15 countries. As before, the results for the pooled sample are more difficult to interpret, but they become clearer when the countries are grouped according to key structural characteristics. Following the classification suggested by the principal component analysis discussed in Section 5, we distinguish between two groups of countries. Group 1 comprises Latin American economies with higher rurality, informality, and poverty. In addition to Peru, this group includes Bolivia, Colombia, Ecuador, El Salvador, Honduras, Mexico, and Paraguay. Group 2 consists of countries with lower rurality, informality, and poverty: Argentina, Brazil, Chile, Costa Rica, the Dominican Republic, Panama, and Uruguay.

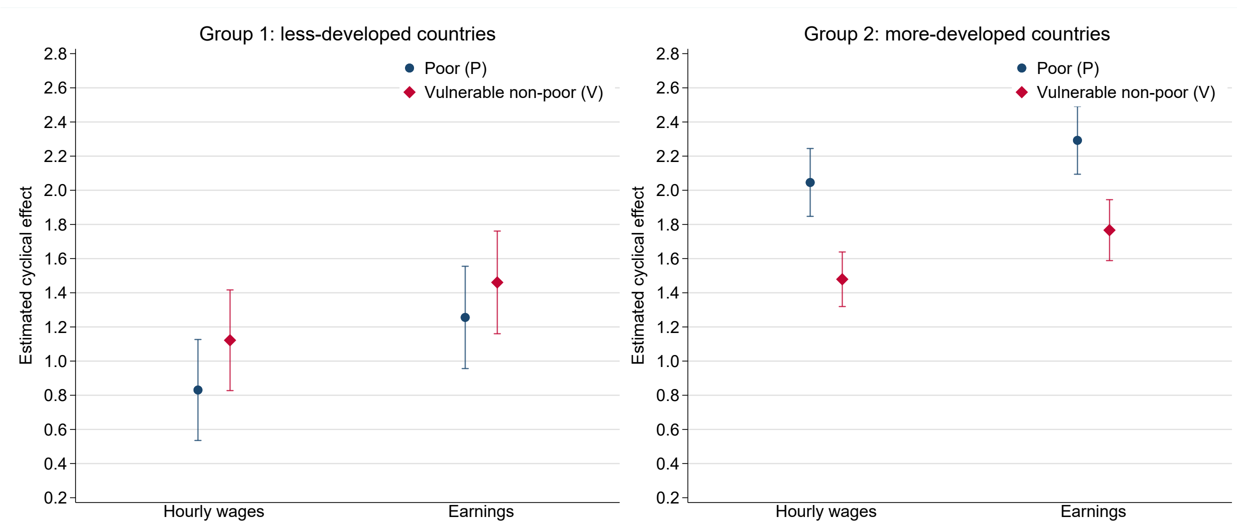
Figure 8 reports the coefficients of the cyclical component of (log) per capita GDP from Equation 1 for a range of labor market outcomes for both groups (see also Appendix Tables A.12 and A.13). Importantly, for both sets of countries, above-trend economic activity is associated with significant improved labor market outcomes for both the poor and the vulnerable. In general, positive cyclical fluctuations are associated with higher employment, lower unemployment, lower informality, and higher wages and earnings for both groups.

Figure 8: Cyclical effects on labor market outcomes for poor and vulnerable non-poor individuals (classification based on predicted income)

a. Labor market status indicators



b. Wages and earnings



Notes: The figure reports the estimated effects of economic fluctuations on labor market outcomes for poor individuals (P) and vulnerable non-poor individuals (V). Poverty and vulnerability status are defined using predicted household income, following the methodology described in Section 5.2. The business-cycle indicator is the cyclical component of log GDP per capita obtained from a Hodrick-Prescott decomposition. Positive values correspond to years in which GDP per capita is above its long-run trend (economic expansions), while negative values indicate economic downturns. Each marker shows the estimated coefficient from Equation 1: γ_1 for P and $\gamma_1 + \gamma_2$ for V, measuring the effect of a one-unit increase in the cyclical component on the corresponding outcome; vertical bars denote 95% confidence intervals based on robust standard errors. All specifications include country fixed effects and individual-level controls. Estimates are reported separately for two groups of countries identified through a principal component analysis based on informality, poverty, and rurality indicators. Group 1 comprises economies with higher informality, poverty, and rurality (Bolivia, Colombia, Ecuador, Honduras, Mexico, Peru, Paraguay, and El Salvador), while Group 2 comprises more developed economies with lower levels of these characteristics (Argentina, Brazil, Chile, Uruguay, the Dominican Republic, and Panama).
Source: Own calculations.

As in the previous subsection, a key difference emerges in the relative gains of P and V. Overall, vulnerable non-poor individuals exhibit stronger cyclical responses to GDP per capita than the poor in less developed countries (Group 1), whereas the opposite holds in more developed economies (Group 2). These patterns are particularly clear within Group 1, where the vulnerable consistently exhibit stronger positive responses across most labor market outcomes, although the differences are not always statistically significant. For example, a 1% increase in GDP per capita relative to trend is associated with an increase in employment of about 0.13 percentage points for the poor, compared to 0.33 percentage points for the vulnerable, in Group 1. In an average above-trend episode—characterized by cyclical growth of about 1.5% per year over roughly three years—this implies cumulative employment gains of close to 0.6 percentage points for the poor and 1.5 percentage points for the vulnerable. In contrast, in Group 2 countries the poor tend to experience either larger improvements than the vulnerable—particularly in hourly wages and earnings—or similar responses across other labor market outcomes.

Another contrast emerges when comparing labor force participation responses across country groups. In less developed economies, cyclical upturns are associated with increases in participation—particularly among the vulnerable—whereas in more developed economies participation tends to decline during periods of economic expansion, consistent with the absence of significant employment responses and the observed decline in unemployment.

5.3 Discussion

The results in this section reveal a consistent procyclical pattern in core labor market outcomes, alongside systematic differences in the strength of cyclical responses between poor and vulnerable non-poor individuals. Both the panel and cross-sectional analyses show that the business cycle is strongly associated with improvements in key labor market indicators in both groups of countries. However, a difference between less and more developed countries emerges in the relative magnitude of the effects across groups P and V. In less developed countries, characterized by higher informality, poverty, and rurality, vulnerable individuals tend to benefit more from favorable cyclical conditions than the poor, whereas in more developed countries the opposite tends to occur. As a result, the gap between vulnerable and poor individuals widens during expansions in the former group and narrows in the latter.

A detailed analysis of the causal drivers of these differences is beyond the scope of this paper. However, some plausible mechanisms can be considered. In Group 1 countries, poor individuals display characteristics consistent with more structural forms of poverty (Table A.5). They are considerably less urban (54%) than the vulnerable (70%) and also less urban than the poor in Group 2 countries (74%). Similar patterns emerge along other relevant dimensions. The poor in

Group 1 countries have particularly low levels of education and are substantially more likely to be employed informally and engaged in low-productivity activities. At the same time, they do not appear to be excluded from employment: Employment rates are relatively high, and unemployment is comparatively low. This suggests that many poor individuals in these less developed countries are already working, often in low-productivity segments of the labor market, rather than being detached from it.

In such settings, improvements in aggregate conditions may not translate into substantial gains for the poor, as their ability to adjust along employment or earnings margins is limited. Also, in such jobs, transitions into formal employment are relatively rare, even during periods of economic expansion (Fields, 2004; Perry, 2007). By contrast, vulnerable individuals, who are more likely to be located close to key margins of adjustment in the labor market, are better positioned to benefit from cyclical upturns. This asymmetry is consistent with the widening gap observed in less developed countries.

In more developed countries (Group 2), the profile of poor individuals differs in ways that are more closely aligned with cyclical labor market dynamics. The poor are more urban, somewhat more educated, and less concentrated in informal, low-productivity segments. More importantly, they exhibit significantly higher unemployment rates and lower employment rates than their counterparts in less developed countries, indicating a stronger attachment to the employment–unemployment margin of the labor market. This suggests that their labor market outcomes are more directly influenced by aggregate demand conditions, which is consistent with the results presented in this section.

More broadly, this interpretation is consistent with segmented labor market models in which aggregate shocks have heterogeneous effects depending on workers' position in the income and productivity distribution. In less developed countries, where labor markets are more segmented and informality is widespread, economic expansions may generate meaningful reallocation and upgrading opportunities primarily for workers near the margin of formal-sector entry—typically the vulnerable—while the poorest, who face bigger obstacles to accessing higher-quality jobs, experience more limited gains in job quality. By contrast, in more developed economies, where a larger share of the poor are attached to the employment–unemployment margin, cyclical upturns can translate more directly into improvements in their labor market outcomes. Of course, these interpretations remain speculative and should be tested through more formal causal analysis.

6 Transitions across socioeconomic groups

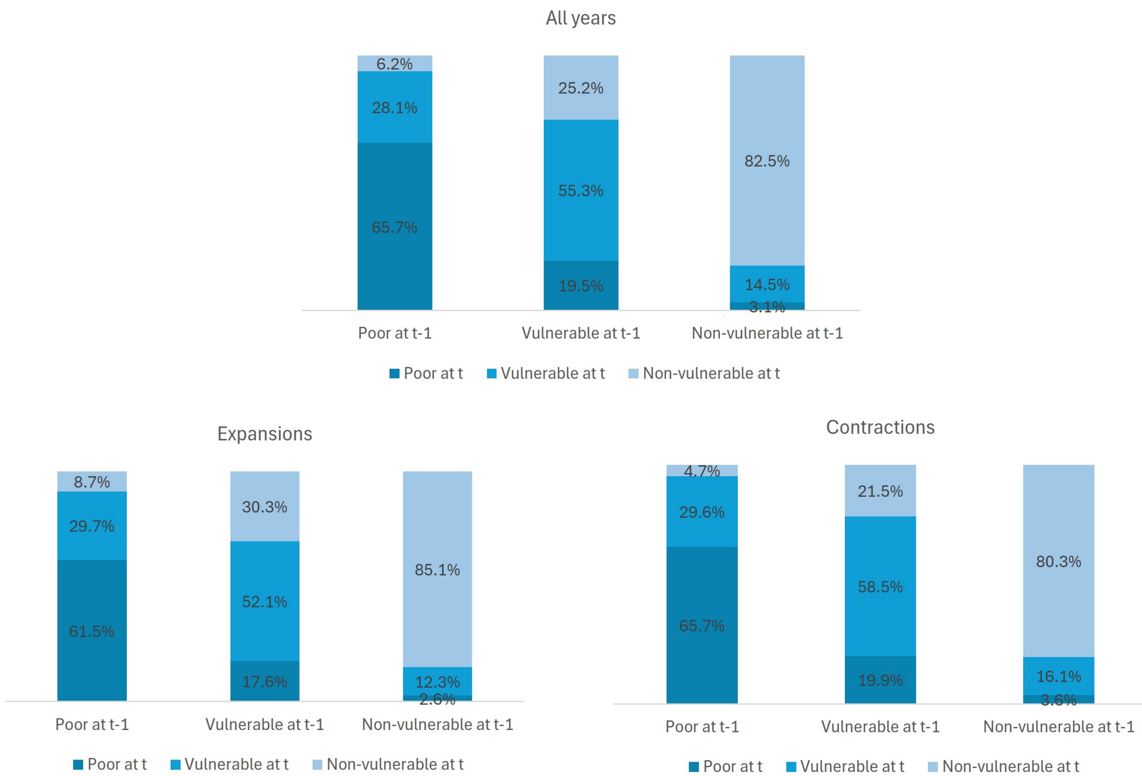
The analysis in the previous section documented how labor market outcomes evolve over the economic cycle for individuals classified into socioeconomic groups based on their predetermined income status. Those results show that cyclical fluctuations are associated with changes in labor market outcomes, which may in turn translate into movements across socioeconomic groups. Building on this evidence, the next subsection examines transitions between P, V, and R over the economic cycle. This entire section is based on the short panels for Argentina, Brazil, Chile, and Peru described in Section 5.1.

6.1 Transitions over the economic cycle

For a first look, Figure 9 presents year-to-year transitions in the pooled sample of the four countries and compares patterns across two macroeconomic environments: strong expansions and large contractions. Expansions are defined as years with GDP growth of at least 3%, while contractions are years with declines of 3% or more. We highlight three main results.

Figure 9: Transition matrices

Distribution of individuals across groups at time t, conditional on their group at time $t-1$



Notes: The figure reports transition matrices between groups P, V, and R, using panel data for Argentina, Brazil, Chile, and Peru. The periods covered are 2004–24 for Argentina; 2016, 2017, and 2020 for Brazil; 2011–19 for Chile; and 2009–23 for Peru. Expansions are defined as years in which GDP increased by at least 3%, while contractions are defined as years in which GDP declined by at least 3%. The whole-period panel pools expansion and contraction years only, excluding intermediate-growth years.
Source: Own calculations based on panel data.

1. High mobility. Although the majority of individuals remain in the same socioeconomic group from one year to the next, transitions across groups are substantial. On average, about 44.7% of individuals classified as vulnerable in a given year move to a different group in the following year. Some of these transitions reflect meaningful changes in economic well-being. However, part of the observed mobility is almost a statistical artifact: Since income is a continuous variable, even relatively small income fluctuations for households located near the cutoff points can generate movements across groups. Consistent with this interpretation, persistence is lowest for the vulnerable group. Being the middle group in the income distribution, and thus bounded by two cutoff points, individuals in group V are more likely to cross at least one threshold from one year to the next.

2. Asymmetric transitions across phases of the business cycle. The magnitude and direction of transitions differ systematically between expansions and contractions. Upward mobility from the vulnerable to the non-vulnerable population is stronger during expansions (30.3%) than during contractions (21.5%). Conversely, downward transitions from vulnerability to poverty are less frequent in expansions (17.6%) than in contractionary periods (19.9%). These asymmetries suggest that macroeconomic conditions play a role in shaping the risks faced by vulnerable households, amplifying downward mobility during downturns and facilitating upward transitions during periods of strong growth. Interestingly, the difference between phases is somewhat larger for upward transitions than for downward ones. This pattern suggests that expansions create substantial opportunities for upward mobility, while downward transitions are more persistent and less responsive to the business cycle.

3. Significant bidirectional reshuffling at the individual level. Even when aggregate economic conditions move clearly in one direction, individual-level transitions occur in all directions. This implies substantial reshuffling within the income distribution that is not fully aligned with the aggregate cycle. For example, focusing on the vulnerable group V, around 18% transition into poverty during expansions, while around 22% move upward into the non-vulnerable population R during contractions. These patterns underscore the coexistence of upward and downward mobility even within well-defined macroeconomic phases. Thus, the vulnerable group emerges as a high-churn segment of the income distribution: Its members face substantial income volatility and frequent transitions, not all of which are aligned with the direction of the business cycle. This finding is consistent with previous evidence for Latin America showing that vulnerability is associated with unstable labor arrangements, informality, and self-employment, which amplify individual-level income fluctuations even when aggregate conditions improve (Ferreira et al., 2012). As a result, economic expansions reduce the average risk of downward mobility but do not eliminate it, while contractions increase such risks without fully suppressing upward movements.

To complement this analysis, we estimate a simple model of transitions:

$$T_{ict}^{VJ} = \alpha + \gamma_1\, cycle_{ct} + \delta_1\, trend_{ct} + X_{ict}'\theta + \lambda_c + \nu_t + \varepsilon_{ict} \quad (4)$$

Here, T_{ict}^{VJ} equals 1 if household i in country c was in group V at time $t-1$ and moves to group J at time t, and 0 otherwise, with $J \in \{P,R\}$. Equation (4) is estimated separately for each destination group J.

Table 3 reports the results for the pooled sample. The coefficient on the cyclical component of GDP growth is negative for transitions from V to P and positive for transitions from V to R, consistent with the descriptive patterns documented above. The estimated coefficients on the time trend are both smaller, and the coefficient is statistically nonsignificant for transitions from V to P.

Table 3: Transitions from vulnerability across the economic cycle

	Transition V to P	Transition V to R
Cycle	-0.938***	0.629***
	(0.0863)	(0.0762)
Trend	-0.020	0.076**
	(0.0336)	(0.0362)
Obs	36969	36969
R2	0.010	0.009

Notes: The table reports estimates of Equation (4) for the pooled panel sample of Argentina, Brazil, Chile, and Peru. The dependent variables are household-level indicators equal to one if a household initially in group V moves to group P or R, respectively. Controls include gender and age-group indicators, country fixed effects, and quarter fixed effects. Regressions are weighted using adjusted household weights. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own calculations based on panel data.

6.2 Which households transition?

In any given period, some vulnerable households successfully transition to the non-vulnerable group, while others remain in group V or fall into poverty. In this section, we explore the characteristics of vulnerable households that experience different income transitions.

Although, as in the rest of the paper, our main interest lies in labor market variables, we begin with an introductory, and more general, analysis that considers other factors. We first focus on vulnerable non-poor households that managed to transition to the non-vulnerable group (R). By definition, these households experienced an increase in household per capita income y_h, where the subscript h indexes households. We begin by documenting the basic mechanical channels through which such an increase in y_h may occur. Household per capita income can be expressed as the sum of labor income (LI_h), other market income (OI_h), and transfers (T_h), divided by household size (N_h):

$$y_h = \frac{LI_h + OI_h + T_h}{N_h} \tag{5}$$

We estimate a set of simple regressions to characterize the role of changes in each of these four components for vulnerable households (V) that successfully transitioned to group R, relative to those that remain in V in our one-year observation window. Specifically, we estimate the following specification:

$$\Delta F_{hct} = \alpha + \beta\, T^{VR}_{hct} + \lambda_c + \nu_t + \varepsilon_{hct} \tag{6}$$

Here, ΔF_{hct} denotes the change in component F for household h in country c between periods $t-1$ and t; T^{VR}_{hct} is an indicator variable capturing whether a household in V in period $t-1$ experienced a transition from vulnerability to non-vulnerability or remained in V;[19] λ_c are country fixed effects; ν_t are time fixed effects; and ε_{hct} is an error term. The analysis is conducted separately for each component F, where $F \in \{LI, OI, T, N\}$.

By design, this empirical strategy is not intended to identify causal relationships, but to provide a synthetic characterization of how different income components—labor income, other market income, transfers, and changes in household size—are associated with upward transitions out of vulnerability.

The first panel of Table 4 reports the results for vulnerable households that transition to the non-vulnerable group. The estimates show that upward transitions are systematically associated with larger increases in household labor income. In the pooled sample, the labor income coefficient is by far the largest among all income components considered, representing an increase of 99% relative to the pre-transition mean. Other market income and transfers also move in the expected direction, but their magnitudes are smaller, amounting to around 61% and 80% of their respective pre-transition means. Household composition also adjusts: Households transitioning from V to R reduce their size by 0.2 members (5% relative to $t-1$) on average, which mechanically raises per capita income. The country-specific estimates confirm this pattern across all four countries, with labor income consistently dominating.

These results are not trivial. One could imagine a situation in which incomes evolve similarly across all vulnerable households, and transitions into group R occur simply because some house-

[19] Households that fall into poverty are excluded from the analysis.

holds happen to be located closer to the vulnerability threshold. The evidence in Table 4 suggests that more is at play: Households that successfully transition into R experience systematically larger income gains, driven primarily by labor income dynamics rather than by initial income positions. In addition, income gains of those transitioning out of vulnerability are substantial. In the pooled sample of four countries, households moving from V to R experience a differential increase in labor income that exceeds the mean labor income in $t-1$, as previously noted.[20]

The second panel presents the corresponding results for vulnerable households that transition into poverty, relative to those that remain in group V. The pattern is broadly symmetric. Downward transitions are associated with large declines in labor income, alongside smaller reductions in other market income and transfers. Household size moves in the opposite direction, reinforcing the decline in per capita income. The sign and ranking of components are consistent across all countries.

Table 4: Income components and transitions from vulnerability

	Labor income	Other market income	Transfers	Household members
Transitions from V to R				
Argentina	879.5***	193.8***	34.5***	-0.206***
Brazil	453.7***	131.4***	12.7***	-0.122***
Chile	578.8***	176.4***	133.3***	-0.165***
Peru	682.9***	128.1***	26.1***	-0.230***
Pool	730.6***	174.9***	66.5***	-0.195***
Transitions from V to P				
Argentina	-530.6***	-103.3***	-31.2***	0.072***
Brazil	-368.9***	-66.7***	-28.7***	0.130***
Chile	-396.9***	-60.3***	-96.1***	0.014
Peru	-423.3***	-52.7***	-13.4***	0.082***
Pool	-467.0***	-76.1***	-34.0***	0.066***
Mean dep. var. $t-1$ (Pool)	735.1	286.7	84.0	3.580

Notes: The table reports estimates of Equation (6). Each coefficient corresponds to a separate regression in which the dependent variable is the change in the indicated household-level component between $t-1$ and t. The coefficient on the transition indicator compares vulnerable households that move to the indicated destination group with vulnerable households that remain in V. Regressions include year and quarter fixed effects. The pooled specification additionally includes country fixed effects. Country-specific regressions use household survey weights, while the pooled specification uses adjusted pooled weights. Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own calculations based on panel data.

We next focus on household labor income, which is the sum of individual labor income across

[20] We also estimate these regressions separately for periods of strong economic expansion and recession and find no substantial differences relative to the aggregate results reported in Table 4.

all household members. Individual labor income is the product of employment status, hours worked, and the hourly wage. Accordingly, household labor income for household h can be written as

$$LI_h = \sum_{i \in h} e_i \, l_i \, w_i, \tag{7}$$

where e_i is a dummy variable that takes value 1 if individual i is employed and 0 otherwise, l_i denotes monthly hours worked, and w_i is the individual hourly wage.

We now estimate a set of regressions to assess whether changes in these three labor market components differ systematically between vulnerable households that successfully transition to group R, relative to those that remained in group V. Specifically, we estimate the following specification:

$$\Delta L_{hct} = \alpha + \beta \, T^{VR}_{hct} + \lambda_c + \nu_t + \varepsilon_{hct} \tag{8}$$

Here, ΔL_{hct} denotes the change in a given labor market outcome for household h in country c between periods $t-1$ and t. The dependent variable L alternatively captures (i) the change in the number of income earners in the household (i.e., individuals with $e_i = 1$), (ii) the change in mean hours worked among household members who were employed in period $t-1$, and (iii) the change in mean hourly wages for that same set of workers. The indicator T^{VR}_{hct} takes value 1 if the household transitions from vulnerability to group R and 0 if it remains in V, while λ_c and ν_t denote country and time fixed effects, respectively.

These regressions allow us to explore the relevance of extensive-margin adjustments (changes in the number of earners) and intensive-margin adjustments (changes in hours worked and wages) in driving upward transitions out of vulnerability.

The first panel of Table 5 reports the results from estimating Equation 8. The estimates show that upward transitions from vulnerability to non-vulnerability are associated with improvements along all three labor market margins. In the pooled sample, households moving from V to R experience an increase in the number of employed members, a sizable increase in hours worked, and a rise in hourly earnings, all relative to the vulnerable population that remains in that group. The increase in hourly income is particularly large relative to its pre-transition mean, suggesting that changes in job quality play an important role in the labor income gains associated with upward transitions. The extensive margin is also relevant, while the change in hours worked is positive but more modest in relative terms. The country-specific estimates confirm the same qualitative pattern across all four countries.

The second panel shows the corresponding results for vulnerable households that transition into poverty. The pattern is broadly symmetric. Downward transitions are associated with reductions in the number of employed household members, hours worked, and hourly earnings. The magnitude of the decline in hourly wages is again especially notable, followed by reductions in employment. These patterns are consistent across countries, although the relative importance of each margin varies somewhat.

Table 5: Labor margins and transitions from vulnerability

	Employed members	Hours worked	Hourly income
Transitions from V to R			
Argentina	0.268***	8.321***	4.010***
Brazil	0.277***	3.888***	1.236***
Chile	0.231***	7.411***	1.414***
Peru	0.163***	12.388***	1.555***
Pool	0.231***	9.209***	2.316***
Transitions from V to P			
Argentina	-0.364***	-17.270***	-1.495***
Brazil	-0.543***	-7.624***	-0.607***
Chile	-0.379***	-18.137***	-0.880***
Peru	-0.260***	-21.011***	-0.898***
Pool	-0.333***	-18.615***	-1.155***
Mean dep. var. $t-1$ (Pool)	1.492	172.447	3.490

Notes: The table reports estimates of Equation (8). Each coefficient corresponds to a separate regression in which the dependent variable is the change in the indicated household-level component between $t-1$ and t. The coefficient on the transition indicator compares vulnerable households that move to the indicated destination group with vulnerable households that remain in V. Regressions include year and quarter fixed effects. The pooled specification additionally includes country fixed effects. Country-specific regressions use household survey weights, while the pooled specification uses adjusted pooled weights. Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* Own calculations based on panel data.

6.3 Who drives household income changes?

Finally, we focus on workers belonging to the vulnerable non-poor group V and explore the differential characteristics of those who experience substantial earnings gains or losses over time. We first analyze workers who register a sizable increase in labor earnings relative to those whose earnings remain broadly unchanged or decline. We then perform the symmetric exercise for workers who experience substantial earnings losses.

We define an indicator variable IE_i, constructed for workers in group V, which takes value 1 if worker i experienced an increase in earnings over the year larger than $M\%$ and 0 if the change in earnings is lower than $m\%$. Analogously, we define an indicator for substantial earnings declines as 1 when labor earnings decline by at least $M\%$ and 0 when the fall is $m\%$ or less (including no change or increases in earnings).

Importantly, large changes in earnings for worker i do not necessarily translate into a household transition across socioeconomic groups. Household mobility depends not only on the worker's own labor-income dynamics, but also on changes in other HH members' earnings, as well as their own transfers, non-labor income, and household composition. For this reason, we focus on substantial individual earnings changes, rather than restricting the analysis to workers whose households simultaneously move across groups.

To analyze the characteristics associated with these earnings changes among vulnerable workers, we estimate regressions of the following form:

$$E_{ict} = \alpha + \mathbf{X}'_{ict}\beta + \lambda_c + \nu_t + \varepsilon_{ict} \tag{9}$$

Here, E_{ict} denotes an indicator for either a substantial earnings increase or a substantial earnings fall for worker i in country c between periods $t-1$ and t. The vector $\mathbf{X}_{ict}$ includes individual characteristics such as age, gender, location, and education, as well as job characteristics such as sector of employment, formality status, hours worked, and initial earnings.

Tables 6 and 7 report the results for our baseline specification (M=25%, and m=1%) in the pooled sample and for each country separately.[21] Several patterns emerge consistently across countries. First, men are significantly more likely to experience substantial earnings gains and less likely to suffer large earnings losses. Prime-age workers also display more favorable earnings dynamics than younger workers, while older workers tend to face weaker upside mobility and, in some cases, greater downside risk.

Second, education is strongly associated with more resilient labor trajectories. Moderately and highly educated vulnerable workers are systematically more likely to experience sizable earnings increases and substantially less likely to incur major losses. The magnitude of these gradients is economically large, especially for highly educated workers in Brazil and Chile, suggesting that human capital remains a key protection mechanism within the vulnerable group.

Third, labor market segmentation appears central. Informal workers are markedly less likely to enjoy substantial earnings gains and substantially more likely to experience large falls in every country considered. This pattern is consistent with the idea that informal jobs provide weaker earnings progression, lower protection against shocks, and more unstable employment relationships.

Fourth, sectoral differences also matter. Relative to primary activities, workers in utilities, public administration, education, health, and other service activities tend to display more favorable earnings dynamics: They are often more likely to experience gains and less likely to experience

[21] An increase of 25% corresponds to the 68th percentile of the earnings distribution, while an increase of 1% corresponds to the 58th percentile in the pooled sample. The results are substantially robust to changes in M and m.

losses. By contrast, domestic service and some low-productivity sectors show weaker upward mobility prospects.[22]

Finally, initial labor income strongly predicts subsequent mean reversion. Workers with lower initial earnings are more likely to record substantial gains, whereas those starting from higher earnings are more exposed to sizable declines. This pattern likely reflects a combination of transitory shocks, earnings volatility, and partial adjustment toward individual longer-run earnings levels.

Overall, the results suggest that exits from vulnerability are disproportionately driven by male workers with stronger labor market attachment, more education, and formal employment, while persistent vulnerability is more common among informal, low-skilled, and older workers facing limited earnings growth and higher downside risk.

[22] This information is not available for Chile.

Table 6: Model of characterization of vulnerable workers with substantial increase in earnings

VARIABLES in $t-1$	Pool	Argentina	Brazil	Chile	Peru
Male	0.128***	0.182***	0.122***	0.158***	0.113***
	(0.004)	(0.010)	(0.004)	(0.012)	(0.008)
[30 - 34 years]	0.0202**	0.0301**	0.0188***	-0.0000	0.0191
	(0.0079)	(0.0138)	(0.0054)	(0.0237)	(0.0140)
[35 - 39 years]	0.0456***	0.0589***	0.0468***	0.0074	0.0425***
	(0.0078)	(0.0138)	(0.0053)	(0.0219)	(0.0138)
[40 - 44 years]	0.0525***	0.0475***	0.0525***	0.0356*	0.0545***
	(0.0078)	(0.0136)	(0.0053)	(0.0212)	(0.0135)
[45 - 49 years]	0.0412***	0.0586***	0.0560***	0.0093	0.0330**
	(0.0080)	(0.0146)	(0.0055)	(0.0211)	(0.0138)
[50 - 54 years]	0.0364***	0.0450***	0.0454***	-0.0148	0.0343**
	(0.0085)	(0.0157)	(0.0058)	(0.0213)	(0.0141)
[55 - 59 years]	0.0195**	0.0176	0.0432***	-0.0308	0.0150
	(0.0091)	(0.0170)	(0.0064)	(0.0244)	(0.0149)
[60 - 64 years]	-0.0091	0.0025	0.0301***	-0.0309	-0.0302*
	(0.0106)	(0.0244)	(0.0082)	(0.0273)	(0.0159)
[65+]	-0.0500**	0.0582	-0.0149	-0.1264*	-0.0650**
	(0.0246)	(0.0489)	(0.0184)	(0.0712)	(0.0303)
Medium education	0.0702***	0.0956***	0.0784***	0.0863***	0.0494***
	(0.0046)	(0.0087)	(0.0032)	(0.0124)	(0.0079)
High education	0.1471***	0.1737***	0.2710***	0.2640***	0.0895***
	(0.0071)	(0.0132)	(0.0062)	(0.0218)	(0.0119)
Urban	-0.0004	0.0000	0.0216***	-0.0186	0.0545***
	(0.0076)	(0.0000)	(0.0037)	(0.0124)	(0.0124)
Low-technology industries	-	0.0458	-0.0143*	-	0.0206
		(0.0325)	(0.0073)		(0.0154)
Rest of manufacturing industry	-	0.0710**	0.0256***	-	0.0144
		(0.0340)	(0.0071)		(0.0203)
Construction	-	-0.0095	0.0094	-	0.0758***
		(0.0311)	(0.0061)		(0.0142)
Wholesale and retail trade, restaurants, hotels, repairs	-	0.0275	0.0249***	-	0.0650***
		(0.0306)	(0.0053)		(0.0101)
Electricity, gas, water, transport, communications	-	0.1126***	0.0473***	-	0.0780***
		(0.0330)	(0.0067)		(0.0135)
Banking, finance, insurance, professional services	-	0.0402	0.0228***	-	0.0348*
		(0.0341)	(0.0072)		(0.0203)
Public administration, defense, and extraterritorial organizations	-	0.0836**	0.0563***	-	0.0162
		(0.0329)	(0.0080)		(0.0170)
Education, health, and personal services	-	0.0776**	0.0442***	-	0.0344**
		(0.0325)	(0.0063)		(0.0138)
Domestic service	-	-0.0133	-0.0141**	-	0.0286
		(0.0328)	(0.0068)		(0.0240)
Informal	-0.0562***	-0.1372***	0.0254***	-0.0898***	-0.0573***
	(0.0047)	(0.0092)	(0.0032)	(0.0121)	(0.0088)
Hours worked	0.000279**	0.000485**	-0.000792***	0.001260***	-0.000017
	(0.000118)	(0.000208)	(0.000124)	(0.000371)	(0.000171)
Labor income in $t-1$	-0.000544***	-0.000568***	-0.000489***	-0.000670***	-0.000568***
	(0.000006)	(0.000011)	(0.000005)	(0.000021)	(0.000011)
Constant	0.722***	0.665***	0.479***	0.636***	0.488***
	(0.023)	(0.040)	(0.010)	(0.037)	(0.025)
Observations	288698	40095	195528	16871	35966
R-squared	0.130	0.176	0.103	0.125	0.137

Notes: The table reports estimates of Equation (9) for substantial increases in individual labor earnings, using the baseline parameters $m = 1\%$ and $M = 25\%$. The sample is restricted to workers aged 25 to 65 who belong to group V in $t-1$ and are employed in both periods. Controls are measured in $t-1$ and include gender, age group, education group, urban residence, informality status, hours worked, and initial labor earnings. Regressions also include region, year, and quarter fixed effects. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own calculations based on panel data.

Table 7: Model of characterization of vulnerable workers with substantial fall in earnings

VARIABLES in $t-1$	Pool	Argentina	Brazil	Chile	Peru
Male	-0.098***	-0.153***	-0.064***	-0.109***	-0.095***
	(0.004)	(0.010)	(0.003)	(0.011)	(0.007)
[30 - 34 years]	-0.0128*	-0.0361***	-0.0080*	0.0085	-0.0100
	(0.0074)	(0.0135)	(0.0044)	(0.0205)	(0.0127)
[35 - 39 years]	-0.0336***	-0.0568***	-0.0243***	-0.0244	-0.0295**
	(0.0072)	(0.0136)	(0.0043)	(0.0184)	(0.0124)
[40 - 44 years]	-0.0392***	-0.0448***	-0.0261***	-0.0414**	-0.0423***
	(0.0071)	(0.0138)	(0.0043)	(0.0178)	(0.0121)
[45 - 49 years]	-0.0281***	-0.0414***	-0.0263***	-0.0267	-0.0241*
	(0.0074)	(0.0144)	(0.0046)	(0.0176)	(0.0124)
[50 - 54 years]	-0.0228***	-0.0366**	-0.0139***	-0.0335*	-0.0137
	(0.0077)	(0.0149)	(0.0048)	(0.0177)	(0.0125)
[55 - 59 years]	-0.0060	-0.0107	-0.0030	-0.0063	0.0010
	(0.0083)	(0.0167)	(0.0054)	(0.0202)	(0.0132)
[60 - 64 years]	0.0350***	0.0185	0.0163**	0.0199	0.0566***
	(0.0097)	(0.0230)	(0.0071)	(0.0222)	(0.0143)
[65+]	0.0769***	-0.0402	0.0690***	0.0566	0.1002***
	(0.0232)	(0.0410)	(0.0191)	(0.0704)	(0.0286)
Medium education	-0.0614***	-0.0682***	-0.0564***	-0.0647***	-0.0569***
	(0.0044)	(0.0085)	(0.0029)	(0.0109)	(0.0075)
High education	-0.1085***	-0.1069***	-0.1300***	-0.1817***	-0.1024***
	(0.0064)	(0.0123)	(0.0047)	(0.0173)	(0.0109)
Urban	-0.0084	0.0000	-0.0176***	0.0183*	-0.0752***
	(0.0065)	(0.0000)	(0.0034)	(0.0102)	(0.0117)
Low-technology industries	-	-0.0739**	-0.0444***	-	0.0134
		(0.0308)	(0.0064)		(0.0142)
Rest of manufacturing industry	-	-0.0994***	-0.0726***	-	0.0036
		(0.0316)	(0.0065)		(0.0197)
Construction	-	-0.0018	-0.0134**	-	-0.0222
		(0.0294)	(0.0060)		(0.0147)
Wholesale and retail trade, restaurants, hotels, repairs	-	-0.0396	-0.0337***	-	0.0051
		(0.0287)	(0.0047)		(0.0092)
Electricity, gas, water, transport, communications	-	-0.1119***	-0.0722***	-	-0.0432***
		(0.0304)	(0.0061)		(0.0130)
Banking, finance, insurance, professional services	-	-0.0855***	-0.0618***	-	-0.0273
		(0.0316)	(0.0060)		(0.0187)
Public administration, defense, and extraterritorial organizations	-	-0.1448***	-0.1147***	-	-0.0599***
		(0.0300)	(0.0063)		(0.0165)
Education, health, and personal services	-	-0.1183***	-0.0781***	-	-0.0342***
		(0.0297)	(0.0054)		(0.0132)
Domestic service	-	-0.0146	-0.0050	-	-0.0316
		(0.0309)	(0.0061)		(0.0231)
Informal	0.1721***	0.1832***	0.1773***	0.1927***	0.1227***
	(0.0045)	(0.0092)	(0.0029)	(0.0106)	(0.0085)
Hours worked	-0.000479***	-0.000567***	-0.000789***	-0.001436***	-0.000366**
	(0.000110)	(0.000204)	(0.000115)	(0.000322)	(0.000155)
Labor income in $t-1$	0.000503***	0.000429***	0.000567***	0.000460***	0.000583***
	(0.000006)	(0.000011)	(0.000006)	(0.000020)	(0.000010)
Constant	-0.022	0.151***	0.059***	0.135***	0.204***
	(0.019)	(0.036)	(0.009)	(0.032)	(0.023)
Observations	286797	39934	189988	17934	38712
R-squared	0.142	0.147	0.153	0.103	0.156

Notes: The table reports estimates of Equation (9) for substantial fall in individual labor earnings, using the baseline parameters $m = 1\%$ and $M = 25\%$. The sample is restricted to workers aged 25 to 65 who belong to group V in $t-1$ and are employed in both periods. Controls are measured in $t-1$ and include gender, age group, education group, urban residence, informality status, hours worked, and initial labor earnings. Regressions also include region, year, and quarter fixed effects. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own calculations based on panel data.

7 Concluding remarks

This paper examines the characteristics and dynamics of the vulnerable non-poor in Latin America, with a particular focus on their labor market outcomes and their responses to macroeconomic fluctuations. Using a large harmonized dataset covering more than three decades and complemented with panel evidence for a subset of countries, we document three main findings.

First, the vulnerable non-poor constitute a large and persistent segment of the population, with socioeconomic characteristics that place them between the poor and the non-vulnerable but often closer to the former. The size of this group has remained relatively stable, highlighting its structural relevance in the region.

Second, labor market outcomes are strongly procyclical for both poor and vulnerable individuals. However, the relative magnitude of these responses differs systematically across countries. In less developed economies, vulnerable individuals tend to benefit more from economic expansions, whereas in more developed economies the poor exhibit stronger responses. This heterogeneity appears to be closely related to differences in labor market structure, particularly the degree of informality and the margins along which workers adjust.

Third, transitions across income groups are substantial and display cyclical patterns. Upward mobility from vulnerability is more frequent during expansions, while downturns increase the risk of falling into poverty. A significant degree of bidirectional mobility persists even within well-defined macroeconomic phases, pointing to considerable income volatility at the individual level. Consistent with this view, transitions out of vulnerability are primarily driven by improvements in labor income—through both employment and earnings—while downward transitions reflect simultaneous deteriorations across multiple labor margins.

Taken together, these findings suggest that the vulnerable non-poor occupy a critical position in the income distribution: They are sufficiently integrated into labor markets to benefit from favorable conditions, yet they remain exposed to significant downside risks. This duality has important implications for policy design. Traditional anti-poverty programs may not fully address the risks faced by this group, while standard labor market policies may overlook their specific constraints.

Future research should further investigate the causal mechanisms underlying the heterogeneous responses documented here, as well as the role of institutions and policies in shaping resilience to economic shocks. A better understanding of these dynamics is essential for designing social protection systems that not only reduce poverty but prevent vulnerability from being translated into persistent economic insecurity.

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A Tables and Figures

Table A.1: National household surveys of Latin America used in the analysis

Country	Survey	Acronym
Argentina	Encuesta Permanente de Hogares – Continua	EPH-C
Bolivia	Encuesta de Hogares	EH
Brazil	Pesquisa Nacional por Amostra de Domicílios – Continua	PNADC
Chile	Encuesta de Caracterización Socioeconómica Nacional	CASEN
Colombia	Gran Encuesta Integrada de Hogares	GEIH
Costa Rica	Encuesta Nacional de Hogares	ENAHO
Dominican Republic	Encuesta Nacional Continua de Fuerza de Trabajo	ECNFT
Ecuador	Encuesta de Empleo, Desempleo y Subempleo	ENEMDU
El Salvador	Encuesta de Hogares de Propósitos Múltiples	EHPM
Honduras	Encuesta Permanente de Hogares de Propósitos Múltiples	EPHPM
Mexico	Encuesta Nacional de Ingresos y Gastos de los Hogares	ENIGH
Panama	Encuesta de Hogares	EH
Paraguay	Encuesta Permanente de Hogares	EPH
Peru	Encuesta Nacional de Hogares	ENAHO
Uruguay	Encuesta Continua de Hogares	ECH

Source: Authors’ own elaboration.

Table A.2: National household surveys used in the study

Year	ARG	BOL	BRA	CHL	COL	CRI	DOM	ECU	HND	MEX	PAN	PER	PRY	SLV	URY
1992	✓	✓		✓		✓			✓	✓					✓
1993	✓		✓			✓			✓						
1994	✓			✓		✓			✓	✓					
1995	✓		✓			✓			✓		✓			✓	✓
1996	✓		✓	✓		✓	✓		✓	✓				✓	✓
1997	✓	✓	✓			✓	✓		✓		✓	✓			✓
1998	✓		✓	✓		✓			✓		✓	✓		✓	✓
1999	✓	✓	✓			✓			✓		✓	✓		✓	
2000	✓	✓		✓		✓	✓			✓	✓	✓		✓	✓
2001	✓	✓	✓		✓	✓	✓		✓		✓	✓	✓	✓	✓
2002	✓	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓	✓	✓
2003	✓		✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
2004	✓		✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2005	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2006	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2007	✓	✓	✓			✓	✓	✓	✓		✓	✓	✓	✓	✓
2008	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2009	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
2010	✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2011	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
2012	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2013	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
2014	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2015	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
2016	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2017	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
2018	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2019	✓	✓	✓		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
2020	✓	✓	✓	✓	✓	✓	✓	✓		✓		✓	✓	✓	✓
2021	✓	✓	✓		✓	✓	✓	✓			✓	✓	✓	✓	✓
2022	✓	✓	✓	✓	✓	✓	✓	✓		✓		✓	✓	✓	✓
2023	✓	✓	✓		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
2024	✓		✓		✓	✓	✓	✓	✓	✓	✓	✓	✓		✓

Source: Authors' own elaboration.

Table A.3: Mean household per capita income - PPP dollars per day - Year 2024

	Poor			Vulnerable			Rest		
	Mean	Median	std.dev	Mean	Median	std.dev	Mean	Median	std.dev
ARG	4.9	5.0	1.5	10.3	10.3	2.2	34.1	26.7	24.8
BOL	4.4	4.9	1.6	10.4	10.4	2.0	32.7	24.2	42.2
BRA	4.4	4.5	1.6	10.3	10.0	2.0	37.2	25.1	42.3
CHL	4.7	5.2	1.8	10.8	10.9	2.0	36.9	26.4	34.6
COL	4.0	4.1	1.7	10.0	9.8	2.0	36.9	24.6	42.1
CRI	5.0	5.5	1.5	10.2	10.1	2.0	39.0	28.8	32.6
ECU	4.4	4.8	1.5	10.1	10.4	2.2	27.5	20.0	24.9
SLV	4.3	4.5	1.7	10.1	9.9	2.0	24.9	20.7	14.7
HND	3.7	3.6	1.9	9.8	9.3	2.2	23.3	19.6	11.6
MEX	4.9	5.1	1.4	10.3	10.2	2.0	30.0	22.5	40.9
PAN	4.5	4.5	1.3	10.3	10.2	2.1	41.4	30.4	39.0
PRY	4.7	5.0	1.6	10.3	10.2	2.0	31.3	22.8	29.2
PER	4.4	4.7	1.5	10.1	9.9	2.1	24.9	20.1	14.9
DOM	4.9	5.2	1.3	10.8	10.9	2.1	27.3	22.3	15.4
URY	5.2	5.4	1.0	10.9	11.0	2.0	36.2	27.9	31.5
Total	4.6	4.8	1.5	10.3	10.2	2.1	32.2	24.1	29.4

Source: Authors' own calculations based on microdata from national household surveys.

Table A.4: Principal Component 1 by country

Country	URY	CHL	ARG	BRA	CRI	DOM	PAN	MEX	COL	BOL	PRY	PER	SLV	ECU	HND
PC 1	-2.56	-2.31	-1.50	-1.24	-1.06	-0.78	-0.15	0.29	0.50	0.73	1.16	1.24	1.33	1.45	2.90

Notes: PC analysis is based on three variables: labor informality, share of rural population, and income poverty rate using the USD 6.85 poverty line.
Source: Own calculations based on microdata from national household surveys.

Table A.5: Characteristics of groups by PC

	Group 1			Group 2		
	Poor	Vulnerable	Rest	Poor	Vulnerable	Rest
Share of the group	26%	34%	40%	11%	27%	62%
Demographics and location						
Mean age	27.4	31.7	38.6	25.1	30.1	39.8
Share [0,14]	45.0	33.8	17.7	47.2	35.7	17.5
Share [65+]	8.7	11.6	15.9	5.2	8.3	18.1
Share [25, 64]	46.3	54.6	66.4	47.6	56.0	64.3
Share women [25,64]	57.3	54.9	50.8	57.1	54.5	49.0
Household size	4.0	3.6	2.7	4.2	3.7	2.6
Number of children	1.8	1.3	0.6	1.9	1.3	0.6
Dependency rate	2.3	1.8	1.4	2.5	1.9	1.4
Share urban	54.2	69.7	82.9	74.0	79.6	84.8
Education						
Years of education [25-65]	7.3	8.8	11.5	8.4	9.4	11.9
Years of education [25-35]	8.9	10.5	12.9	9.6	10.8	13.3
Years of education [36-45]	7.7	9.2	12.0	8.5	9.9	12.4
Years of education [46-65]	5.6	7.1	10.2	7.0	7.9	10.8
Share low education [25-65]	64.1	53.8	34.5	63.8	55.1	35.5
Share medium education [25-65]	26.4	34.4	37.7	30.0	36.2	36.5
Share high education [25-65]	9.5	11.8	27.8	6.2	8.6	27.9
Gross enrolment rates [13-17]	80.5	86.4	88.1	94.4	95.2	97.1
Gross enrolment rates [18-23]	28.5	36.2	50.2	30.8	39.6	51.9
Labor market						
Labor force participation	66.9	74.2	83.3	64.2	73.5	84.2
Female labor force participation	51.2	59.8	73.7	48.9	62.2	76.1
Employment	61.1	69.3	81.0	52.5	66.8	81.7
Unemployment	8.7	6.6	2.8	18.3	9.0	3.0
Duration of unemployment	2.8	5.8	4.3	4.7	5.5	5.6
Informality productive	81.4	62.4	38.4	72.8	56.8	33.8
Informality social protection	86.3	72.8	47.0	77.2	59.2	34.9
Hourly wages	2.2	3.6	7.1	2.5	3.7	7.6
Hours of work	38.1	42.3	45.0	33.6	37.6	41.0
Earnings	298.0	571.2	1221.6	320.8	552.1	1254.3

Source: Authors' own calculations based on microdata from national household surveys.

Table A.6: Panel data sources by country and period

Country	Period	Survey
Argentina	2003–2024	Permanent Household Survey (EPH)
Brazil	2012–2022	Continuous National Household Sample Survey (PNADC)
Chile	2011–2022	National Employment Survey (NENE)
Peru	2008–2023	National Household Survey (ENAHO)

Source: Authors' own elaboration.

Table A.7: Coefficients of the cycle component in labor outcomes regressions. P and V groups based on income in t-1. Perú

	Labor force participation	Employment	Unemployment	Informality	Hourly wages	Earnings
Cycle (γ_1)	0.242***	0.275***	-0.043	-0.179***	0.644***	0.857***
	(0.071)	(0.075)	(0.037)	(0.054)	(0.171)	(0.190)
Cycle × V (γ_2)	0.224***	0.316***	-0.136***	-0.239***	0.367*	0.630***
	(0.082)	(0.087)	(0.047)	(0.073)	(0.194)	(0.213)
$\gamma_1 + \gamma_2$	0.466***	0.591***	-0.179***	-0.418***	1.011***	1.487***
	(0.076)	(0.081)	(0.046)	(0.076)	(0.170)	(0.183)
Other controls in X	yes	yes	yes	yes	yes	yes
Country fixed effects	yes	yes	yes	yes	yes	yes
R-squared	0.067	0.066	0.010	0.107	0.128	0.239
Observations	128,853	128,853	113,627	161,897	119,343	121,985

Notes: The table reports the coefficients on the cyclical component from Equation 1. All regressions are estimated at the individual level. The dummy variable V equals 1 for vulnerable non-poor individuals and 0 for poor individuals based on income in t-1. All specifications include country fixed effects and individual-level controls: gender, five-year age groups, and a COVID-19 indicator. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own calculations based on panel data.

Table A.8: Coefficients of the cycle component in labor outcomes regressions. P and V groups based on income in t-1. Argentina, Brazil and Chile

	Labor force participation	Employment	Unemployment	Informality	Hourly wages	Earnings
Cycle (γ_1)	-0.040	0.379***	-0.645***	-0.166***	-0.070	0.533***
	(0.052)	(0.055)	(0.058)	(0.058)	(0.102)	(0.118)
Cycle $\times$ V (γ_2)	0.032	-0.142**	0.302***	0.063	0.005	-0.060
	(0.064)	(0.068)	(0.069)	(0.074)	(0.127)	(0.143)
$\gamma_1 + \gamma_2$	-0.008	0.236***	-0.343***	-0.103**	-0.065	0.473***
	(0.041)	(0.045)	(0.039)	(0.052)	(0.088)	(0.093)
Other controls in X	yes	yes	yes	yes	yes	yes
Country fixed effects	yes	yes	yes	yes	yes	yes
R-squared	0.171	0.153	0.022	0.099	0.124	0.187
Observations	1,138,189	1,138,189	736,208	814,623	760,915	768,824

Notes: The table reports the coefficients on the cyclical component from Equation 1. All regressions are estimated at the individual level. The dummy variable V equals 1 for vulnerable non-poor individuals and 0 for poor individuals based on income in t-1. All specifications include country fixed effects and individual-level controls: gender, five-year age groups, and a COVID-19 indicator. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own calculations based on panel data.

Table A.9: Coefficients of the cycle component in labor outcomes regressions. P and V groups based on income in t-1. Argentina, 2003-2024

	Labor force participation	Employment	Unemployment	Informality	Hourly wages	Earnings
Cycle (γ_1)	0.239**	0.567***	-0.574***	-0.036	-0.225	0.632**
	(0.112)	(0.118)	(0.133)	(0.125)	(0.213)	(0.246)
Cycle $\times$ V (γ_2)	-0.096	-0.305**	0.388**	-0.073	0.315	0.205
	(0.133)	(0.139)	(0.152)	(0.152)	(0.258)	(0.286)
$\gamma_1 + \gamma_2$	0.143*	0.262***	-0.186***	-0.109	0.090	0.837***
	(0.074)	(0.079)	(0.068)	(0.093)	(0.173)	(0.169)
Other controls in X	yes	yes	yes	yes	yes	yes
R-squared	0.183	0.166	0.020	0.074	0.059	0.197
Observations	143,417	143,417	97,836	112,487	102,451	109,602

Notes: The table reports the coefficients on the cyclical component from Equation 1. All regressions are estimated at the individual level. The dummy variable V equals 1 for vulnerable non-poor individuals and 0 for poor individuals, based on observed income in $t-1$. Source: Own calculations based on yearly panels at the individual level constructed from Argentina's EPHC over the period 2003–2024.

Table A.10: Coefficients of the cycle component in labor outcomes regressions. P and V groups based on income in t-1. Brazil, 2012-2022

	Labor force participation	Employment	Unemployment	Informality	Hourly wages	Earnings
Cycle (γ_1)	-0.093***	0.495***	-0.914***	-0.159***	0.197***	0.567***
	(0.026)	(0.028)	(0.025)	(0.036)	(0.049)	(0.056)
Cycle $\times$ V (γ_2)	-0.113***	-0.326***	0.434***	0.170***	-0.192***	-0.341***
	(0.034)	(0.036)	(0.032)	(0.046)	(0.059)	(0.067)
$\gamma_1 + \gamma_2$	-0.205***	0.169***	-0.480***	0.011	0.005	0.226***
	(0.025)	(0.026)	(0.020)	(0.033)	(0.039)	(0.042)
Other controls in X	yes	yes	yes	yes	yes	yes
R-squared	0.172	0.150	0.029	0.077	0.093	0.165
Observations	940,896	940,896	601,911	661,197	622,676	622,927

Notes: The table reports the coefficients on the cyclical component from Equation 1. All regressions are estimated at the individual level. The dummy variable V equals 1 for vulnerable non-poor individuals and 0 for poor individuals, based on observed income in $t-1$. Source: Own calculations based on yearly panels at the individual level constructed from Brazil's PNADC over the period 2012–2022.

Table A.11: Coefficients of the cycle component in labor outcomes regressions. P and V groups based on income in t-1. Chile, 2010-2019

	Labor force participation	Employment	Unemployment	Informality	Hourly wages	Earnings
Cycle (γ_1)	0.781	1.032*	-0.480	-0.278	-0.107	-0.510
	(0.531)	(0.576)	(0.484)	(0.739)	(1.378)	(1.488)
Cycle $\times$ V (γ_2)	-1.100*	-0.872	-0.174	-0.077	-0.494	1.040
	(0.606)	(0.665)	(0.558)	(0.835)	(1.489)	(1.632)
$\gamma_1 + \gamma_2$	-0.320	0.160	-0.654**	-0.355	-0.601	0.530
	(0.291)	(0.331)	(0.278)	(0.388)	(0.558)	(0.668)
Other controls in X	yes	yes	yes	yes	yes	yes
R-squared	0.173	0.151	0.013	0.066	0.084	0.180
Observations	53,876	53,876	36,461	40,939	35,788	36,295

Notes: The table reports the coefficients on the cyclical component from Equation 1. All regressions are estimated at the individual level. The dummy variable V equals 1 for vulnerable non-poor individuals and 0 for poor individuals, based on observed income in $t-1$. Source: Own calculations based on yearly panels at the individual level constructed from Chile's NENE over the period 2010–2019.

Table A.12: Coefficients of the cycle component in labor outcomes regressions. P and V groups based on predicted income. Group 1

	Labor force participation	Employment	Unemployment	Informality	Hourly wages	Earnings
Cycle (γ_1)	0.069	0.129**	-0.083***	-0.272***	0.831***	1.256***
	(0.057)	(0.059)	(0.027)	(0.062)	(0.151)	(0.153)
Cycle × V (γ_2)	0.182**	0.203***	-0.035	-0.128	0.291	0.205
	(0.072)	(0.074)	(0.035)	(0.085)	(0.183)	(0.186)
$\gamma_1 + \gamma_2$	0.251***	0.332***	-0.118***	-0.401***	1.122***	1.461***
	(0.059)	(0.062)	(0.031)	(0.078)	(0.150)	(0.153)
Other controls in X	yes	yes	yes	yes	yes	yes
Country fixed effects	yes	yes	yes	yes	yes	yes
R-squared	0.197	0.181	0.019	0.067	0.104	0.177
Observations	756,869	756,869	579,177	525,499	637,624	657,494

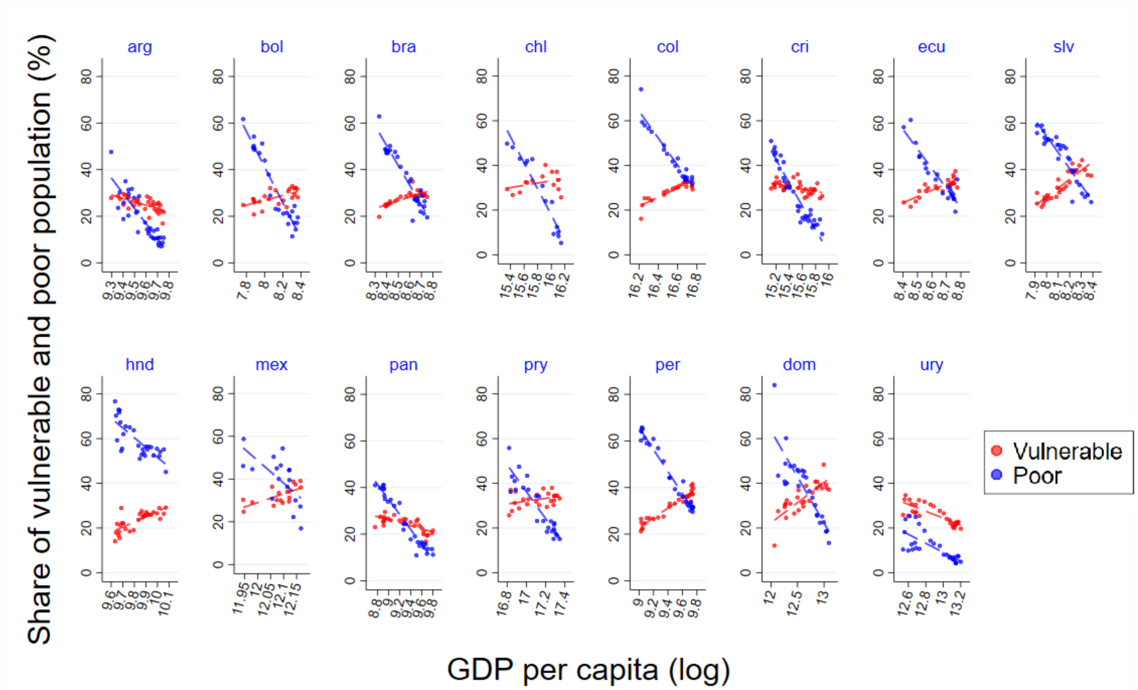
Notes: The table reports the coefficients on the cyclical component from Equation 1. All regressions are estimated at the individual level. The dummy variable V equals 1 for vulnerable non-poor individuals and 0 for poor individuals based on predicted income. All specifications include country fixed effects and individual-level controls: gender, five-year age groups, and a COVID-19 indicator. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own calculations based on microdata from national household surveys (1992 - 2024).

Table A.13: Coefficients of the cycle component in labor outcomes regressions. P and V groups based on predicted income. Group 2

	Labor force participation	Employment	Unemployment	Informality	Hourly wages	Earnings
Cycle (γ_1)	-0.135***	0.048	-0.231***	-0.087	2.046***	2.292***
	(0.044)	(0.048)	(0.040)	(0.065)	(0.101)	(0.101)
Cycle × V (γ_2)	-0.001	-0.023	0.038	0.189**	-0.567***	-0.526***
	(0.057)	(0.063)	(0.051)	(0.088)	(0.127)	(0.134)
$\gamma_1 + \gamma_2$	-0.135***	0.024	-0.193***	0.101	1.479***	1.767***
	(0.039)	(0.043)	(0.034)	(0.063)	(0.082)	(0.091)
Other controls in X	yes	yes	yes	yes	yes	yes
Country fixed effects	yes	yes	yes	yes	yes	yes
R-squared	0.203	0.184	0.021	0.075	0.158	0.186
Observations	580,494	580,494	412,868	376,659	449,159	459,688

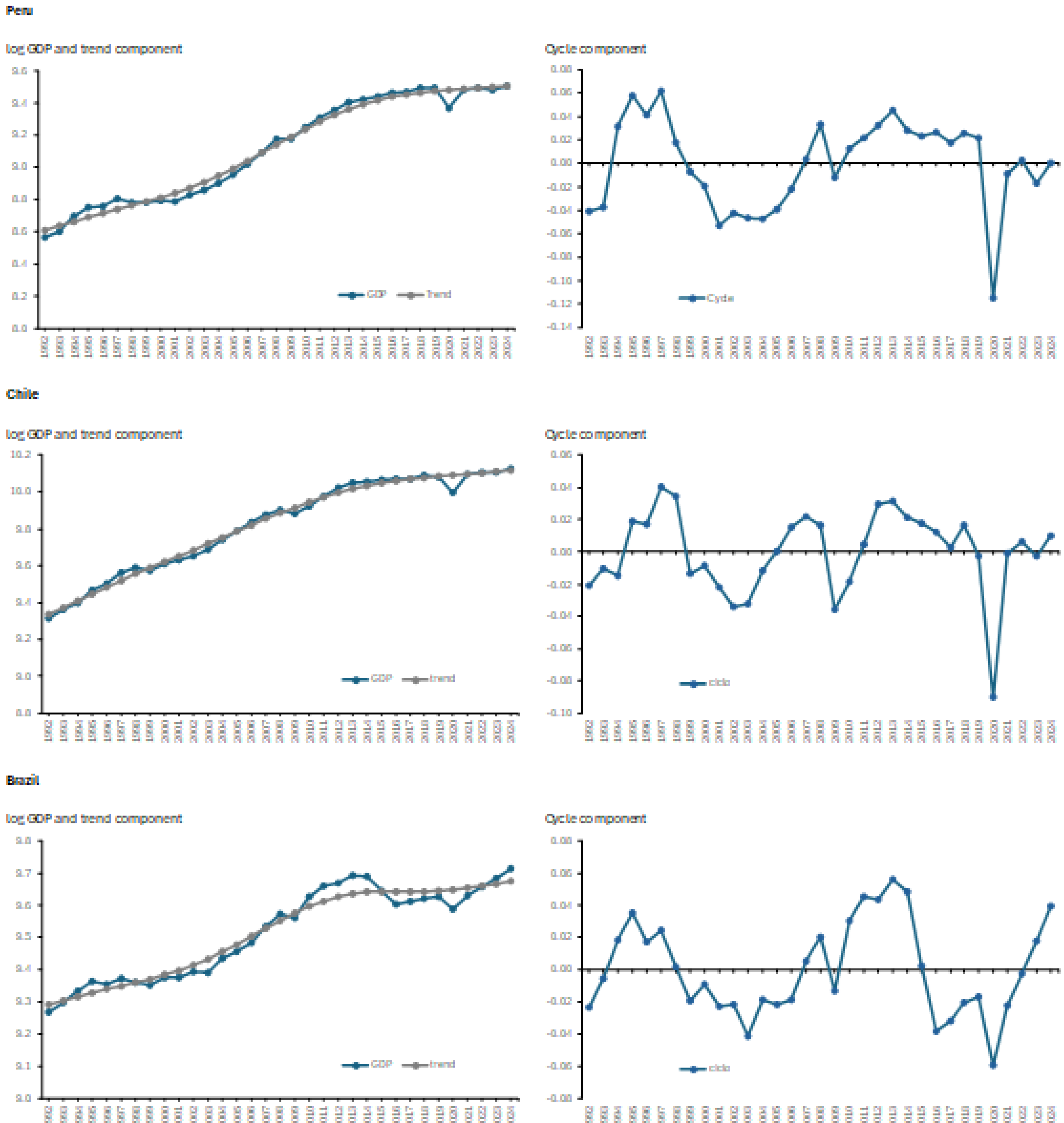
Notes: The table reports the coefficients on the cyclical component from Equation 1. All regressions are estimated at the individual level. The dummy variable V equals 1 for vulnerable non-poor individuals and 0 for poor individuals based on predicted income. All specifications include country fixed effects and individual-level controls: gender, five-year age groups, and a COVID-19 indicator. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own calculations based on microdata from national household surveys (1992 - 2024).

Figure A.1: Log real GDP per capita and the shares of the vulnerable and the poor in Latin America



Source: Authors' own calculations based on microdata from national household surveys and WDI.

Figure A.2: GDP per capita: trend and cycle components. Peru, Chile and Brazil



Notes: Values in logs. GDP cyclical component in percent deviations from trend.
Source: Authors' own calculations based on GDP values from International Monetary Fund.

B Characterization of income groups

This Appendix complements the analysis in Section 3.2.

B I Descriptive statistics by country

Table B.1: Characterization of income groups. Demographics and location. Year 2024.

	Latin America	ARG	BOL	BRA	CHL	COL	CRI	DOM	ECU	SLV	HND	MEX	PAN	PRY	PER	URY
Mean age																
Poor	26.6	24.0	27.7	25.5	26.3	29.3	28.3	25.4	28.4	27.9	27.0	26.3	26.1	31.2	21.8	23.5
Vulnerable	31.2	28.6	28.9	31.6	30.0	33.3	34.2	33.7	32.4	31.3	32.1	30.1	29.0	34.6	30.7	27.9
Rest	39.4	41.1	34.9	41.5	40.3	40.1	43.1	39.0	38.3	38.1	39.1	38.7	35.2	40.6	38.7	41.6
Total	34.7	35.1	31.9	35.6	36.9	34.6	39.4	33.2	33.5	31.5	34.5	35.4	31.8	35.3	33.5	38.1
Share [0,14]																
Poor	45.7	49.4	45.6	43.7	42.4	39.6	42.3	49.8	41.3	43.8	44.8	49.6	48.0	38.0	57.5	49.8
Vulnerable	34.4	38.9	39.3	29.3	34.5	27.9	32.0	32.0	30.6	34.5	31.9	41.6	39.0	27.8	36.6	40.7
Rest	17.2	16.7	22.8	13.9	16.0	14.3	11.9	20.3	16.2	16.5	16.3	22.7	21.8	14.6	18.5	16.5
Total	27.5	27.3	31.4	23.8	21.9	26.1	19.9	32.2	28.1	34.1	26.7	29.6	31.4	27.2	30.3	22.7
Share [65+]																
Poor	7.2	2.3	7.9	3.6	4.3	10.1	7.2	10.1	8.9	9.1	7.1	8.9	7.2	12.7	4.6	3.5
Vulnerable	10.7	7.6	9.9	7.3	7.8	11.4	17.2	10.8	11.2	11.0	11.1	13.1	9.0	13.6	11.5	7.2
Rest	17.3	21.4	11.1	18.9	18.0	16.2	22.7	17.1	14.0	17.4	16.1	18.3	11.4	17.0	17.1	22.1
Total	13.8	15.0	10.3	12.8	14.8	12.9	19.9	12.9	11.6	11.8	12.8	16.2	10.0	14.3	13.4	18.3
Share [25, 64]																
Poor	47.1	48.3	46.5	52.7	53.2	50.3	50.4	40.1	49.8	47.2	48.2	41.6	44.8	49.3	37.8	46.7
Vulnerable	54.9	53.6	50.8	63.4	57.7	60.7	50.8	57.1	58.2	54.5	57.0	45.3	52.0	58.6	51.8	52.1
Rest	65.5	61.9	66.1	67.2	66.0	69.5	65.4	62.6	69.9	66.2	67.6	59.0	66.8	68.4	64.5	61.5
Total	58.7	57.7	58.4	63.4	63.3	60.9	60.3	54.8	60.3	54.2	60.5	54.2	58.6	58.5	56.3	59.0
Share women [25,64]																
Poor	57.1	59.4	56.2	57.2	55.6	56.1	55.9	55.7	55.9	56.9	54.4	57.7	58.5	55.2	66.0	56.5
Vulnerable	55.0	52.7	53.0	53.2	56.5	53.0	58.2	57.2	58.1	55.3	55.5	55.8	53.2	54.9	53.8	54.4
Rest	50.2	49.0	48.5	49.2	47.8	49.6	53.3	48.4	54.1	54.9	51.7	52.2	50.4	47.5	48.0	49.0
Total	52.6	51.1	50.7	51.5	50.1	52.2	54.6	53.2	56.0	55.8	53.4	53.3	52.2	52.5	51.6	50.2
Household size																
Poor	4.1	4.0	3.9	3.5	3.8	3.5	4.0	5.1	3.8	4.2	4.5	4.5	4.3	3.8	3.9	4.5
Vulnerable	3.6	4.0	3.7	3.2	3.7	3.1	3.4	3.5	3.3	4.0	3.8	4.0	3.9	3.6	3.3	3.8
Rest	2.7	2.4	2.7	2.4	2.6	2.4	2.6	2.8	2.6	3.1	2.8	3.0	3.0	2.8	2.3	2.6
Total	3.1	2.9	3.1	2.7	2.9	2.9	2.9	3.5	3.1	3.8	3.3	3.3	3.4	3.4	2.7	2.8
Number of children																
Poor	1.8	1.9	2.0	1.5	1.7	1.4	1.7	2.2	1.7	1.7	2.0	1.7	2.1	1.6	2.0	1.9
Vulnerable	1.3	1.5	1.4	0.9	1.4	1.0	1.3	1.3	1.1	1.5	1.3	1.8	1.4	1.2	1.4	1.4
Rest	0.6	0.6	0.8	0.5	0.6	0.4	0.5	0.8	0.6	0.6	0.7	0.8	0.7	0.6	0.6	0.7
Total	1.1	1.0	1.1	0.8	0.9	0.9	0.8	1.4	1.1	1.4	1.1	1.1	1.1	1.2	1.0	0.9
Dependency rate																
Poor	2.4	2.7	1.6	2.7	2.2	2.6	2.4	2.1	3.0	2.3	2.5	1.8	2.5	2.3	2.2	2.6
Vulnerable	1.9	2.2	1.4	1.8	1.9	2.0	2.1	1.7	2.1	2.0	1.9	1.5	1.9	1.8	1.7	2.2
Rest	1.4	1.4	1.3	1.3	1.4	1.4	1.5	1.5	1.5	1.5	1.4	1.2	1.4	1.4	1.2	1.4
Total	1.7	1.7	1.4	1.6	1.5	1.9	1.7	1.7	2.1	2.0	1.7	1.3	1.7	1.8	1.5	1.5
Share urban																
Poor	61.0		33.7	80.5	88.2	60.2	50.1	64.3	43.0	42.4	56.0	52.9	42.5	61.7	83.6	94.4
Vulnerable	72.7		59.2	85.6	88.6	75.4	61.9	75.3	57.2	60.6	74.9	61.9	54.5	83.0	85.2	93.7
Rest	83.2		82.5	91.8	88.6	89.5	78.2	75.0	68.0	75.9	87.8	81.0	72.9	93.0	85.6	95.5
Total	76.3		70.5	88.6	88.6	78.1	72.7	73.1	58.9	57.9	79.7	75.5	63.9	80.5	85.3	95.2

Source: Own calculations based on microdata from national household surveys.

Table B.2: Characterization of income groups. Education. Year 2024.

	Latin America	ARG	BOL	BRA	CHL	COL	CRI	DOM	ECU	SLV	HND	MEX	PAN	PRY	PER	URY
Years of education [25-65]																
Poor	7.7	9.9	7.0	7.7	10.6	7.7	7.0	7.7	6.1	5.3	7.7	8.0	6.8	8.1	8.5	7.6
Vulnerable	8.9	10.7	9.4	8.6	11.2	9.0	7.4	8.8	7.6	7.5	9.2	8.6	8.9	9.9	9.3	8.1
Rest	11.6	13.1	12.3	11.1	12.9	12.2	10.5	11.4	9.7	10.2	12.1	12.1	11.7	12.1	11.1	11.3
Total	10.2	12.2	10.9	9.9	12.4	10.1	9.5	9.7	8.2	7.5	10.6	11.1	10.3	10.2	10.2	10.6
Years of education [25-35]																
Poor	9.1	10.2	10.1	9.3	11.7	9.3	8.6	9.8	8.0	6.5	8.9	8.9	8.3	9.6	9.5	8.2
Vulnerable	10.5	11.6	11.1	10.2	12.4	10.7	8.3	11.4	9.4	9.4	10.8	9.8	10.8	11.7	10.5	8.7
Rest	13.0	13.7	14.0	12.5	14.2	13.3	11.7	13.8	11.8	11.6	13.7	12.9	13.2	13.8	12.2	12.0
Total	11.6	12.6	12.7	11.2	13.7	11.5	10.6	12.2	10.1	9.0	11.9	11.9	12.0	11.8	11.3	11.1
Years of education [36-45]																
Poor	8.0	10.4	7.2	7.9	10.8	8.0	6.3	7.4	6.4	5.2	8.2	8.6	7.3	8.8	9.5	7.4
Vulnerable	9.4	10.7	10.1	9.4	11.6	9.7	7.7	10.0	8.2	7.8	9.6	8.7	9.4	10.8	9.0	8.3
Rest	12.1	13.3	13.3	12.0	13.5	13.0	11.0	11.6	10.7	10.5	12.5	12.3	12.2	12.9	11.1	11.6
Total	10.5	12.2	11.5	10.5	12.9	10.6	9.9	10.0	8.7	7.3	10.8	11.3	10.6	10.8	10.2	10.8
Years of education [46-65]																
Poor	6.2	9.0	4.7	5.3	9.2	5.8	6.0	6.0	4.1	4.3	6.1	7.0	5.2	6.4	6.5	7.1
Vulnerable	7.3	9.7	6.8	6.7	9.8	7.1	6.5	7.1	5.4	5.5	7.8	7.7	6.5	8.3	7.9	7.4
Rest	10.4	12.7	10.5	9.8	11.5	11.1	9.4	9.8	7.6	8.9	11.0	11.6	10.1	10.7	10.2	10.7
Total	9.0	11.8	9.0	8.5	11.1	8.7	8.7	8.1	6.2	6.3	9.4	10.7	8.6	8.8	9.2	10.2
Share low education [25-65]																
Poor	64.4	56.2	63.6	68.2	51.3	61.5	69.8	57.4	67.5	76.4	59.3	60.1	74.8	62.9	61.3	75.1
Vulnerable	55.3	47.0	53.3	55.5	45.2	49.5	68.2	53.4	56.7	61.1	45.7	58.3	63.7	46.4	59.2	66.0
Rest	35.3	26.4	35.5	38.2	30.5	28.2	40.5	40.1	41.9	40.5	27.6	33.4	40.0	29.4	39.0	38.0
Total	47.0	36.6	45.3	48.9	35.4	45.1	50.5	50.0	54.1	62.7	39.5	41.8	53.1	46.7	49.5	45.3
Share medium education [25-65]																
Poor	27.7	38.0	24.6	29.6	39.0	30.7	24.1	29.2	23.4	14.0	33.1	27.0	22.3	32.5	26.3	21.7
Vulnerable	34.7	43.4	32.8	39.3	41.7	41.3	27.9	32.9	33.9	26.5	43.0	29.2	29.3	39.4	29.3	30.7
Rest	37.1	39.8	29.2	37.1	37.6	40.3	35.5	32.4	38.1	38.0	42.4	39.9	32.1	35.9	38.1	40.2
Total	34.5	40.6	29.7	36.2	38.7	37.5	32.4	31.7	32.7	23.8	41.0	36.1	29.7	36.2	33.3	37.4
Share high education [25-65]																
Poor	7.9	5.8	11.8	2.2	9.7	7.7	6.1	13.4	9.1	9.7	7.6	12.9	2.9	4.6	12.4	3.2
Vulnerable	10.0	9.5	13.9	5.3	13.1	9.2	3.9	13.7	9.5	12.4	11.3	12.5	7.0	14.2	11.5	3.3
Rest	27.6	33.8	35.3	24.7	31.9	31.5	24.0	27.5	20.0	21.5	30.0	26.7	27.9	34.7	22.9	21.7
Total	18.6	22.9	25.0	14.8	25.9	17.4	17.0	18.3	13.2	13.5	19.4	22.1	17.2	17.0	17.3	17.2
Gross enrollent rates [13-17]																
Poor	86.4	94.8	87.2	94.1	95.5	83.6	85.1	95.8	82.5	57.4	68.8	89.1	90.1	92.8	82.5	95.9
Vulnerable	90.6	97.3	95.2	95.6	98.7	84.4	96.4	96.0	87.5	62.9	79.2	95.5	90.9	88.8	97.8	92.5
Rest	92.2	96.8	97.2	96.7	99.0	90.4	95.1	99.9	92.6	76.1	89.0	97.8	95.3	90.8	71.0	95.1
Total	90.0	96.6	94.4	95.6	98.6	85.4	94.2	97.0	87.3	62.0	80.2	95.7	92.5	91.1	84.8	94.4
Gross enrollent rates [18-23]																
Poor	29.5	41.2	49.3	25.4	43.5	27.7	30.4	14.0	15.7	24.8	19.4	20.1	34.1	40.8	30.1	26.4
Vulnerable	38.6	47.2	56.7	22.2	60.7	34.4	51.3	39.4	28.6	12.7	29.9	50.7	31.7	46.5	30.3	36.7
Rest	51.4	56.6	64.4	40.4	60.5	44.4	57.3	50.4	38.4	36.9	48.7	59.2	46.7	62.8	47.3	56.9
Total	43.2	51.3	60.1	31.0	59.4	35.9	52.7	31.2	28.9	25.8	37.7	52.8	40.2	50.1	39.5	51.2

Source: Own calculations based on microdata from national household surveys.

Table B.3: Characterization of income groups. Labor market variables. Year 2024.

	Latin America	ARG	BOL	BRA	CHL	COL	CRI	DOM	ECU	SLV	HND	MEX	PAN	PRY	PER	URY
Labor force participation																
Poor	64.4	63.7	83.1	53.2	61.6	66.1	45.8	60.2	54.1	51.3	67.1	64.5	66.6	81.9	67.0	80.1
Vulnerable	72.9	78.0	77.7	69.8	68.0	75.7	59.7	70.2	68.0	72.3	72.8	71.4	74.8	82.1	73.6	80.0
Rest	83.1	86.8	84.0	83.5	83.6	84.8	74.4	80.0	83.4	79.0	80.2	82.6	86.3	88.4	84.0	85.0
Total	77.2	81.9	82.2	75.1	79.2	77.4	69.1	72.5	71.6	66.2	76.0	79.2	80.6	84.2	79.0	84.0
Female labor force participation																
Poor	48.9	50.7	72.7	38.6	47.4	48.2	30.1	31.6	31.6	29.3	46.7	53.4	51.3	72.3	55.2	74.1
Vulnerable	59.6	67.8	61.2	58.4	54.1	60.8	43.1	63.3	53.2	56.6	56.8	56.8	58.6	72.9	59.9	70.8
Rest	73.9	80.7	73.9	75.9	74.4	76.7	62.3	66.5	74.0	67.0	68.6	73.3	79.0	83.3	73.1	80.4
Total	65.3	73.4	70.1	64.5	68.0	64.2	55.5	58.5	57.2	48.8	61.5	68.4	69.3	75.9	66.4	78.4
Employment																
Poor	55.7	53.1	75.9	41.5	41.2	55.8	31.9	57.4	53.2	48.2	64.4	52.4	59.7	78.6	60.0	61.9
Vulnerable	67.3	69.0	70.4	65.3	57.5	69.3	54.1	69.1	66.8	69.4	70.9	59.1	71.3	79.6	68.9	68.8
Rest	80.7	84.2	80.6	82.1	79.7	80.6	71.7	79.2	82.6	76.7	78.9	77.6	83.5	87.6	83.5	81.6
Total	73.4	76.8	77.2	71.2	73.2	71.0	65.0	71.3	70.6	63.4	74.3	72.2	77.1	82.0	76.5	78.7
Unemployment																
Poor	14.0	16.6	8.6	22.0	33.7	15.6	30.2	4.6	1.7	6.1	4.0	18.8	10.3	4.0	10.3	22.7
Vulnerable	7.8	11.6	9.4	6.5	16.0	8.5	9.5	1.5	1.8	3.9	2.6	17.3	4.7	3.0	6.4	14.0
Rest	2.9	3.0	4.1	1.7	4.8	5.0	3.6	1.0	0.9	2.9	1.7	6.1	3.2	1.0	0.7	4.1
Total	5.0	6.3	6.0	5.2	8.0	8.3	6.0	1.8	1.4	4.2	2.3	8.8	4.3	2.5	3.2	6.3
Duration of unemployment																
Poor	3.8	5.5		12.8	1.6	4.7	3.6	2.6		2.8		3.7	2.9	1.0	1.8	2.8
Vulnerable	5.6	9.5		12.5	2.4	5.5	5.9	3.1		2.2		14.0	3.5	1.4	5.8	1.9
Rest	5.1	8.8		13.8	1.8	5.4	6.1	3.7		2.5		6.0	3.7	1.1	6.5	2.1
Total	4.9	8.3		12.9	2.0	5.1	5.5	3.0		2.5		8.2	3.5	1.2	4.9	2.1
Informality productive																
Poor	77.6	66.8	96.5	65.2	61.2	84.6	75.7	83.7	78.1	81.7	62.2	88.5	92.9	84.1	75.6	67.3
Vulnerable	59.4	51.2	83.0	50.0	42.6	58.4	50.0	74.5	60.6	63.4	50.9	68.6	66.4	61.6	53.2	56.2
Rest	35.9	31.1	52.7	28.8	24.3	27.8	29.5	49.7	41.6	44.1	29.4	32.4	40.8	39.6	39.9	27.9
Total	46.9	38.4	65.3	37.4	28.3	47.8	34.8	64.1	53.9	61.5	40.2	41.0	52.7	59.6	45.8	33.2
Informality social protection																
Poor	81.6	74.7	97.2	69.1	66.1	87.8	70.4	85.5	85.4	94.2	77.3	90.4	96.8	88.5	69.9	70.8
Vulnerable	65.6	61.9	87.3	48.4	42.2	61.4	45.3	74.1	69.9	91.1	68.5	76.1	77.4	70.6	57.8	51.4
Rest	40.6	33.3	56.8	25.6	22.2	25.9	24.1	53.9	47.3	73.6	45.2	34.7	52.0	49.9	42.2	22.1
Total	51.6	43.1	69.2	35.2	26.8	48.4	29.6	66.2	61.1	86.4	56.5	44.0	62.9	67.7	48.9	27.9
Hourly wages																
Poor	2.3	2.5	2.2	2.2	2.8	1.8	2.5	2.5	1.8	1.6	2.0	3.2	2.1	1.9	2.7	2.8
Vulnerable	3.6	4.0	4.2	3.0	4.0	2.8	3.9	3.6	3.2	3.5	3.1	4.9	3.3	2.9	3.8	4.0
Rest	7.4	7.7	8.3	7.3	8.9	7.3	8.7	6.5	5.5	6.8	6.5	11.1	6.8	5.1	6.0	8.1
Total	5.9	6.5	6.8	5.8	7.9	4.9	7.6	4.8	4.0	4.2	4.9	9.7	5.5	3.5	5.1	7.4
Hours of work																
Poor	36.2	32.6	42.6	35.0	37.0	39.7	37.1	31.7	41.8	42.7	41.6	25.2	37.1	35.2	36.1	28.4
Vulnerable	40.3	35.1	42.1	39.0	39.4	44.8	41.3	31.8	42.6	48.3	44.4	32.7	43.8	41.9	41.5	36.3
Rest	43.3	37.9	46.8	41.2	41.8	46.4	44.4	38.8	45.7	46.1	45.7	40.2	46.5	45.0	43.9	39.9
Total	41.7	36.8	45.0	40.1	41.2	44.5	43.6	34.9	43.9	45.7	44.8	37.9	44.9	41.1	42.5	39.0
Earnings																
Poor	311	274	337	310	381	295	350	350	298	277	310	221	320	265	381	290
Vulnerable	569	543	715	476	613	544	650	516	526	632	513	557	581	469	614	583
Rest	1254	1204	1480	1251	1435	1398	1519	1082	995	1051	1147	1727	1233	892	1082	1321
Total	983	984	1191	973	1270	933	1324	752	707	685	838	1456	983	581	883	1188

Source: Own calculations based on microdata from national household surveys.

B II Between-groups comparison based on regressions

This analysis complements that in Section 3.2 by estimating Equation 10 for year 2024:

$$X_{ict} = \alpha + \beta_1 V_{ict} + \lambda_c + \varepsilon_{ict}, \tag{10}$$

where X_{ict} includes individual and household characteristics, such as education or number of children; and V_{ict} is a dummy variable indicating whether the individual (or household) i in country c and year t belongs to group V. Equation 10 is estimated twice using different samples: the first specification uses only individuals in groups V and P, while the second uses only individuals in groups V and R. Accordingly, the reference category is P in the former and R in the latter. λ_c are country dummies that capture systematic differences across countries, and ε_{ict} is the error term. Hence, β_1 measures how, on average, individuals in V differ from those in the corresponding reference group, once systematic cross-country differences are accounted for. Standard errors are clustered at the regional level within each country to account for the potential correlation of the error term over time within regions.

After that, we examine whether the observable differences between V and the other groups have changed over time. To that end, we estimate Equation 11 using the pooled sample of repeated cross-sections for the period 1992-2024:

$$X_{ict} = \alpha + \beta_1 V_{ict} + \beta_2 (V_{ict} \cdot t) + \lambda_c + \nu_t + \tau_c \cdot t + \varepsilon_{ict}, \tag{11}$$

where $(V_{ict} \cdot t)$ is an interaction term that allows the gap between both groups to vary over time, ν_t are year dummies, and $(\tau_c \cdot t)$ are country-specific linear trends. The coefficient β_2 thus measures the presence and direction of such temporal changes beyond common shocks and country-specific gradual trajectories in the dependent variable.[23]

Demographics

Table B.4 reports the estimates of Equation 10, which quantify the demographic gaps between groups in 2024. The columns on the left present estimates for the V–P comparison, while the columns on the right report the corresponding V–R gaps. In this specification, β_1 captures the

[23] To estimate the pooled regressions, we normalize survey weights within each country–year cell so that each country–year contributes equally to the analysis, regardless of population size. In practice, the individual weights are divided by the sum of weights within each country–year, and the resulting normalized weights are used as probability weights in the regressions.

average difference between groups conditional on country dummies. Across all demographic variables, the estimated coefficients for the V dummy closely mirror the patterns in Table 1. In particular, the vulnerable are generally closer to the poor than to the non-vulnerable—notice that the absolute values of the coefficients are typically larger when contrasting V with R than with P. The only exceptions are the dependency rate and urban residence, where the vulnerable more closely resemble the non-vulnerable population.

Table B.4: Regressions of demographic variables, cross-sectional estimates (2024)

	Vulnerable vs Poor		Vulnerable vs Rest	
	β_1	Obs	β_1	Obs
Age	4.674***	121,276	-8.099***	172,708
Children [0,14]	-9.494***	121,276	13.821***	172,708
Elderly [65+]	2.502***	121,276	-5.891***	172,708
Prime age [25,64]	7.306***	121,276	-10.655***	172,708
Woman prime age [25,64]	-1.860**	55,521	4.826***	92,536
Household size	-0.471***	34,757	0.953***	62,586
N° children	-0.511***	34,757	0.630***	62,586
Dependency rate	-0.533***	34,054	0.486***	62,472
Urban	12.846***	34,757	-9.649***	62,586

Notes: Poor, Vulnerable, and Rest are defined as in Section 3.1. All age regressions and the regression for women are estimated at the individual level, while the remaining regressions are estimated at the household level. The table reports estimates of Equation 10 for 2024 (or the latest available year). For all binary dependent variables, estimated coefficients are multiplied by 100 so that gaps are expressed in percentage points. See Table 1 for variable definitions. *Source:* Own calculations based on microdata from national household surveys.

The over-time analysis shows that these gaps exhibit interesting dynamics. Table B.5 presents the estimated coefficients β_1 and β_2 from Equation 11, which allows us to assess how the demographic gaps between groups evolve over time. For ease of interpretation, Figure B.1 plots the implied linear trajectories, computed as $\beta_1 + \beta_2 \cdot t$.

The figure reveals that in terms of age structure, the three groups have become increasingly differentiated. Since 1992, the average age gap between the vulnerable and the poor has widened by about 1.2 years (32%), while the gap between the non-vulnerable and the vulnerable has increased by nearly 4 years (88%). These trends reflect a growing concentration of elderly individuals in the non-vulnerable population—and, to a lesser extent, among the vulnerable—relative to the poor, combined with a rising concentration of children in both the poor and the vulnerable compared with the non-vulnerable.

Table B.5: Regressions of demographic variables, over-time estimates (1992-2024)

	Vulnerable vs Poor			Vulnerable vs Rest		
	β_1	β_2	Obs	β_1	β_2	Obs
Age	3.738***	0.036*	3,185,076	-4.425***	-0.121***	3,183,570
Children [0,14]	-11.703***	0.028	3,185,076	8.885***	0.140***	3,183,570
Elderly [65+]	1.156**	0.049**	3,185,076	-1.736**	-0.134***	3,183,570
Prime age [25,64]	7.239***	-0.001	3,185,076	-8.462***	-0.068***	3,183,570
Woman prime age [25,64]	-0.785**	-0.030	1,348,514	-0.343	0.146***	1,644,812
Household size	-0.840***	0.009***	798,647	0.815***	0.005**	1,041,647
N° children	-0.840***	0.007***	798,647	0.551***	0.003**	1,041,647
Dependency rate	-1.153***	0.022***	780,713	0.650***	-0.006***	1,040,477
Urban	18.819***	-0.123	798,647	-8.263***	-0.091	1,041,647

Notes: Poor, Vulnerable, and Rest are defined as in Section 3. All age regressions and the regression for women are estimated at the individual level, while the remaining regressions are estimated at the household level. The table reports estimates of Equation 11 using the pooled sample for 1992–2024. For all binary dependent variables, estimated coefficients are multiplied by 100 so that gaps are expressed in percentage points. *Source:* Own calculations based on microdata from national household surveys.

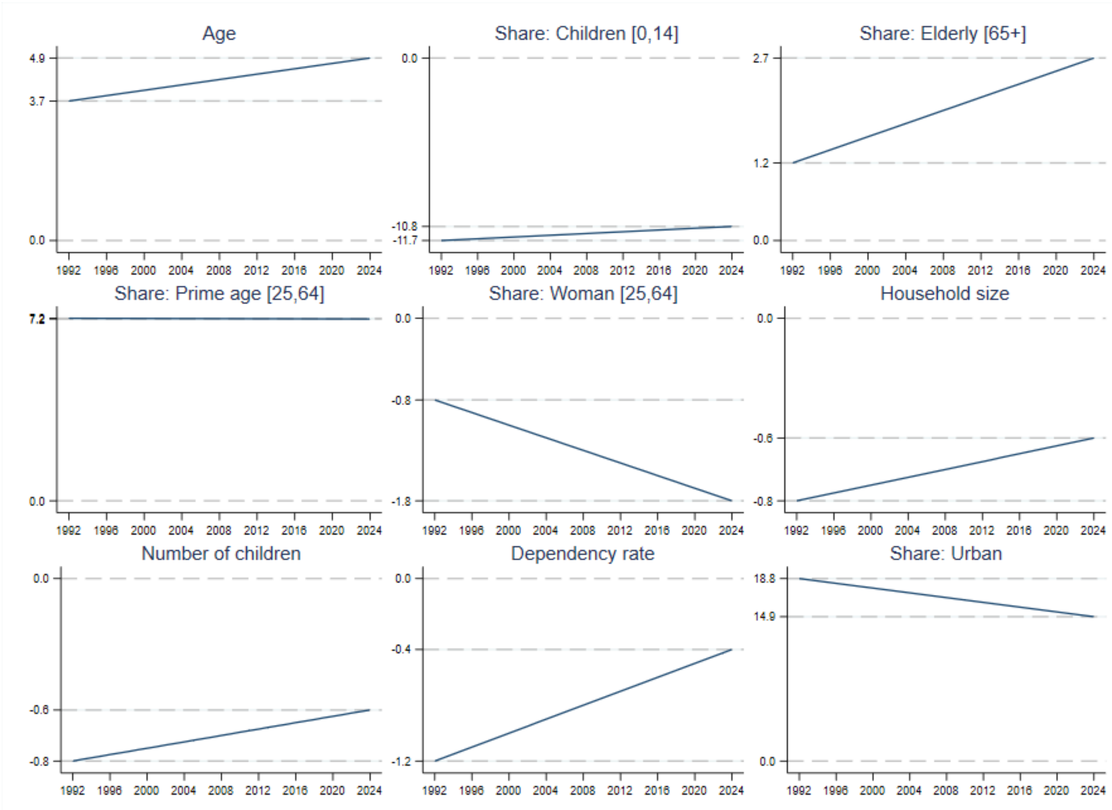
Gender composition exhibits a similar divergence over time. The share of prime-age women has increased among the poor relative to the vulnerable (+1pp), while the gap between the vulnerable and the non-vulnerable has widened even more (+4.6pp). This indicates that, over time, the vulnerable have become relatively less female than the poor and more distinct from the non-vulnerable along this dimension.

In the remaining demographic dimensions, the distance between the vulnerable and the non-vulnerable has also widened over time. The $V-R$ trajectories for household size, number of children, and urban residence move steadily away from zero, indicating that the vulnerable have become increasingly distinct from the non-vulnerable in these aspects. By contrast, the $V-P$ trajectories for these same variables tend to converge toward zero, suggesting that vulnerable and poor households have grown more similar in their family structure and geographic location. The only dimension in which all groups have become more alike is the dependency rate, whose gap narrows steadily over time, leaving the three groups more similar in 2024 than in 1992.

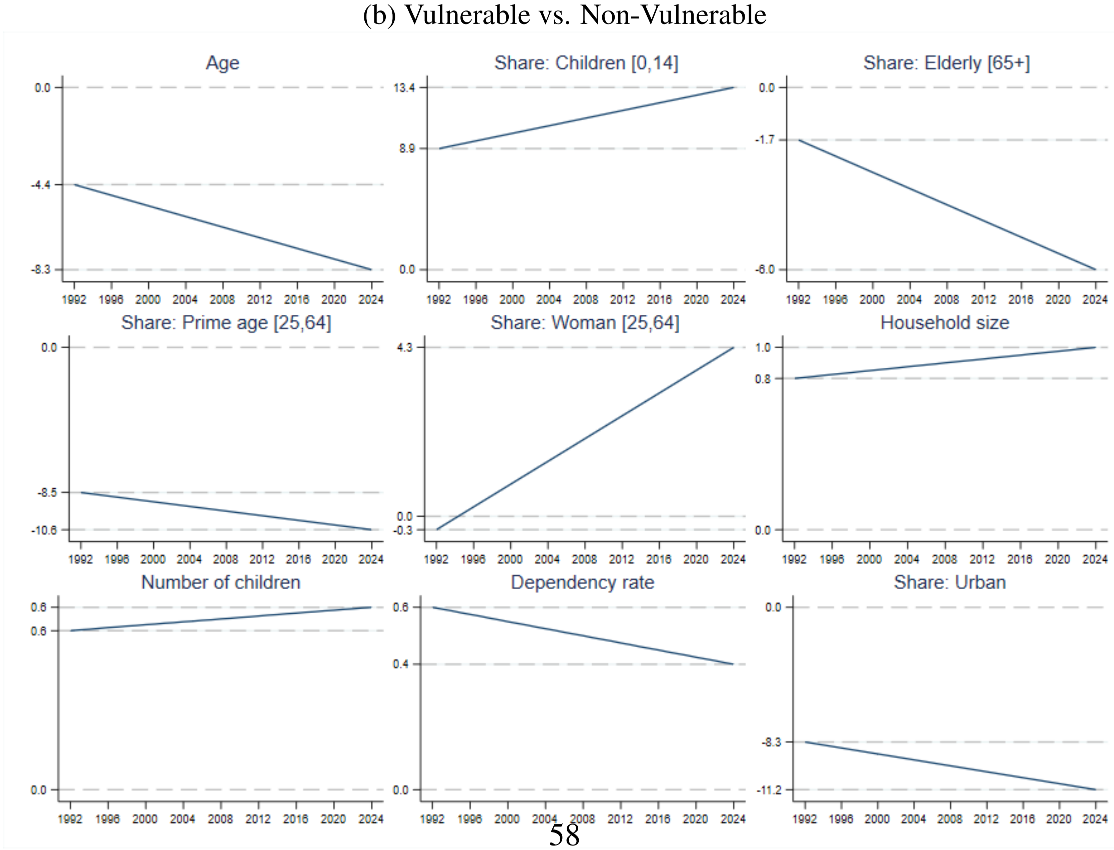
Taken together, these patterns show a sharpening segmentation of the population along demographic lines. Age structure and gender composition increasingly differentiate the three groups, with the vulnerable drifting away from both the poor and the non-vulnerable—though much more sharply from the latter. By contrast, in dimensions related to family structure and geographic location, the vulnerable have moved closer to the poor while simultaneously becoming more distinct from the non-vulnerable.

Figure B.1: Evolution of demographic differences (1992–2024)

(a) Vulnerable vs. Poor



(b) Vulnerable vs. Non-Vulnerable



Notes: The figure shows the evolution of demographic differences between the vulnerable and the poor (panel a) and between the vulnerable and the non-vulnerable (panel b) from 1992 to 2024. Each panel plots the implied linear trajectories obtained from Equation 11—computed as $\beta_1 + \beta_2 \cdot t$—using the coefficients reported in panel b of Table B.4. Positive (negative) values indicate

Education

Table B.6 reports the β_1 coefficients estimated from Equation 10. As before, the left columns present the V–P comparison, while the right columns report the corresponding V–R gaps. Across nearly all education variables, the vulnerable lie between the poor and the non-vulnerable, with smaller V–P gaps and larger V–R gaps—mirroring the socioeconomic gradient in Table 1. Two exceptions stand out. First, medium education shows a larger difference between the vulnerable and the poor than between the vulnerable and the non-vulnerable, reflecting the high concentration of medium-educated adults among the vulnerable. Second, enrollment among adolescents aged 13–17 displays almost no difference between the vulnerable and the non-vulnerable, while the gap with the poor remains sizable.

Table B.6: Regressions of education variables, cross-sectional estimates (2024)

	Vulnerable vs Poor		Vulnerable vs Rest	
	β_1	Obs	β_1	Obs
Years of education [25-65]	1.403***	56,365	-2.604***	94,460
Years of education [25-35]	1.537***	18,204	-2.443***	27,611
Years of education [36-45]	1.699***	15,885	-2.674***	23,870
Years of education [46-65]	1.310***	22,276	-2.985***	42,979
Low education	-10.112***	121,276	19.886***	172,708
Medium education	7.640***	121,276	-2.159**	172,708
High education	2.471***	121,276	-17.727***	172,708
Enrolled [13-17]	4.179**	12,438	-1.548	11,835
Enrolled [18-23]	8.671***	11,536	-12.580***	15,490

Notes: Poor, Vulnerable, and Rest are defined as in Section 3.1. All regressions are estimated at the individual level. The table reports estimates of Equation 10 for 2024 (or the latest available year). For all binary dependent variables, estimated coefficients are multiplied by 100 so that gaps are expressed in percentage points. See Table 1 for variable definitions. *Source:* Own calculations based on microdata from national household surveys.

Table B.7 reports the estimated coefficients from Equation 11, which trace the evolution of educational gaps over time while Figure B.2 illustrates the implied linear trajectories. The overall pattern is one of convergence: for most indicators—years of education, especially in younger cohorts, low- and medium-education shares, and enrollment rates—the gaps between groups have narrowed steadily since the early 1990s. This reflects the broad expansion of basic education across the region, which has disproportionately benefited the poor and the vulnerable, reducing their distance from the non-vulnerable. The main exception is tertiary education. For higher-education attainment, both the V–P and—more markedly—the V–R trajectories move further away from zero, indicating widening gaps as the non-vulnerable have pulled ahead in tertiary completion.

Taken together, these results point to a dual dynamic in educational inequality. On one hand, the expansion of enrollment and completion in the early stages of schooling has substantially narrowed gaps between the poor, the vulnerable, and the non-vulnerable, especially among younger cohorts. On the other hand, the rapid rise in tertiary attainment among the non-vulnerable—outpacing gains among both the vulnerable and the poor—has led to a growing divide at the upper end of the educational distribution.

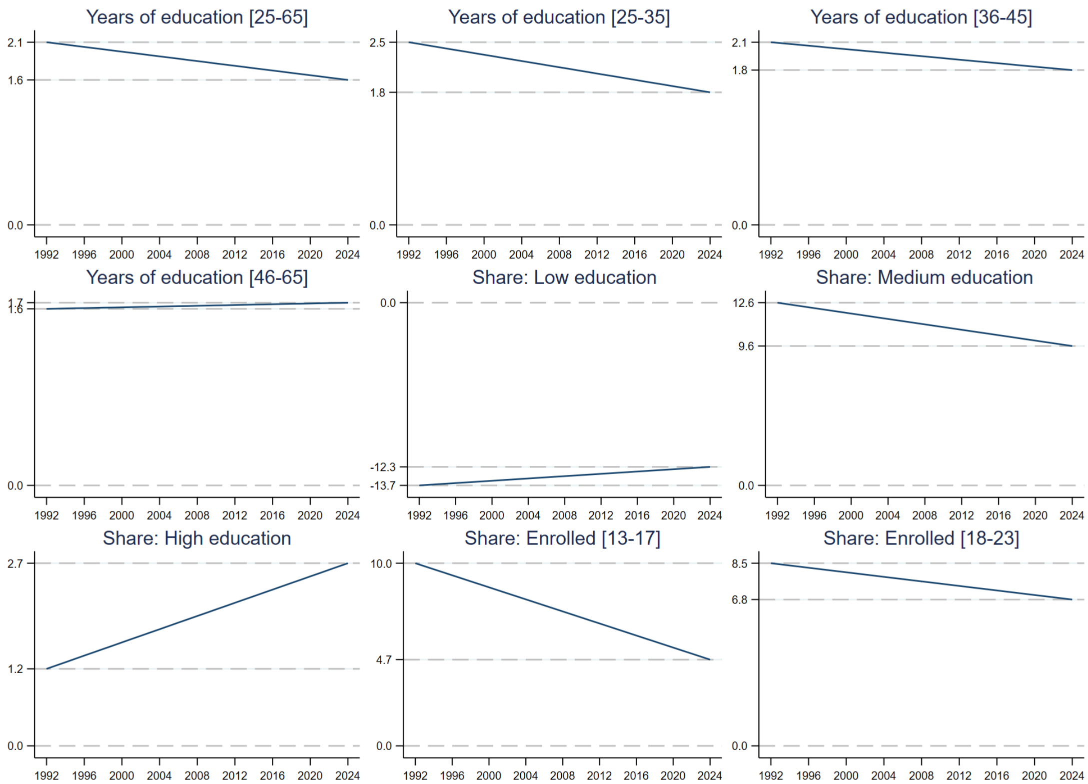
Table B.7: Regressions of education variables, over-time estimates (1992-2024)

	Vulnerable vs Poor			Vulnerable vs Rest		
	β_1	β_2	Obs	β_1	β_2	Obs
Years of education [25-65]	2.054***	-0.013*	1,362,339	-3.195***	0.011**	1,669,864
Years of education [25-35]	2.495***	-0.021***	487,958	-3.094***	0.011**	525,368
Years of education [36-45]	2.124***	-0.010	390,953	-3.343***	0.011	431,518
Years of education [46-65]	1.607***	0.002	483,428	-3.560***	0.011	712,978
Low education	-13.710***	0.043	3,185,240	20.168***	0.012	3,183,666
Medium education	12.553***	-0.093**	3,185,240	-8.363***	0.195***	3,183,666
High education	1.157**	0.050***	3,185,240	-11.804***	-0.207***	3,183,666
Enrolled [13-17]	9.987***	-0.165***	349,986	-11.513***	0.285***	248,488
Enrolled [18-23]	8.495***	-0.053	335,814	-19.071***	0.176***	330,124

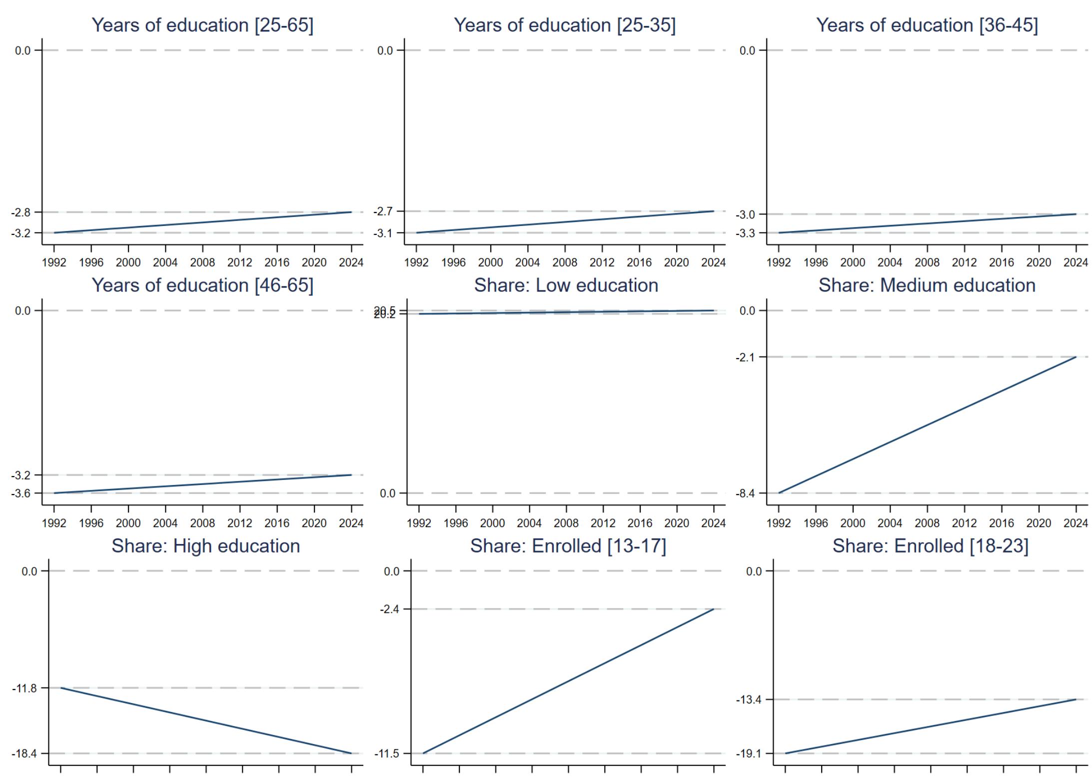
Notes: Poor, Vulnerable, and Rest are defined as in Section 3. All regressions are estimated at the individual level. The table reports estimates of Equation 11 using the pooled sample for 1992–2024. For all binary dependent variables, estimated coefficients are multiplied by 100 so that gaps are expressed in percentage points. *Source:* Own calculations based on microdata from national household surveys.

Figure B.2: Evolution of educational differences (1992–2024)

(a) Vulnerable vs. Poor



(b) Vulnerable vs. Non-Vulnerable



Notes: The figure shows the evolution of educational differences between the vulnerable and the poor (panel a) and between the vulnerable and the non-vulnerable (panel b) from 1992 to 2024. Each panel plots the implied linear trajectories obtained from Equation 11—computed as $\beta_1 + \beta_2 \cdot t$—using the coefficients reported in panel b of Table B.6. Positive (negative) values indicate

Labor market

Table B.8 reports the β_1 coefficients estimated from Equation 10. As before, the estimates for the V dummy closely mirror the socioeconomic gradients documented in Table 1. Labor force participation, female labor force participation, employment, and hours of work are all significantly higher in V than in P, and significantly lower in V than in R, placing the vulnerable consistently in the middle of the distribution.[24] The same pattern holds for hourly wages and monthly earnings. In most cases, the absolute values of the coefficients are larger in the V–R comparison than in the P–V comparison, indicating that the vulnerable are generally closer to the poor than to the non-vulnerable.

A similar gradient appears for informality. Both productive informality and lack of social-protection coverage are substantially lower in V than in P, but considerably higher in V than in R, again locating the vulnerable in an intermediate position. Unemployment offers an additional nuance: although unemployment rates are lower in V than in P and higher than in R, the duration of unemployment is slightly longer among the vulnerable than among the poor, which could be related to the composition effects mentioned above.

Table B.8: Regressions of labor variables, cross-sectional estimates (2024)

	Vulnerable vs Poor		Vulnerable vs Rest	
	β_1	Obs	β_1	Obs
Labor force participation	9.452***	56,380	-10.304***	94,493
Female labor force participation	12.969***	31,682	-14.544***	49,827
Employment	11.840***	56,380	-13.398***	94,493
Unemployment	-4.617***	38,796	4.615***	73,446
Duration of unemployment	1.957**	3,561	1.209	3,141
Informality productive	-18.422***	34,633	23.113***	69,316
Informality social protection	-15.835***	34,692	24.731***	69,727
Hours of work	3.995***	44,276	-2.971***	85,791
Hourly wages	0.559***	40,840	-0.600***	82,738
Earnings	0.690***	41,730	-0.714***	84,211

Notes: Poor, Vulnerable, and Rest are defined as in Section 3.1. All regressions are estimated at the individual level. The table reports estimates of Equation 10 for 2024 (or the latest available year). For all binary dependent variables, estimated coefficients are multiplied by 100 so that gaps are expressed in percentage points. See Table 1 for variable definitions. *Source:* Own calculations based on microdata from national household surveys.

Table B.9 and Figure B.3 reveal divergent temporal patterns across labor market dimensions. While gaps in labor force participation, employment, unemployment, and informality have widened steadily since the early 1990s, gaps in hourly wages and monthly earnings have instead narrowed,

[24]Gender differences in labor market outcomes are explored in more detail in Appendix C . Specifically, we explore whether differences in women's labor market outcomes play a key role in determining whether a household falls into poverty or not.

bringing the groups closer together along income-related dimensions.

For labor force participation and employment, both the $V–P$ and $V–R$ trajectories move persistently away from zero. The employment gap between V and P expands by 2.8 percentage points over the period, while the $V–R$ gap grows by 4.1 percentage points. The patterns for unemployment mirror these trends: the $V–P$ gap becomes increasingly negative, and the $V–R$ gap increasingly positive, reflecting a growing stratification in joblessness across the distribution.

The most striking divergence appears in informality, particularly the measure based on lack of social protection. The $V–P$ gap widens by 4.3 percentage points, while the $V–R$ gap widens by more than 10 percentage points between 1992 and 2024. These trends imply that, despite improvements in basic labor market attachment, the quality of employment has polarized.

While hours worked diverge between V and P but narrow slightly between V and R, both sets of trajectories converge over time, suggesting that real wage growth has been relatively broad-based across the distribution. One possible explanation is that wage floors, sectoral minimum wages, and the expansion of cash-transfer programs may have compressed the lower tail of the earnings distribution.

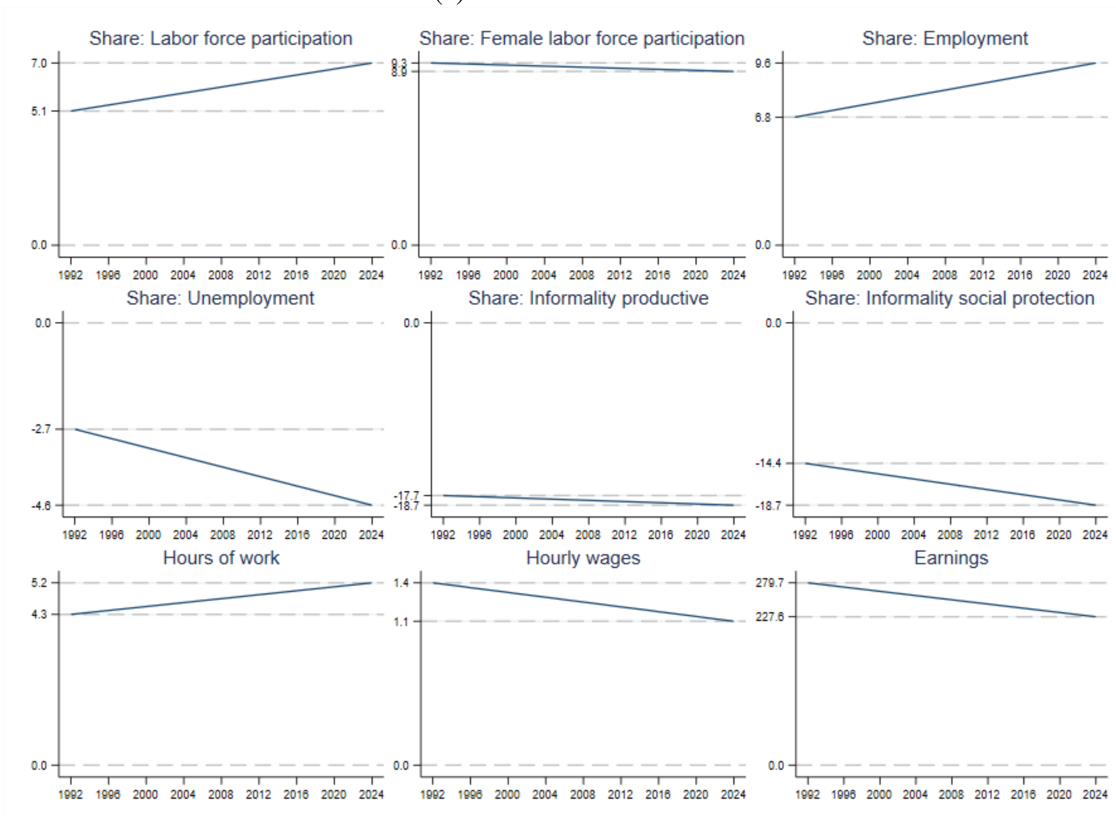
Table B.9: Regressions of labor market variables, over-time estimates (1992-2024)

	Vulnerable vs Poor			Vulnerable vs Rest		
	β_1	β_2	Obs	β_1	β_2	Obs
Labor force participation	5.147***	0.058	1,365,671	-5.961***	-0.101***	1,673,278
Female labor force participation	9.341***	-0.014	739,634	-11.564***	-0.075*	877,767
Employment	6.765***	0.090*	1,365,671	-7.526***	-0.129***	1,673,279
Unemployment	-2.656***	-0.059*	975,166	2.416***	0.039	1,306,020
Duration of unemployment	1.780***	-0.038	76,773	-0.628*	0.013	56,696
Informality productive	-17.715***	-0.031	871,448	16.866***	0.262***	1,220,039
Informality social protection	-14.392***	-0.134**	863,673	16.247***	0.329***	1,209,908
Hours of work	4.330***	0.028	1,238,550	-2.784**	0.019	1,588,006
Hourly wages	0.581***	-0.002*	1,030,741	-0.697***	0.003**	1,456,465
Earnings	0.690***	-0.000	1,060,574	-0.725***	-0.000	1,492,976

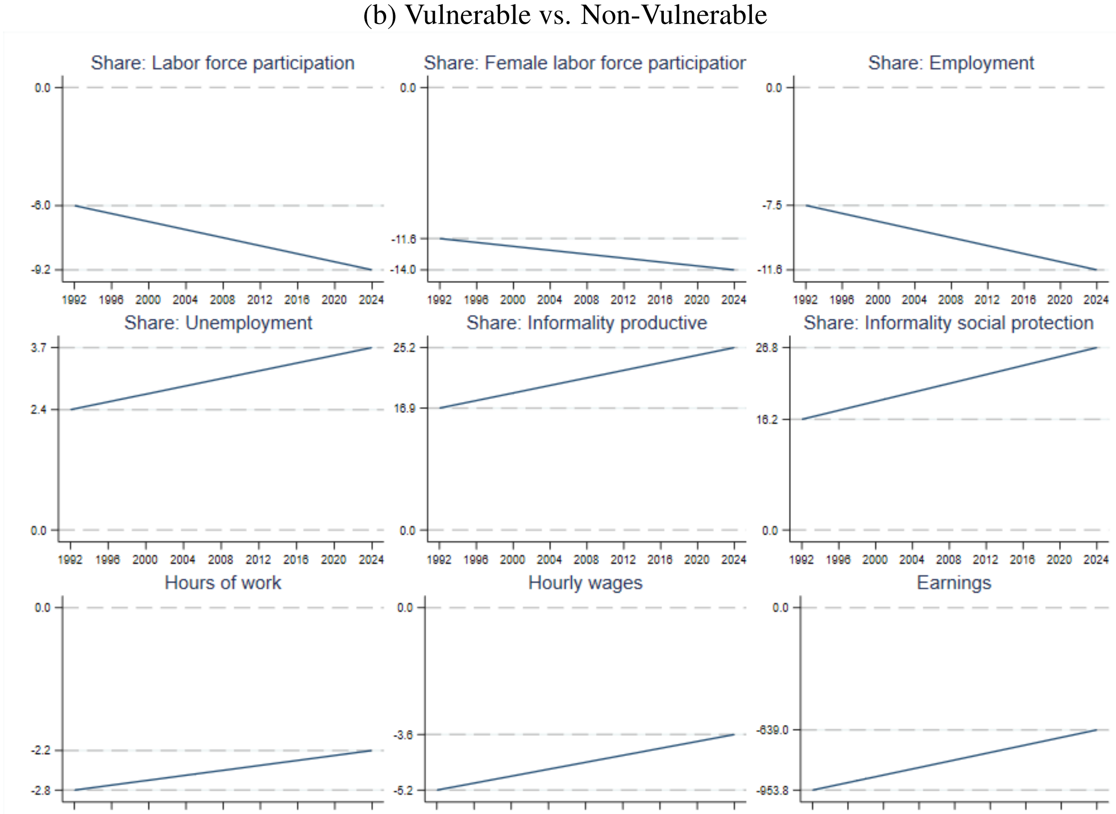
Notes: Poor, Vulnerable, and Rest are defined as in Section 3. All regressions are estimated at the individual level. The table reports estimates of Equation 11 using the pooled sample for 1992–2024. For all binary dependent variables, estimated coefficients are multiplied by 100 so that gaps are expressed in percentage points. *Source:* Own calculations based on microdata from national household surveys.

Figure B.3: Evolution of labor market differences (1992–2024)

(a) Vulnerable vs. Poor



(b) Vulnerable vs. Non-Vulnerable



Notes: The figure shows the evolution of educational differences between the vulnerable and the poor (panel a) and between the vulnerable and the non-vulnerable (panel b) from 1992 to 2024. Each panel plots the implied linear trajectories obtained from Equation 11—computed as $\beta_1 + \beta_2 \cdot t$—using the coefficients reported in panel b of Table B.8. Positive (negative) values indicate

C Gender gaps along the poverty–vulnerability gradient

This appendix explores more deeply whether the patterns described in Section 3.2 differ by gender. The descriptive analysis revealed higher female labor force participation among the vulnerable compared to the poor, raising the question of whether women's labor market outcomes play a key role in lifting households out of poverty. To explore this hypothesis, we assess how gender gaps in employment, hours worked, wages, and job quality vary across income groups. We estimate the following specification:

$$L_{ict} = \alpha + \beta_1 V_{ict} + \eta_1 Female_{ict} + \eta_2 (V_{ict} \cdot Female_{ict}) + \lambda_c + \nu_t + \tau_c \cdot t + \varepsilon_{ict}, \tag{12}$$

where η_2 captures whether gender gaps differ between vulnerable and poor individuals. When η_1 is negative, a positive η_2 suggests that women's labor outcomes are closer to men's among the vulnerable than among the poor. The sum of the coefficients on *Vulnerability* and its interaction with *Female* (β_1 + η_2) measures how outcomes for vulnerable women differ from those of poor women. A positive and statistically significant value indicates that vulnerable women perform better than poor women in the corresponding labor outcome.

Table B.10 presents results from estimating Equation 12 for the pooled sample of countries and years using labor force participation, employment, hours worked, and job quality indicators (wage employment and informality) as dependent variables. The estimated values of β_1 + η_2 (see last row of the table) reveal that vulnerable women significantly outperform poor women in the labor market, substantially narrowing the gender gap observed among the poor in the region.

Table B.10: Gender differences in labor market outcomes among the vulnerable and the poor.

	(1) In LF	(2) Employed	(3) Hours	(4) Informal (P)	(5) Informal (SP)	(6) Wage Emp. Emp.
Vulnerable (β_1)	0.011***	0.040***	3.331***	-0.192***	-0.196***	0.151***
	(0.002)	(0.002)	(0.102)	(0.003)	(0.004)	(0.003)
Female (η_1)	-0.427***	-0.416***	-11.878***	0.129***	0.105***	-0.087***
	(0.002)	(0.002)	(0.134)	(0.003)	(0.005)	(0.003)
V . Female (η_2)	0.087***	0.075***	2.465***	0.012***	-0.021***	0.036***
	(0.003)	(0.003)	(0.178)	(0.004)	(0.006)	(0.004)
Constant	0.928***	0.875***	43.223***	0.707***	0.497***	0.398***
	(0.005)	(0.006)	(0.288)	(0.008)	(0.013)	(0.008)
Observations	1,348,052	1,348,052	886,591	864,243	422,069	882,956
R-squared	0.205	0.194	0.144	0.094	0.160	0.099
$\beta_1 + \eta_2$	0.0984***	0.114***	5.796***	-0.180***	-0.216***	0.187***
	(0.00246)	(0.0025)	(0.149)	(0.00296)	(0.00496)	(0.00332)

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Notes: The table reports the results from estimating Equation 12 for the pooled sample of LAC countries and years, using labor force participation, employment, hours worked, "productive informality," "social protection informality," and wage employment as dependent variables. All regressions include country and year fixed effects, as well as country-specific linear trends. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Source: Authors' calculations based on national household surveys.

As shown in column (1) of Table B.10, labor force participation differs minimally between poor and vulnerable men ($\beta_1 \approx +1$ pp), yet women in vulnerable households participate at considerably higher rates than poor women ($\beta_1 + \eta_2 \approx$+10 pp). Employment patterns follow a similar pattern: while the employment gap between vulnerable and poor men stands at +4 pp, it reaches +11.4 pp among women (column 2).

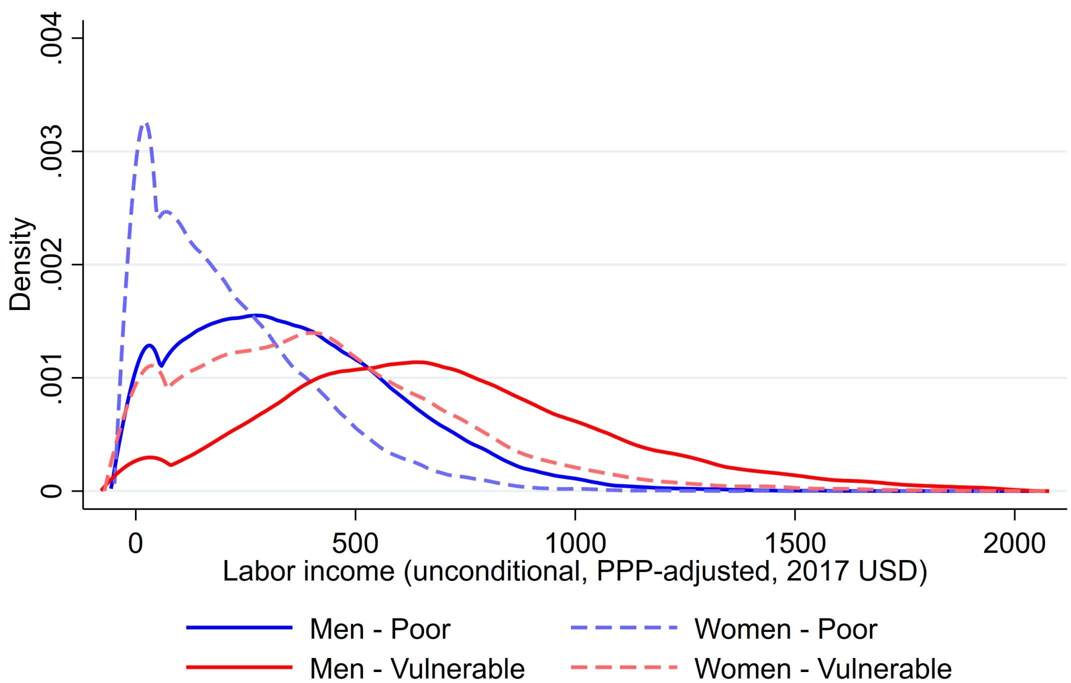
Hours worked also reveal a narrowing gender divide among the vulnerable. Women in vulnerable households work 5.8 additional hours per week compared to poor women, while vulnerable men work just over 3 additional hours relative to poor men (see $\beta_1 + \eta_2$ and β_1 in column 3, respectively).

Across other employment dimensions, vulnerable men predictably hold better jobs than poor men, yet the improvement is even more pronounced among women. Both women and men in vulnerable households exhibit higher rates of wage employment (column 6) and, conditional on wage employment, to work formally (column 5). Hence, beyond higher labor participation of both vulnerable men and women, they are also more concentrated in better-quality jobs, as captured here by formal wage employment. These differences are larger for women (η_2 equals +3.6 pp in wage employment and -2.1 pp in informality). The only exception arises in "productive informality" (column 4), where the gap between the vulnerable and the poor are very similar for both men and women, being only slightly smaller for women.

Overall, the results presented in Table B.10 suggest that women's labor market involvement may be a key factor determining whether households fall into poverty or not.

Given these findings on women's changing labor market role when comparing poor and vulnerable households, how does women's contribution to household labor income shift accordingly? Figure B.4 sheds light on this question by displaying the distribution of labor income for women (dashed lines) and men (solid lines) in poor (blue) and vulnerable (red) households. As shown in the figure, the income distribution of vulnerable women closely resembles that of poor men and diverges markedly from that of poor women.

Figure B.4: Labor income (unconditional on working)



Notes: The figure displays kernel density estimates of the labor income distribution (unconditional on working) by gender and vulnerability status for individuals aged 25-64 years old for the pooled sample of LAC countries and years. Labor income is expressed in PPP-adjusted 2017 USD. Blue lines represent poor households, while red lines represent vulnerable households. Solid lines correspond to men and dashed lines to women. *Source:* Authors' calculations based on national household surveys.

A similar pattern emerges when estimating Equation 12 using labor income as the dependent variable. The results, reported in Table B.11, indicate that while vulnerable women clearly earn more than poor women (as indicated by the sum of the vulnerability coefficient and its interaction with female in the last row of Columns 1 and 2), the gender earnings gap actually widens among the vulnerable. Nevertheless, the higher earnings of vulnerable women translate into a 6 pp greater contribution to household labor income compared to women in poor households (column 3 for all women and column 4 for women aged 25-64). Overall, these patterns suggest that women may be playing a critical role in enabling households to move out of poverty.

Table B.11: Gender differences in labor earnings among the vulnerable and the poor.

	(1) Labor income (conditional on working)	(2) Labor income (unconditional)	(3) Share of female income	(4) Share of female income (25-64)
Vulnerable (β_1)	318.487***	338.002***	0.059***	0.056***
	(2.010)	(2.012)	(0.002)	(0.002)
Female (η_1)	-224.329***	-141.558***		
	(1.207)	(1.563)		
Vulnerable X Female (η_2)	-167.471***	-122.923***		
	(2.346)	(2.699)		
Constant	325.605***	363.389***	0.337***	0.298***
	(4.639)	(5.511)	(0.008)	(0.008)
Observations	1,338,305	842,150	647,260	647,260
R-squared	0.300	0.277	0.021	0.021
$\beta_1 + \eta_2$	151***	215.1***		
	(1.323)	(1.936)		

Notes: Columns 1 and 2 report results from estimating Equation 12 for the pooled sample of LAC countries and years, using labor income conditional and unconditional on working as the dependent variables, respectively. Both regressions include country and year fixed effects, as well as country-specific linear trends. Columns 3 and 4 report the Vulnerable coefficient from regressions of the share of household income contributed by female household members on a vulnerability indicator, along with country and year fixed effects and country-specific linear trends. Column 3 shows the share of household labor earnings contributed by all female members, while column 4 focuses on contributions from females aged 25-64. In columns 1 and 2, the unit of observation is individuals aged 25-64 years old, while in columns 3 and 4, the unit is households. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Source: Authors' calculations based on national household surveys.