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Poverty Traps and Intergenerational Mobility: Evidence from 33 years of Labor Surveys for Ecuador.

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AGRADECIMIENTOS

A mis padres, quienes con su amor infinito me han cobijado, impulsado y apoyado de manera incondicional a lo largo de mi vida. Es gracias a ellos que he podido seguir la carrera de mis sueños y culminarla sobrepasando hasta mis propias expectativas.

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RESUMEN

En este documento, estudio la presencia de trampas de pobreza y movilidad intergeneracional en la dinámica de ingresos laborales de Ecuador desde 1990 hasta 2022. Empleo enfoques paramétricos y semiparamétricos para determinar la relación entre los ingresos laborales pasados y actuales para rezagos de orden superior y grupos heterogéneos, así como el estimador de movilidad de ingresos laborales condicional y no condicional. Utilizo datos de la Encuesta Nacional de Empleo, Desempleo y Subempleo de Ecuador (ENEMDU), realizada anualmente desde 1988. Mis resultados indican una ausencia de trampas de pobreza, a pesar de las no linealidades en la dinámica de ingresos. Identifico niveles significativos de inmovilidad condicional en los ingresos laborales para diferentes cohortes demográficas, independientemente del nivel educativo. Aunque existe cierto grado de movilidad, persisten barreras sustanciales para grupos específicos, destacando los desafíos perdurables al ascender en la escalera de ingresos en Ecuador.

Palabras clave: Trampa de pobreza, mobilidad intergeneracional, Ecuador

ABSTRACT

In this paper, I study the presence of poverty traps and intergenerational mobility in Ecuador's labor income dynamics from 1990 to 2022. I employ parametric and semi-parametric approaches to determine the mapping between past and current labor income for higher-order lags and heterogeneous groups, as well as the conditional and unconditional labor income mobility estimator. I use data from Ecuador's National Survey of Employment, Unemployment, and Underemployment (ENEMDU), which has been conducted annually since 1988. My results indicate an absence of poverty traps, despite non-linearities in income dynamics. I identify significant levels of conditional immobility in labor income for different demographic cohorts, regardless of educational attainment. Although there is some degree of mobility, substantial barriers persist for specific groups, highlighting the enduring challenges in climbing the income ladder in Ecuador.

Keywords: Poverty Traps, Intergenerational Mobility, Ecuador

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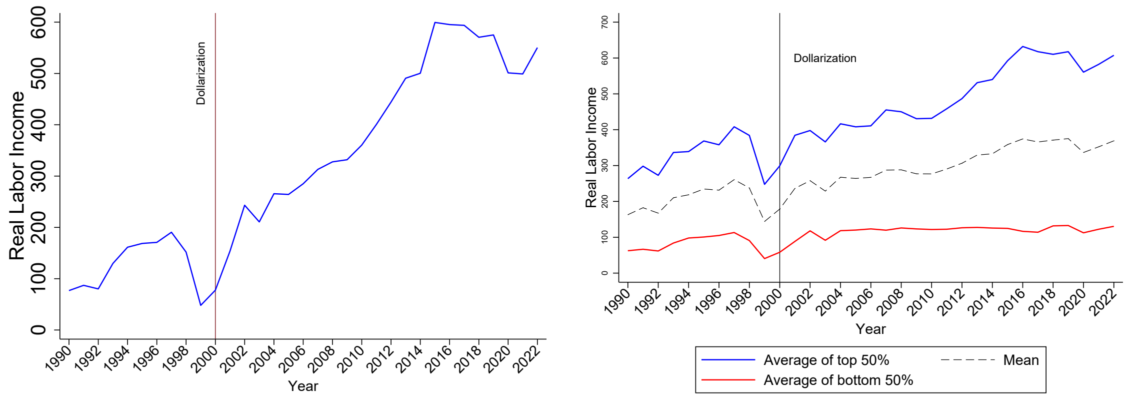
1. Introduction

The persistence of poverty and the mechanisms underlying income dynamics have long been central concerns in economic research, particularly in the context of developing countries. In Ecuador, a pressing question arises: Are labor income trends indicative of persistent poverty traps or established intergenerational mobility? In this paper, I explore Ecuador's labor income dynamics from 1990 to 2022 around the presence of poverty traps and the level of intergenerational mobility within the country.



(a) Mean Real Labor Income (b) Mean Real Labor Income by Median Group

Figure 1: **Labor Income dynamics.** *Panel* (*a*) illustrates the trajectory of real labor income over the years of analysis. The previous decline in the years leading up to the 1999 economic crisis can be attributed to inflation and the depreciation of the Sucre (Solimano, 2002). The impact of the 2000 currency switch to the US Dollar is visible, and a recovery in labor income is observable until the next visible stagnation, which coincided with the global pandemic of 2020. *Panel* (*b*) shows the evolution of the real labor income for those who are above the median level of labor income and those below. We can see a clear stagnation for people below the median level compared to the visible growth experienced by the top 50% over the period of analysis.

During the late 1990s, Ecuador encountered notable economic difficulties characterized by a severe crisis, which led to the adoption of the US dollar as its official currency in 2000. Figure 1a illustrates the trajectory of real labor income over the years of my analysis. The previous decline in the years leading up to the 1999 economic crisis can be attributed to high inflation and the depreciation of the Sucre (Solimano, 2002). The impact of the currency switch to the US dollar is clear, and a recovery in labor income is observable until the next visible stagnation, which coincided with the global pandemic in 2020.

Now, it is crucial to break down the analysis of people's earnings for a deeper comprehension of the labor market in Ecuador. Figure 1b illustrates the trends in average real labor income for individuals earning above and below the median income. This figure highlights a clear stagnation in labor income for those earning below the median, in contrast to the growth experienced among the top 50%. This output prompts my investigation to unravel potential underlying dynamics, like poverty traps, that could explain the absence of growth for this group in over 30 years.

For this, I use a pseudo-panel approach, estimating non-linear dynamics in labor income, looking at the relationship between past and present income levels (Moffitt, 1993), covering approximately 16 generations (cohorts). Through semi-parametric Gaussian Kernel estimations, I assess the existence of poverty traps in labor income across various demographic groups, including educational levels, gender, age cohorts, and employment status, with a further analysis of intergenerational mobility.

I am using data from the Ecuador National Survey of Employment, Unemployment and Underemployment (ENEMDU), which has been conducted annually since 1988. This survey is one of the most significant statistical instruments for studying employment, the labor market, economic activity, and the income sources of Ecuadorian citizens. I harmonized the data to ensure comparability over the years, making it the first dataset that offers comparable insights into socioeconomic and labor trends before and after Ecuador's dollarization.

My results indicate an absence of poverty traps in all generations analyzed, despite non-linearities in income dynamics, especially when considering higher-order lags and heterogeneous groups. For this, I analyze the estimated derivatives at the intersection points between current and lagged income with the mapping function. The necessary and sufficient condition for a poverty trap is that this derivative exceeds the unity. A condition that, in every case, was not satisfied. Further analysis with semi-parametric estimations reveals a unique stationary equilibrium in income dynamics, challenging the notion of poverty traps in Ecuador's labor market[1].

My analysis of mobility levels reveals varying degrees of economic advancement opportunities in demographic groups in Ecuador. Despite some mobility, significant barriers persist for specific cohorts, such as women, young individuals, and formal workers, who exhibit high immobility in labor income. The elderly demonstrate high labor income mobility, contrasting previous research findings (Cuesta et al., 2011). In addition, regardless of educational attainment, all cohorts experience high immobility in labor income, emphasizing the enduring challenges in ascending the income ladder.

Robustness checks using a B-Spline and Polynomial OLS models support my findings. There is no substantial evidence for poverty traps in labor income dynamics. In addition, there is high immobility in labor income in all cohorts. While polynomial OLS results present potential biases, both B-spline and Gaussian Kernel estimations consistently refute the presence of poverty traps and confirm the low mobility in labor income for Ecuadorians between 1990 and 2022.

[1]Ecuador has one of the highest degrees of informality in the labor market in Latin America and the Caribbean (Velín-Fárez, 2021). Higher levels of informal employment can lead to segmented labor markets and lower intergenerational mobility, which in turn can contribute to the persistence of poverty across generations. Documented studies reinforce the premise that informal work tends to be sporadic, low-paying, and often precarious, hindering workers' ability to invest and accumulate wealth. As a result, this lack of investment perpetuates poverty and reinforces social exclusion, creating a self-reinforcing and persistent poverty trap (Janz et al., 2023).

Relation to Literature

The concept of poverty traps has been extensively studied in the literature, highlighting the persistent barriers that constrain economic mobility and perpetuate cycles of poverty (McKay & Perge, 2013). Previous research has identified multiple approaches to examine poverty traps, including parametric and semi-parametric methods, each offering unique insights into the complex dynamics of various factors (Antman & McKenzie, 2007), such as asset dynamics, macroeconomic shocks, consumption patterns, and limited access to credit and employment opportunities (Gentilini et al., 2021; Janz et al., 2023; Loría, 2020).

Within the context of labor income, poverty traps should be evident, as specific income levels make it difficult for individuals or households to progress (Antman & McKenzie, 2007). Factors such as restricted access to essential goods and services contribute to the persistence of poverty traps, impeding both personal financial advancement and overall economic development (McKay & Perge, 2013).

In Latin America, studies highlight the relatively low levels of mobility in the region and significant country-specific differences in poverty mobility (Cuesta et al., 2011). However, the specific dynamics of poverty traps and income mobility in Ecuador remains relatively understudied.

My analysis delivers two important contributions. Firstly, it builds on previous research that has focused on the dynamics of labor income in Ecuador for 33 years. I consider factors such as educational attainment, gender, age groups, and labor market informality (Cuesta et al., 2011; Loría, 2020) to empirically demonstrate the absence of poverty traps in Ecuadorian labor incomes and low intergenerational mobility between 1990 and 2022.

Secondly, most research often relies on a single lag for estimations (Michael & Martin, 2004; Antman & McKenzie, 2007; Cuesta et al., 2011; Lokshin & Ravallion, 2004; McKay & Perge, 2013). In contrast, I utilize up to 10 lags in my analysis to provide a more comprehensive examination. This approach allows for a more precise representation of persistent poverty, a key indicator of poverty traps, by examining the connection between current income and incomes from various previous years.

Finally, I identify particular groups facing substantial obstacles to economic progress within the inflexible Ecuadorian labor market. Through this examination of labor income dynamics and intergenerational mobility, my research contributes valuable insights to policymakers and researchers seeking to address economic inequality in Ecuador and similar contexts.

The remainder of this paper is divided as follows. Section 2 explores the Slow Model modified to capture its dynamics with poverty traps. Section 3 explains my identification strategy from semi-parametric to parametric estimations. In Section 4, I detail the data used, the harmonization process for each variable used, as well as an overview of the data set. Section 5 presents my results, showing the absence of poverty traps in labor income dynamics and an analysis of intergenerational mobility. In Section 7 are some policy implications of my findings, particularly in light of high intergenerational immobility despite the absence of identified poverty traps, while in Section 8 I explain my conclusions.

2. Solow Model with Poverty Traps

The Solow model is a key framework for analyzing the dynamics of economic growth and the transition to long-term steady states. This model describes how the combinations of labor, capital, and technology interact and determine the economy's rate of production and growth. The model assumes a closed economy with a constant labor force, a constant savings rate, and a decreasing marginal product of capital. The production function represents the relationship between the inputs and outputs of production (Snowdon, 2009; Capasso et al., 2010).

In a steady state, the capital-labor ratio, output, and consumption per capita do not grow or decline, and the capital growth rate becomes zero (Barro & Sala-i Martin, 2004). Consider the evolution of capital per capita k_t as

$$k_{t+1} - k_t = sf(k_t) - (\delta + n)k_t,$$

where δ is the capital depreciation rate, s is the economy savings rate and n is the constant population growth rate. Following Capasso et al. (2010), I assume the savings rate to be $s = 1$, and the population growth rate in time to be $n(t) = 0$. Therefore, in a steady state, the evolution of capital per capita is

$$k_{t+1} - k_t = 0,$$

and the production function equals the depreciated capital: $f(k_t) = \delta k_t$. In this state, the economy reaches a balanced growth path in which the capital stock grows at the same rate as the labor force and technological progress (Snowdon, 2009; Grassetti et al., 2018).

In Figure 2, we observe the steady state and balanced growth path in the classic Solow model with a unique equilibrium at the capital level k_t^*. The production function $f(k_t)$ follows the standard economic properties[2], and the economy consistently converges to a unique steady state E^*, irrespective of the initial capital level. However, the

[2] $f(k_t) > 0, f'(k_t) > 0, f''(k_t) < 0, \forall k_t > 0$

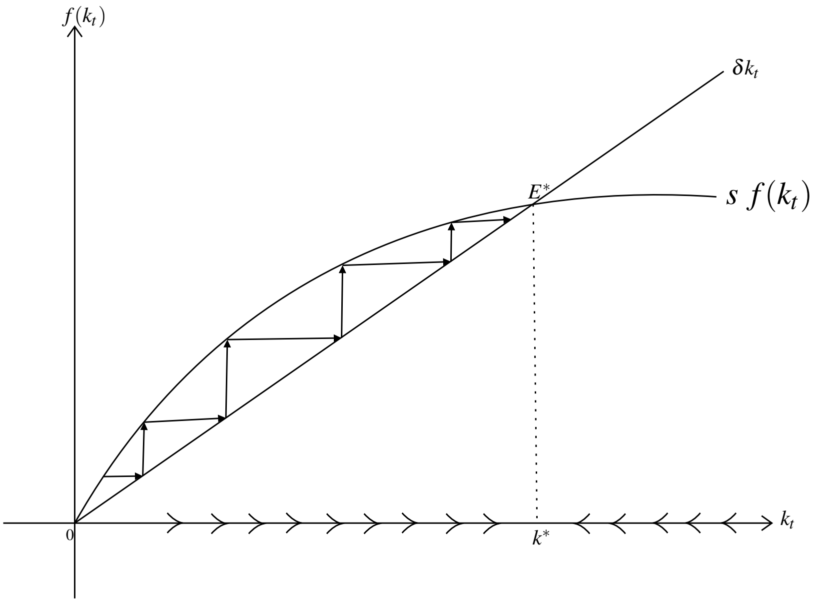


Figure 2: **Solow Model with convergence to a steady state** E^*: This Figure displays a Cobb-Douglas production function $f(k_t)$. The effective depreciation rate for k_t is δ. The change in k_t is given by the vertical distance between $f(k_t)$ and δk_t. The steady-state level of capital k_t determines the single equilibrium E^* at the intersection of $f(k_t)$ curve with δk_t line.

Solow model can incorporate poverty traps[3] by considering the possibility of multiple long-term equilibria.

These traps are characterized by low levels of capital accumulation and high levels of poverty. They can be caused by coordination and market failures (Barrett et al., 2019; Snowdon, 2009), lack of access to credit markets, limited technology and education, and low levels of human capital (Michael & Martin, 2004).

To frame the Solow model with poverty traps, I follow Capasso et al. (2010), and use a non-concave production function of parametric class:

$$f(k_t) = \frac{\alpha k_t^p}{1 + \beta k_t^p}. \tag{1}$$

with α and β above zero, this production function has an S-shaped behavior when

[3]"A poverty trap is any self-reinforcing mechanism which causes poverty to persist" (Azariadis & Stachurski, 2005).

$p \geq 2$.

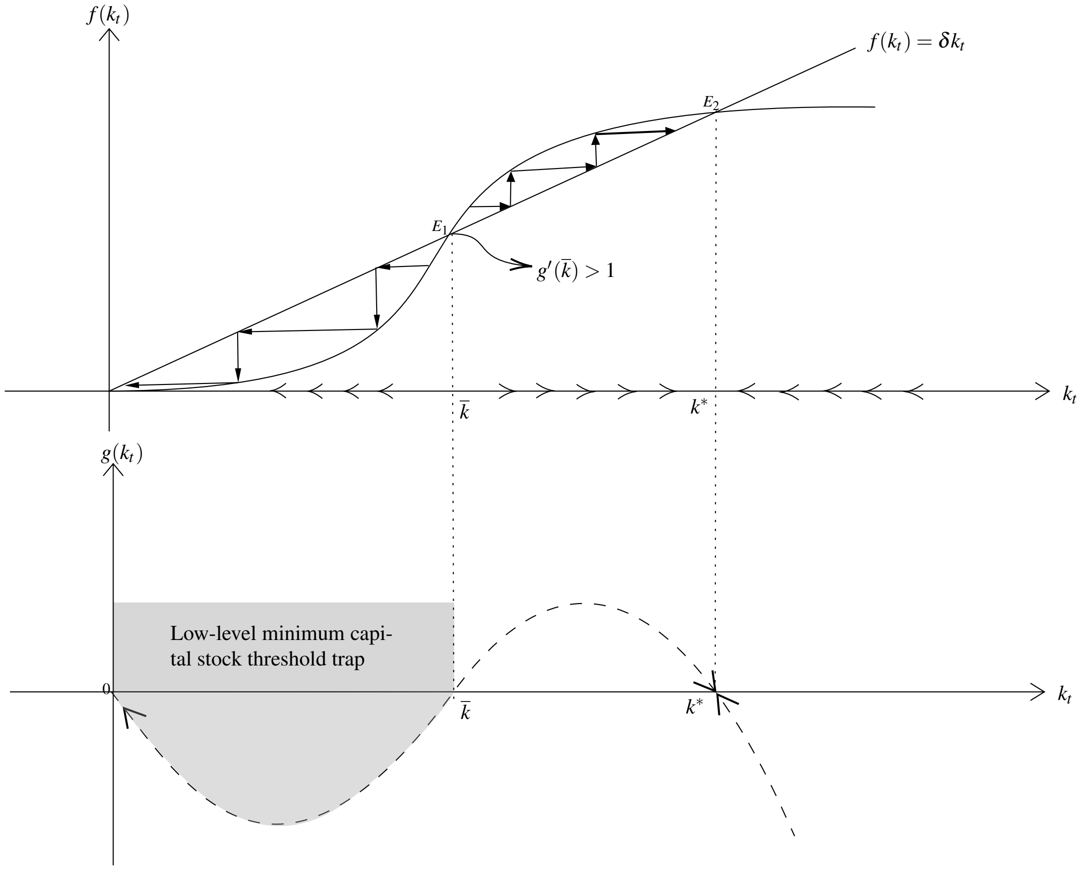


Figure 3: **Solow Model with Poverty Trap**: This Figure displays a production function of parametric class $f(k_t)$. The production function exhibits increasing marginal returns for any $k_t < \bar{k}$, and decreasing marginal returns for $k_t > \bar{k}$. There is a poverty trap at level $\bar{k}$ because if a country begins below $\bar{k}$, the economy will always be below this threshold, converging to 0. On the contrary, starting above $\bar{k}$, the economy will converge to a high equilibrium E_2.

Brianzoni et al. (2015) shows that Equation (1) belongs to the class of Variable Elasticity of Substitution (VES) production functions, as the elasticity of substitution $\sigma(k_t)$ depends on the level of capital per capita k_t and the constant p. This condition allows us to break the assumption that for little to no capital, the economy can gain infinitely high returns by investing only a small amount of money.

For a poverty trap, we need a capital level threshold $\bar{k} > 0$ that determines the type of equilibrium to be reached. To obtain this threshold level, we need to establish conditions on the depreciation rate of capital δ. In Appendix A, I follow Capasso et al. (2010) to demonstrate that, for a depreciation rate $\delta < \delta^* = \alpha \left(\frac{p-1}{\beta}\right)^{\frac{p-1}{p}}$, there is a poverty trap at a capital threshold $\bar{k}$.

In Figure 3, the production function $f(k_t)$ exhibits increased marginal product of capital at low levels of capital $(k_t < \bar{k})$. Thus, there exists an unstable equilibrium E_1 at $\bar{k}$. When the economy starts below $\bar{k}$ it will always be below $\bar{k}$, trapped in poverty[4]. If the economy starts above $\bar{k}$, it will always be above $\bar{k}$ and can grow to reach high equilibrium E_2 (Edmond, 2004; Matsuyama, 2010).

2.1. Poverty trap in Labor Income Dynamics

In this subsection, I model the relationship between past and present labor income, looking for a threshold that would determine a cohort's[5] labor income growth path and long-term equilibria.

Incorporating lags into the analysis of labor income dynamics can result in the presence of nonlinear dynamics, along with a historical dependence on long-term behavior. Ferrara et al. (2014) shows that models that allow delays may better capture this long-term relationship between variables.

In Figure 4, we have a non-linear labor income function $\bar{y}_{i,t} = g(\bar{y}_{i,t-p}) + \alpha_i$, where $\bar{y}_{i,t}$ is the current mean income for cohort i, $g(\cdot)$ is a general non-linear function, $\bar{y}_{i,t-p}$ is the mean income for cohort i at time p years earlier, α_i is a fixed effect for cohort i. This figure illustrates the case of a labor income poverty trap at the threshold level of

[4]Matsuyama (2010) expresses that "this should not be taken too literally. The essential message of poverty traps is that poverty tends to persist and that it is difficult, but not necessarily impossible, for the economy to escape from it."

[5]Stable groups of individuals (Khandker & Haughton, 2009).

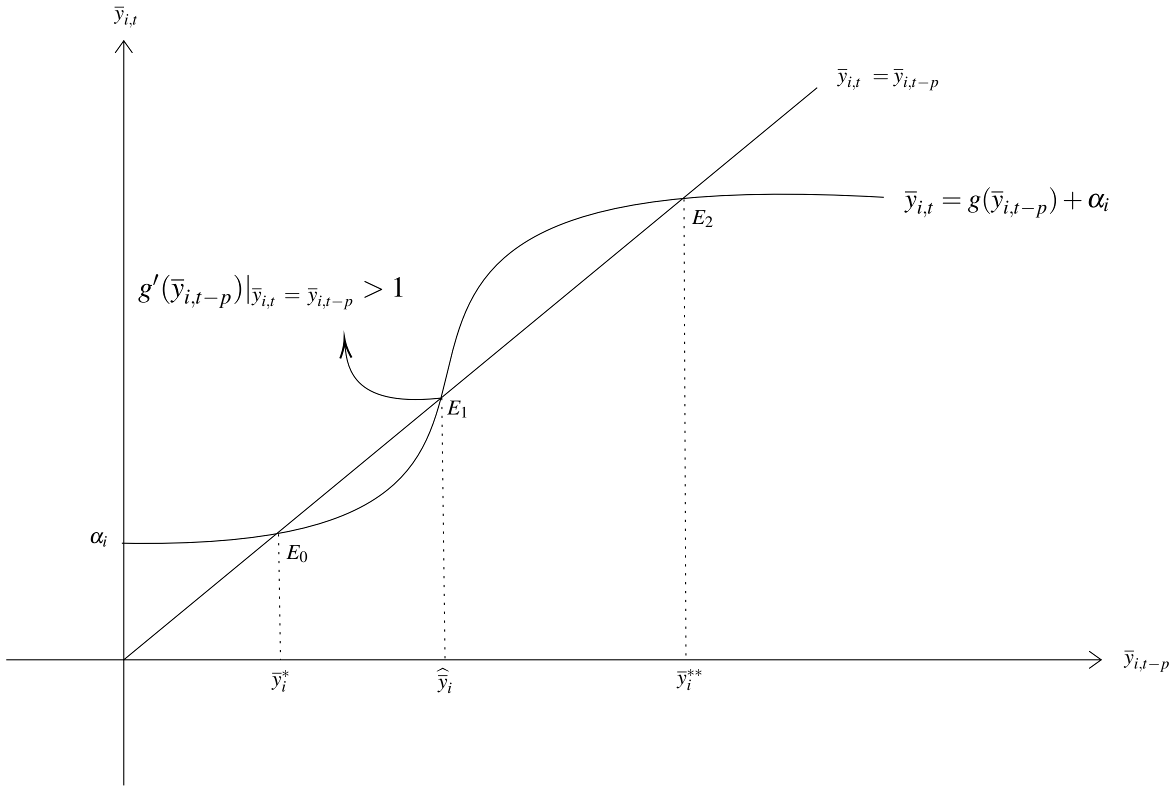


Figure 4: **Labor Income Dynamics with Poverty Trap**: This Figure displays a non-linear labor income function $\overline{y}_{i,t} = g(\overline{y}_{i,t-p}) + \alpha_i$, where $\overline{y}_{i,t}$ is the current mean income for cohort i, $g(\cdot)$ is a general nonlinear function, $\overline{y}_{i,t-p}$ is the mean income for cohort i at time p years before, α_i is a fixed effect for cohort i. This figure illustrates the case of a labor income poverty trap at the threshold level of $\hat{\overline{y}}_i$, as the derivative at the intersection point between the production function $f(k_t)$ and 45° line (where past and present labor income is the same) is greater than one (i.e. $g'(\overline{y}_{i,t-p}) > 1$). Starting with an income level below this threshold would mean the cohort labor income converges to the low equilibrium E_0, and starting above $\hat{\overline{y}}_i$ implies the cohort converges to the high steady-state E_2.

$\hat{\overline{y}}_i$. This point determines the kind of long-term equilibria reached.

A cohort i with a labor income $\overline{y}_i < \hat{\overline{y}}_i$ will fall to low steady-state equilibrium E_0. This would imply that, despite the cohort's efforts to rise on the labor income ladder, it would not be possible because the initial level of labor income has already determined the equilibrium reached. In contrast, for a labor income greater than $\hat{\overline{y}}_i$, the cohort will reach the high-level equilibrium E_2 regardless of anything but its initial level. In this setup, the lagged term $t - p$ captures this historical dependency, reflecting how the past labor income influences the present labor income.

3. Identification Strategy

In this investigation, I adopt a pseudo-panel framework following the approach outlined by Antman & McKenzie (2007). Pseudo-panel methods offer a valuable approach to analyzing longitudinal microdata when panel data are unavailable (Khandker & Haughton, 2009). These methods have been widely used to estimate price or income elasticities and life-cycle analysis (Guillerm, 2017), instead of observing individuals over time, pseudo-panels observe cohorts and replace their characteristics with their intra-cohort means.

Formally, I estimate the following model:

$$\bar{y}_{i,t} = g(\bar{y}_{i,t-p}) + \alpha_i + \bar{\varepsilon}_{i,t}, \tag{2}$$

where $\bar{y}_{i,t}$ is the current mean income for cohort i, $g(\cdot)$ is a general nonlinear function, $\bar{y}_{i,t-p}$ is the mean income for cohort i at time p years before for $p = \{1,3,5,10\}$, α_i is a fixed effect for cohort i and $\bar{\varepsilon}_{i,t}$ is the error term. I estimate (2) semi-parametrically, using a Gaussian Kernel and B-spline method such as Janz et al. (2023) and McKay & Perge (2013).

To look for a poverty trap, I examine the relationship between past and present labor income. This analysis is conducted through the derivative of (2) at the labor income mapping where both past and present incomes are equal, this means, at the intersection with the 45-degree line. So, the necessary and sufficient condition for a poverty trap is:

$$g'(\bar{y}_{i,t-p})|_{\bar{y}_{i,t}=\bar{y}_{i,t-p}} > 1. \tag{3}$$

If (3) holds, it indicates the presence of a poverty trap in that income level. A derivative exceeding one implies that the labor income mapping crosses the 45-degree line from below, which means that at that point a threshold would be established beyond which low-income individuals would have limited chances of increasing their income, thus remaining trapped in poverty.

For parametric estimations, I use both a third- and fifth-degree polynomial regression to estimate the relationship between $\bar{y}_{i,t}$ and $\bar{y}_{i,t-p}$, with $p = 5$. This general form can be captured as:

$$\bar{y}_{i,t} = \sum_{k=1}^{u} \left[\beta_k \left(\frac{1}{p_c} \sum_{i=1}^{p_c} \left(y_{i,t-p}^{k} \right) \right) \right] + \alpha_i + \bar{\varepsilon}_{i,t}, \tag{4}$$

where $\frac{1}{p_c} \sum_{i=1}^{p_c} \left(y_{i,t-p}^{k} \right)$ is the mean labor income over the p_c people in cohort i at time $t-p$. The functional form of Equation (4) goes from lineal when $k = 1$, to u-degree for $k = u$. To estimate (4) I use cohort fixed-effects and Ordinary Least Squares (OLS). To confirm (3), I am using a non-linear solver that uses cubic splines to interpolate the mean income mapping function resulting from estimating (2) or (4), to later find the derivatives at the intersection between the income mapping function and the 45° line.

To analyze intergenerational mobility, the measure of elasticity between past and present labor income exposes whether a cohort has high labor income immobility, intermediate labor income mobility, or high labor income mobility. Following Cuesta et al. (2011), I define elasticities exceeding 0.75 as indicative of high labor income immobility. Moderate immobility is characterized by elasticities ranging between 0.6 and 0.75. Finally, elasticities below 0.6 are indicative of high mobility in their labor income.

The elasticity for any cohort i can be represented as:

$$\varepsilon_i = \overline{g'}(y_{i,t-p}) \frac{\bar{y}_{i,t-p}}{\bar{y}_{i,t}},$$

where $\overline{g'}(y_{i,t-p})$ is the average of the derivatives at each point of the income mapping function. $\bar{y}_{i,t}$ and $\bar{y}_{i,t-p}$ represent the average of current and $t-p$ years before labor income for the cohort i, respectively.

To understand the values of ε_i, it is necessary to analyze both components that determine its values: the average of derivatives $\overline{g'}(y_{t-p})$, and the ratio of past and present income $\frac{\bar{y}_{i,t-p}}{\bar{y}_{i,t}}$, to determine the type of labor income mobility within each cohort. Cuesta et al. (2011) explains that "although there are no ex-ante restrictions on the range of values that [the elasticity] should take, they are regularly within the [0,1] interval".

A value of elasticity close to 1 implies that the relationship between past and present labor income is high, as the average of the derivatives would be close to 1, indicating that past labor income significantly influences present labor income. Analyzing the ratio of past to present income, the values of past and present labor income would be practically equal, indicating a high immobility in labor income.

Conversely, an elasticity close to 0 implies there is no relationship between past and present labor income, as the average of the derivatives approaches 0. Furthermore, present labor income should exceed past labor income, indicating high mobility in labor income for the cohort i.

Examining the labor income dynamics following the crossing point at $\bar{y}_{i,t} = \bar{y}_{i,t-p}$, implies that a negative estimate of time-dependent income mobility suggests that after reaching equilibrium, future labor income is expected to decrease compared to the income level at the intersection point over time. In contrast, a positive derivative indicates an expected increase in future labor income relative to the income level observed at the intersection point. Moreover, a derivative close to zero implies that the anticipated future income remains stagnant compared to the levels of labor income p years ago.

4. Data

To search for a poverty trap in labor income, as well as determine the conditional and unconditional labor income mobility estimator, I use The National Survey of Employment, Unemployment, and Underemployment (ENEMDU) which has been conducted annually since 1988. I use specific variables from The ENEMDU, including labor income, total years of education, sector of the economy: formal or informal, gender, and age of respondents. To have these variables comparable for the analyzed period, I harmonized the data since 1990, exclusively using December waves, this month has the most observations and allows me to mitigate biases related to seasonality. Also, as this survey started to analyze the Rural area after 2003, to make a consistent analysis before and after dollarization, I only take into consideration the Urban area. Furthermore, I modify the selected variables for comparability across years[6].

For the Total Years of Education variable, I combined Education Level with Approved Years of Education. During the pre-dollarization period[7], Education Level categories included Literacy Courses, Primary, Secondary, and Higher Education. In the most recent editions, five additional categories were introduced, while the original five were retained. Combining this information with the number of approved years of education[8], I generated a variable that measures the total years of education and set a cut-off after 13 years of total education.

I identify informal individuals in the labor market as those who are not contribut-

[6]For further information on how the variables have changed, the methodology employed, and access to the forms from which the information was derived, please refer to the Statistical Information Bank of Ecuador.

[7]Which cover years from 1990 to 1999.

[8]For Literacy Center, Kinder garden, Basic education and None level of education, I added 0 years to the approved years of education reported. For Secondary school, I added 7 years. For Primary school 8, for Middle education 10, for Non-university higher and University Higher education, I added 13 years. For Post-graduate education, I added 18 years to the approved years reported.

ing to Social Security. Until 2000, the respondents were directly asked about their contribution to the Ecuadorian Institute of Social Security (IESS). However, starting at 2001, the survey question was modified to reflect the type of insurance contracted. So, I created a new variable that indicates whether the respondent's insurance option (Option 1 or Option 2) corresponded to IESS, ISSFA, or ISSPOL[9], capturing workers with formally required social security, indicative of the formal sector.

For labor income comparability, first, I use the Sucre-Dollar exchange rate for the pre-dollarization years to express the series in dollars, subsequently deflated the whole series with the Real Effective Exchange Rate index (REER)[10], which determines changes in a country's competitiveness in price terms. These adjustments facilitated the creation of a monthly real labor income series for both pre and post-dollarization periods, detailed in Figure **??**, Panel (a).

This study spans 16 generations for 33 years and is further segmented by gender, resulting in 32 distinct cohorts. Each cohort, representing a 5-year-of-birth interval, is assigned a specific number based on the respondents' year of birth. This approach enables the analysis of specific socioeconomic and labor trends for each generation.

In the main analysis, I focus on observations from urban areas and people between 18 and 60 years of age. Extreme values of labor income were identified as outliers through cumulative distribution percentages and subsequently removed to ensure a robust analysis within the specified age range.

Table 1 provides a condensed overview of the dataset, presenting real mean labor income categorized by gender and age groups. The selected years: 1990, 2000, 2008,

[9]ISSFA and ISSPOL are the Social Security for Armed Forces and Police, respectively, in Ecuador
[10]"The REER is defined as the measure of nominal exchange rates adjusted for price differentials between the home country and its trading partners". (Opoku-Afari, 2004).

and 2022, represent significant periods within the analytical time frame[11]. The cohorts displayed correspond to men and women born between 1925 and 1949 as elderly, from 1950 to 1979 as middle-aged, and from 1980 to 2004 as the youngest.

One can see that there is an increase in labor income from year to year, with the biggest changes post-dollarization. Between 2000 and 2008, there was an average increase of 22.5% in labor income for elderly people, 22% for middle-aged people, and 17% for young people. Furthermore, middle-aged people are predominant in the data, accounting for 64% of the sample, followed by young people with 28%, the remaining 8% of the individuals are part of the elderly population.

	Labor Income Evolution by Age Group				
	1990	*2000*	*2008*	*2014*	*2022*
Panel A: Elderly (1925 - 1949)					
Men	\$86.00	\$85.00	\$333.00	\$361.00	-
Women	\$58.00	\$54.00	\$271.00	\$400.00	-
Headcount	562,439	383,227	223,110	28,991	-
Panel B: Middle-Aged (1950 - 1979)					
Men	\$74.00	\$79.00	\$360.00	\$525.00	\$530.00
Women	\$55.00	\$62.00	\$279.00	\$414.00	\$458.00
Headcount	1,273,107	2,102,889	2,250,092	2,323,188	1,860,337
Panel C: Young (1980 - 2004)					
Men	-	\$40.00	\$241.00	\$452.00	\$538.00
Women	-	\$37.00	\$208.00	\$410.00	\$467.00
Headcount	-	186,725	892,062	1,715,003	2,572,096

Table 1: **Labor Income evolution by Age Group**: This table illustrates the evolution of labor income by age group for the years 1990, 2000, 2008, 2014, and 2022. Panels A, B, and C represent the elderly, middle-aged, and young age groups, respectively. The Headcount refers to the total number of individuals in each age group regardless of their sex.

[11] The year 1990 is the base-point of the study, therefore an important comparing point. The 2000 is the pivotal year from which Ecuador formalized its transition to a dollarized economy. In 2008 a new constitution was approved. In the last trimester of 2014, the country experienced a contraction in the economy because of the fall in oil prices. Finally, 2022 is the last year of harmonized data, and will serve as a concluding point to the analysis.

5. Results

In this section, I present findings related to income mobility and whether there is evidence of poverty traps in labor income within the analyzed cohorts. Taking advantage of the large data set, I conducted semi-parametric Kernel estimations using labor income lagged by 1, 3, 5, and 10 years.

Much of the literature on poverty traps and intergenerational mobility is based solely on one lag for estimations (Michael & Martin, 2004; Antman & McKenzie, 2007; Cuesta et al., 2011; Lokshin & Ravallion, 2004; McKay & Perge, 2013). However, employing more lags in the estimations would give a broader analysis. Persistent poverty, which should be an indicator of a poverty trap, would be more accurately reflected in the relationship between present income and income from multiple past years.

My analysis reveals no discernible evidence supporting the existence of poverty traps within labor income across various lag specifications. Figure 6 displays panels corresponding to the estimations outcome comparing current with lagged labor income across varying numbers of lags.

Table 2 presents the outcomes from semi-parametric Kernel estimations comparing current and lagged labor income. Each *Crossing point* indicates where $\bar{y}_{i,t} = \bar{y}_{i,t-p}$, while the *Income level* is determined by adding the crossing point with the mean cohort effect (205.32). The *Elasticity* is the estimate of time-dependent income mobility (Cuesta et al., 2011), with bootstrap standard errors reported in parentheses, and the *Derivative* at each crossing point.

From this table, the elasticity of current concerning past labor incomes is 0.95 for a one-year lag, decreasing to 0.71 for a 10-year lag, demonstrating a low degree of labor income mobility throughout different time specifications. However, it is crucial to consider individual heterogeneities that could potentially influence the relationship between past and current labor income, as well as their income mobility indicator.

Gaussian Kernel Estimations				
Number of lags	*Crossing point*	*Income*	*Derivative*	*Elasticity*
1	219.39	\$424.71	0.57	0.95 (0.01)
3	211.05	\$416.37	0.11	0.79 (0.03)
5	210.59	\$415.91	−0.15	0.76 (0.03)
10	-	\$205.32	-	0.71 (0.05)

Table 2: **Results of semi-parametric Gaussian Kernel estimations**: This table presents the outcomes from semi-parametric Gaussian Kernel estimations comparing current and lagged income. Each *Crossing point* indicates where $\bar{y}_{i,t} = \bar{y}_{i,t-p}$, while the *Income level* is determined by adding the crossing point with the mean cohort effect (205.32). The *Elasticity* is the estimate of time-dependent income mobility. Bootstrap standard errors are reported in parentheses.

The estimated labor-income mobility changes heterogeneously once I analyze heterogeneous groups. Figure 7 shows three panels corresponding to the result of the income mapping estimates between the current and 5-year lag labor income for each group without considering labor status (formal or informal). *Panel A* shows the mean labor income mapping for people with more than and less than 13 years of total education. On *Panel B*, I show the mean labor income mapping for both men and women across all generations. *Panel C* depicts the mean labor income mapping for cohorts of men and women born between 1925 and 1949 as the oldest, from 1950 to 1979 as middle-aged and from 1980 to 2004 as the youngest. In Figure 8 I show each heterogeneity test related to labor status, with *Panel D* showing the mean labor income mapping for all formal and informal workers.

Both Figure 7 and Figure 8 show how every labor income mapping function that crosses the 45° line does it only once, not fulfilling the first condition for a poverty trap (multiple equilibria). Table 3 offers detailed results for derivatives and elasticities across heterogeneous groups. With all derivatives below unity, Equation (3) does not hold. Consequently, my findings do not provide substantial evidence of poverty traps in these scenarios.

Heterogeneous Effects				
	Crossing point	*Income*	*Derivative*	*Elasticity*
Panel A: Education				
Above 13 years of education	223.43	\$428.74	−0.12	0.76
				(0.04)
Up to 13 years of education	160.36	\$365.68	0.24	0.78
				(0.03)
Panel B: Gender				
Men	181.46	\$386.77	−0.22	0.75
				(0.05)
Women	242.98	\$448.30	−0.30	0.78
				(0.04)
Panel C: Age Groups				
Old (1925 - 1949)	–	\$205.32	–	0.52
				(0.12)
Middle Age (1950 - 1979)	215.29	\$420.61	−0.14	0.64
				(0.07)
Young (1980 - 2004)	196.33	\$401.65	0.25	0.76
				(0.07)
Panel D: Status on the labor market				
Informal Worker	137.19	\$342.51	0.31	0.69
				(0.03)
Formal Worker	315.34	\$520.66	−0.07	0.82
				(0.03)

Table 3: **Heterogeneous Effects**: This table displays the outcomes of semi-parametric Gaussian Kernel estimations for current and 5-year lag income. Each *Crossing point* is where $\bar{y}_{i,t} = \bar{y}_{i,t-p}$. The *Income Level* is determined by adding the crossing point and the average cohort effect (205.32). The *Elasticity* is the estimate of time-dependent labor income mobility. Bootstrap standard errors are reported in parentheses. *Panel A* reports the results by education level: above 13 years of education and up to 13 years of education. The results for *Panel B* are distinguished by gender. In *Panel C*, we report the results for cohorts of men and women born between 1925 and 1949 as the oldest, from 1950 to 1979 as middle-aged, and from 1980 to 2004 as the youngest. In *Panel D* we show the estimations for all formal and informal workers (formal workers are identified by their membership of the IESS, ISSFA, or ISSPOL).

Regarding the estimated mobility results, the fact that there is little, moderate, or some mobility in the indicator implies the existence or absence of opportunities to improve one's economic position. In the case of high mobility, the generation has a greater chance to climb the socioeconomic ladder, whereas high immobility limits the opportunities to improve people's economic position.

I identified significant levels of conditional temporal labor income immobility across diverse demographic cohorts, regardless of educational attainment. In particular, women exhibit **high immobility**, alongside young individuals and formal workers. **Moderate immobility** is observed among men and middle-aged individuals. Elderly individuals demonstrate **high labor income mobility**. Regarding educated people, I found that whether they have up to 13 years of education or more, everyone has **high immobility** in labor income.

These results reinforce the idea that specific demographic groups, while experiencing some level of mobility, still face significant obstacles in moving up the income ladder in Ecuador. However, I found a significant difference with respect to Cuesta et al. (2011) in labor income mobility in relation to the elderly and total years of education. My results show the elderly with more mobility than the rest of the sample, and regardless of the years of education for every cohort, all have high immobility. Cuesta et al. (2011) found that young individuals had higher mobility than everyone else, as well as people with more education.

These differences may be due to a tighter labor market in Ecuador, which acts as a restraint for young individuals to have an adequate job. In 2023, of the $8,4$ million people who are eligible to be part of the Economically Active Population[12], young people (which represent 52% of this group) had a $7,7\%$ unemployment rate, twice the national rate (Astudillo, 2023). This labor market environment explains why it is harder for a

[12] PEA by its initials in Spanish

young individual to move upward the labor income ladder.

The observed high mobility in labor income for the elderly may potentially be attributed to a selection bias[13]. It is plausible that those who remain in the sample are more productive, thus contributing to the increase in average labor income despite a decrease in the total number of individuals within the age group. This phenomenon likely explains the elevated level of income mobility observed. To mitigate this bias, in further analysis, I should use a Heckman correction to the sample, ensuring that it accurately reflects the elderly individuals who continue to participate in the workforce.

Regarding total years of education, my findings indicate that they make no difference when trying to move forward the labor income ladder, this may not be interpreted as education does not matter for improving one's situation, as the labor income equilibrium of people with more than 13 years of education ($428.74) is higher than those with up to 13 years ($365.68). Instead, it shows that in the Ecuadorian labor market, it is as difficult to move up the labor income ladder for people with more than 13 years of education and those with up to 13 years of education.

6. Robustness

6.1. Kernel vs Spline

In this subsection, I explain why the Gaussian Kernel method is preferred over a B-spline method. While both approaches have their merits, Kernel offers several advantages over Spline estimations (Wakefieldet al. , 2013).

[13]Selection bias is a problem that arises when nonrandom selection of cases results in inferences that are not statistically representative of the population. (Collier, 1995)

Gaussian Kernels are based on a local weighting approach: Given a new observation x (in this case, the value of the mean labor income $t-p$ years ago of the cohort i: $\bar{y}_{i,t-p}$), one computes its predicted value y (the value of mean labor income of cohort i at time t: $\bar{y}_{i,t}$) as a weighted average of the target values of the k-closest neighbors of x. These weights are given by a Kernel function (Wakefieldet al. , 2013).

The Gaussian Kernel method assigns the heaviest weight to the closest neighbor and gradually decreases the weight of more distant neighbors. Furthermore, a bandwidth parameter, which determines the degree of smoothing, needs to be optimized or cross-validated, making this method computationally expensive (Hastie et al., 2009).

Alternatives to the Gaussian Kernel, such as the B-spline method works by specifying a fixed set of knots along the function domain and then approximating a polynomial function across the intervals bounded by the knots (Wakefieldet al. , 2013).

One of the main advantages of the Kernel Gaussian over B-splines is its ability to capture non-linearities in the data. Since the weights are local and depend on the distance to the new observation, the Kernel approach is more flexible in capturing complex relationships between the input variable ($\bar{y}_{i,t-p}$) and the target variable ($\bar{y}_{i,t}$), as well as local features in the data, such as peaks or valleys (Wakefieldet al. , 2013).

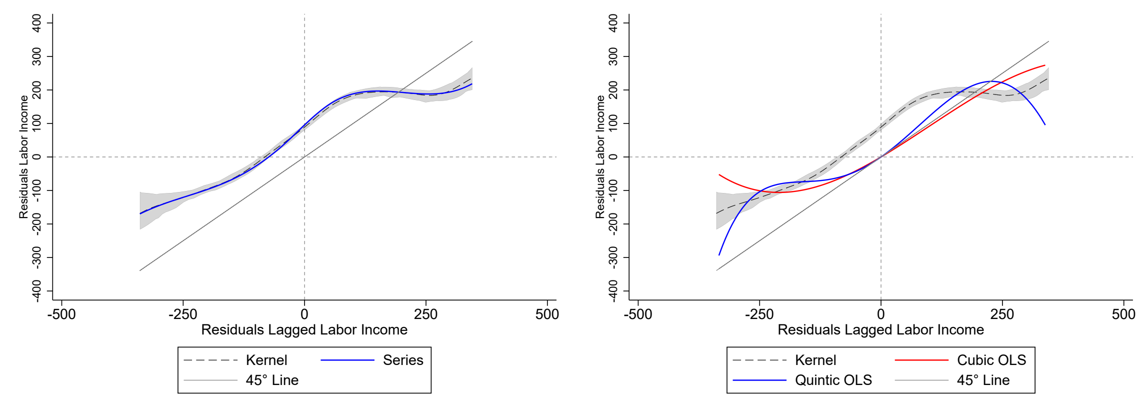
Hastie et al. (2009) points out that the main difference between these two estimations is that Kernel-based methods are more flexible in representing the data, which makes them computationally demanding; while B-spline calculations are more efficient and less flexible.

6.2. Robustness Results

In this subsection, I show that my results are robust to changes in the semi-parametric specification while using a B-spline semi-parametric method. Even with a Polynomial OLS, which is a parametric approach, my main results do not change.

Figure 5 displays the results of robustness estimations using both Gaussian Kernel and polynomial methods, analyzing current labor income with its 5-year lag. For the cubic and quintic OLS, I employed Equation (4) with $u = 3$ and $u = 5$ respectively.

Figure 5a shows that the fit I obtain using splines is virtually identical to the model estimated using Kernels. While contrasting the estimations between both Spline and Kernel with the quintic OLS, Figure 5b shows that this method provides a biased estimation, and therefore, a biased relationship between past and current labor income.



(a) Kernel vs Spline

(b) Polynomials vs Kernel

Figure 5: **Robustness results**: This figure displays the results of robustness estimations using both Gaussian Kernel, B-spline, and polynomial methods, analyzing current labor income with its 5-year lag. For the cubic and quintic OLS, I employed Equation (4) with $u = 3$ and $u = 5$ respectively.

Table 4 displays the outcomes of B-spline and Kernel estimations. As well as the different Polynomial OLS solutions comparing current and five-year lag labor income. Each *Crossing point* is where $\bar{y}_{i,t} = \bar{y}_{i,t-p}$, and the *Income level* is determined by adding the crossing point with the average cohort effect (205.32). The *Elasticity* is the estimate of time-dependent income mobility.

My results show that with the B-spline approach, Equation (3) does not hold, since the derivative at the crossing point is -0.19. The elasticity with the B-spline estimation is above 0.75, indicating **high** labor income immobility. This degree of immobility and the absence of evidence supporting a labor income poverty trap are also obtained when using the Gaussian Kernel method.

Robustness Checks				
Estimation Method	*Crossing Point*	*Income Level*	*Derivative*	*Elasticity*
Kernel	210.92	\$416.232	-0.14	0.76
Spline	211.57	\$416.89	-0.19	0.76
Polynomial, Cubic OLS	0.00	\$205.32	0.88	0.74
Polynomial, Quintic OLS Sol. 1	249.58	\$454.89	0.04	0.65
Polynomial, Quintic OLS Sol. 2	0.00	\$205.32	1.05	0.65

Table 4: **Results of Robustness Checks**: This table displays the outcomes of semi-parametric B-spline and semi-parametric Gaussian Kernel estimations, as well as the different polynomial OLS solutions comparing current and five-year lag labor income. Each *Crossing point* is where $\bar{y}_{i,t} = \bar{y}_{i,t-p}$, and the *Income level* is determined by adding the crossing point with the average cohort effect (205.32). The *Elasticity* is the estimate of time-dependent income mobility.

For polynomial estimations, I observe **moderate** labor income mobility. The cubic OLS fails to provide substantial evidence for poverty traps, as its derivative where the income mapping intersects the 45° line is consistently below one.

For the quintic OLS, however, the income mapping crosses twice through the 45° line, indicating two potential solutions. When examining the derivatives of these solutions, the first one does not imply a poverty trap, as it is equal to 0.04. The second crossing point exhibits a derivative above 1, which means that Equation (3) holds, suggesting the presence of a poverty trap at a labor income level of \$205.32.

We can observe biased results for this parametric method. Both functional forms do not accurately capture the underlying relationship between past and present labor income, therefore, I do not take this result as a definitive indicator of a poverty trap. Moreover, Antman & McKenzie (2007) caution against the use of higher-order polynomial models, emphasizing the need for additional assumptions and corrections to estimate accurate parameters while accounting for higher-order moments of measurement errors. Polynomial estimations offer valuable insight, but their interpretation requires careful consideration of the methodological limitations and the broader contextual factors in the existing literature.

7. Discussion

In this section, I present several policy implications to consider, even though results and robustness checks didn't find sufficient evidence for poverty traps in labor income, despite a high degree of intergenerational immobility.

The lack of evidence for poverty traps in labor income does not imply that poverty is transitory (Cuesta et al., 2011). High intergenerational immobility suggests that cohorts struggle to improve their labor income regardless of educational background, sex, or labor status.

Increasing intergenerational mobility requires attention to institutional and structural weaknesses in the economy such as the unequal distribution of opportunity, concentration of power, and lack of access to social protection. Policies aimed at strengthening labor markets, such as reducing discrimination, improving working conditions, and increasing access to social protection, are essential for promoting upward mobility in the labor market, as pointed out by Velín-Fárez (2021).

A second policy area must focus on enhancing the access of marginalized populations to social and economic opportunities, including improved access to public goods, financial services, and other forms of social support such as healthcare and housing. Policies that benefit poor families in early childhood, such as nutritional and health interventions, as well as education and job training that specifically target disadvantaged groups, are also essential to promote intergenerational mobility. In order to implement such policies, it is necessary to have accurate data on the specific needs and characteristics of different populations and to work collaboratively with communities, Non Governmental Organizations, and private sector actors (Cuesta et al., 2011; Letta et al., 2018; Barrett et al., 2019).

Therefore, investing in human capital, job training, and community development (Ribas, 2022), as well as social policies and health care support (Khandker & Haughton, 2009; Letta et al., 2018; Ribas, 2022) can boost intergenerational mobility in the labor market, this policy approach simultaneously addresses structural weaknesses in the economy and barriers to social and economic mobility.

8. Conclusions

My study analyzed Ecuador's labor income dynamics from 1990 to 2022 around the presence of poverty traps and the type of intergenerational mobility within the country's labor market. I employed parametric and semi-parametric approaches to determine the mapping between past and current labor income for various lag periods and heterogeneous groups, as well as the conditional and unconditional labor income mobility estimator.

My research incorporated the first dataset that covers socioeconomic and labor trends before and after Ecuador's dollarization, covering 33 years from Ecuador's National Survey of Employment, Unemployment and Underemployment (ENEMDU). My results indicated the absence of evidence of poverty traps in all generations analyzed, suggesting a lack of income stagnation at specific levels. Semi-parametric estimations revealed a unique stationary equilibrium in income dynamics, challenging the notion of poverty traps in Ecuador's labor market.

My analysis of mobility levels revealed varying degrees of economic advancement opportunities across demographic groups in Ecuador. Despite some mobility, significant barriers persist for specific cohorts, emphasizing the enduring challenges in ascending the income ladder in Ecuador. Also, I found some differences in my results with respect to previous research that could be attributed to a potential selection bias. Nevertheless, robustness checks using a B-Spline and Polynomial OLS models confirmed my findings. There is no substantial evidence for poverty traps in labor income dynamics. Although polynomial OLS results present potential biases, both B-spline and Gaussian Kernel estimations consistently refute the presence of poverty traps and confirm the low level of intergenerational mobility in labor income.

When planning future research, it is crucial to consider some inherent limitations of my study. First, to reduce the potential selection bias, it would be advantageous to incorporate a Heckman correction, especially when analyzing long-term datasets like the one used in this research. Second, although my study provides important insights into labor income dynamics, it is narrowly focused on labor income, which does not fully capture the complex nature of poverty traps.

A more extensive investigation that includes different types of income and socioeconomic factors might yield a deeper understanding of the dynamics of poverty. However, the ability to extend the analysis beyond the income of the labor force is limited by the availability of data in Ecuador. Thus, despite the significant insights my study offers into the income dynamics within the Ecuadorian context, it is essential to recognize these limitations and the necessity for more comprehensive future research.

9. References

Antman, F. & McKenzie, D. (2007). Poverty traps and nonlinear income dynamics with measurement error and individual heterogeneity. *The journal of development studies*, *43*(6), 1057–1083.

Astudillo, E. (2023). Cámara de industrias y producción. Accessed on April 08, 2024.

Azariadis, C. & Stachurski, J. (2005). Poverty traps. *Handbook of economic growth*, *1*, 295–384.

Barrett, C. B., Carter, M. R., Chavas, J.-P., & Carter, M. R. (2019). *The economics of poverty traps*. University of Chicago Press Chicago.

Barro, R. & Sala-i Martin, X. (2004). Economic growth second edition.

Brianzoni, S., Mammana, C., & Michetti, E. (2015). Local and global dynamics in a neoclassical growth model with nonconcave production function and nonconstant population growth rate. *SIAM Journal on applied mathematics*, *75*(1), 61–74.

Capasso, V., Engbers, R., & La Torre, D. (2010). On a spatial solow model with technological diffusion and nonconcave production function. *Nonlinear Analysis: Real World Applications*, *11*(5), 3858–3876.

Collier, D. (1995). Translating quantitative methods for qualitative researchers: The case of selection bias. *American Political Science Review*, *89*(2), 461–466.

Cuesta, J., Ñopo, H., & Pizzolitto, G. (2011). Using pseudo-panels to measure income mobility in latin america. *Review of Income and Wealth*, *57*(2), 224–246.

Edmond, C. (2004). Advanced macroeconomic techniques. *Lecture notes, University of Melbourne*.

Ferrara, M., Guerrini, L., & Sodini, M. (2014). Nonlinear dynamics in a solow model with delay and non-convex technology. *Applied Mathematics and Computation*, *228*, 1–12.

Gentilini, U., Khosla, S., & Almenfi, M. (2021). Cash in the city: emerging lessons from implementing cash transfers in urban africa.

Grassetti, F., Mammana, C., & Michetti, E. (2018). Poverty trap, boom and bust periods and growth. a nonlinear model for non-developed and developing countries. *Decisions in Economics and Finance*, *41*(2), 145–162.

Guillerm, M. (2017). Pseudo-panel methods and an example of application to household wealth data. *Economie et Statistique*, *491*(1), 109–130.

Hastie, T., Tibshirani, R., Friedman, J. H., & Friedman, J. H. (2009). *The elements of statistical learning: data mining, inference, and prediction*, volume 2. Springer.

Janz, T., Augsburg, B., Gassmann, F., & Nimeh, Z. (2023). Leaving no one behind: Urban poverty traps in sub-saharan africa. *World Development*, *172*, 106388.

Khandker, S. & Haughton, J. (2009). *Handbook on poverty and inequality*. World Bank Publications.

Letta, M., Montalbano, P., & Tol, R. S. (2018). Temperature shocks, short-term growth and poverty thresholds: Evidence from rural tanzania. *World Development*, *112*, 13–32.

Lokshin, M. & Ravallion, M. (2004). Household income dynamics in two transition economies. *Studies in Nonlinear Dynamics & Econometrics*, *8*(3).

Loría, E. (2020). Poverty trap in mexico, 1992-2016. *International Journal of Development Issues*, *19*(3), 277–301.

Matsuyama, K. (2010). Poverty traps. In *Economic Growth* (pp. 215–221). Springer.

McKay, A. & Perge, E. (2013). How strong is the evidence for the existence of poverty traps? a multicountry assessment. *The Journal of Development Studies*, *49*(7), 877–897.

Michael, L. & Martin, R. (2004). Household income dynamics in two transition economies. *Studies in Nonlinear Dynamics & Econometrics*, *8*, 1–33.

Moffitt, R. (1993). Identification and estimation of dynamic models with a time series of repeated cross-sections. *Journal of Econometrics*, *59*(1-2), 99–123.

Opoku-Afari, M. (2004). Measuring the real effective exchange rate (reer) in ghana. Technical report, CREDIT Research Paper.

Ribas, R. P. (2022). Using pseudo-panels to analyse labour market transitions. *International Labour Organization*.

Snowdon, B. (2009). The solow model, poverty traps, and the foreign aid debate. *History of Political Economy*, *41*(Suppl_1), 241–262.

Solimano, A. (2002). Crisis and dollarization: An overview. *Crisis and Dollarization in Ecuador: Stability, Growth and Social Equity, World Bank, Washington DC*, 1–16.

Velín-Fárez, M. (2021). Population and labor dynamics in large informal markets: Implications for pension systems with evidence from ecuador. *Contemporary Economics*, *15*(2), 164–186.

Wakefield, J. et al. (2013). *Bayesian and frequentist regression methods*, volume 23. Springer.

10. Appendix

10.1. Appendix A: Conditions over δ for a poverty trap in the Solow Model

Recalling the capital dynamics from discrete-time Solow Model in steady state, assuming like Capasso et al. (2010) that $sA = 1$ and $n(t) = 0$. With an equilibrium in $k_t^* \neq 0$:

$$f(k_t^*) = \delta k_t^*.$$

$$k_{t+1} - k_t = sAf(k_t) - (\delta + n)k_t.$$

$$\frac{\alpha (k_t^*)^p}{1 + \beta (k_t^*)^p} = \delta k_t^*.$$

The following is the process to find the condition for δ to have a poverty trap at a threshold $\bar{k}$:

$$\delta = \frac{\alpha k_t^{p-1}}{1 + \beta k_t^p} \rightarrow \xi(k_t)$$

$$\xi(\tilde{k}_t) = \delta^*$$

$$\xi'(k_t) = \frac{pk_t^{p-2}\alpha - k_t^{p-2}\alpha - k_t^{2p-2}\alpha\beta}{(1 + k_t^p\beta)} = 0$$

$$pk_t^{p-2}\alpha - k_t^{p-2}\alpha - k_t^{2p-2}\alpha\beta = 0$$

$$k_t^{p-2}(p\alpha - \alpha - k_t^p\alpha\beta) = 0$$

$$\alpha(p-1) = k_t^p\alpha\beta$$

$$k_t = \left(\frac{p-1}{\beta}\right)^{\frac{1}{p}} \rightarrow \tilde{k}_t$$

Over $\tilde{k}_t$ we define $\overline{k}$ and k^* :

$$\overline{k} \leq \tilde{k}_t \leq k^*$$

$$\overline{k} \leq \left(\frac{p-1}{\beta}\right)^{\frac{1}{p}} \leq k^*$$

Defining $g(k_t) = f(k_t) - \delta k_t$:

$$g(k_t) = \frac{\alpha k_t^p}{1+\beta k_t^p} - \delta k_t$$

$$g'(k_t) = \frac{\alpha p k_t^{p-1}}{(1+\beta k_t^p)^2} - \delta$$

The point $g'(k^*) < 0$ is a stable steady state. I defined $\overline{k}$ as the threshold over which we have a poverty trap, therefore $g'(\overline{k}) > 1$. This happens when:

$$\frac{\alpha p \left(\frac{p-1}{\beta}\right)^{\frac{p-1}{p}}}{\left(1+\beta\left(\frac{p-1}{\beta}\right)\right)^2} - \delta > 1$$

$$\frac{\alpha p (\frac{p-1}{\beta})^{\frac{p-1}{p}}}{p^2} - \delta > 1$$

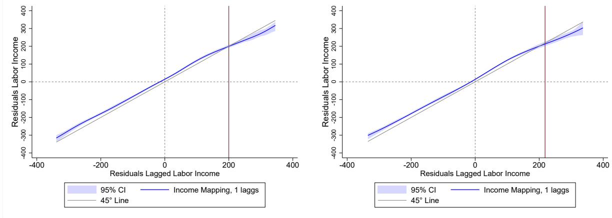
$$\alpha(\frac{p-1}{\beta})^{\frac{p-1}{p}} - \delta > 1$$

$$\delta < \alpha\left(\frac{p-1}{\beta}\right)^{\frac{p-1}{p}}$$

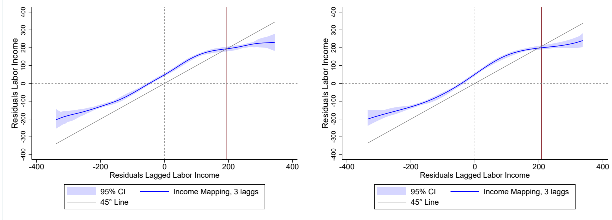
So, there is a poverty trap at a capital level of $\overline{k}$, which is when $\delta < \delta^* = \alpha\left(\frac{p-1}{\beta}\right)^{\frac{p-1}{p}}$

10.2. Appendix B: Estimations Results

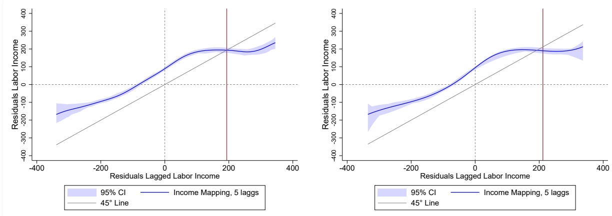
Kernel **Spline**



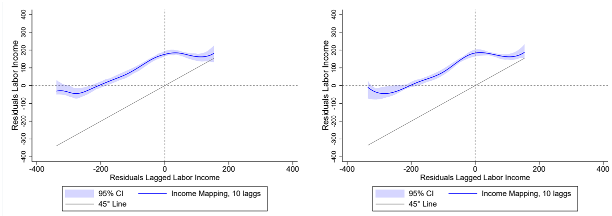
Panel 1: One year lag



Panel 2: Three years lag



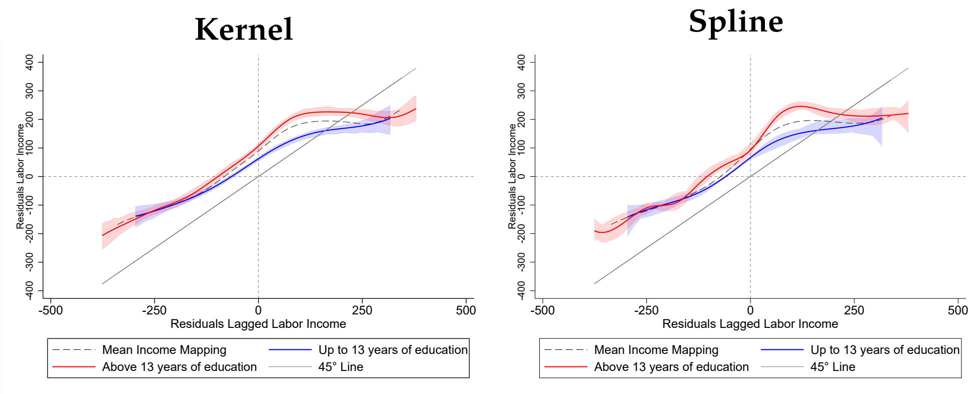
Panel 3: Five years lag



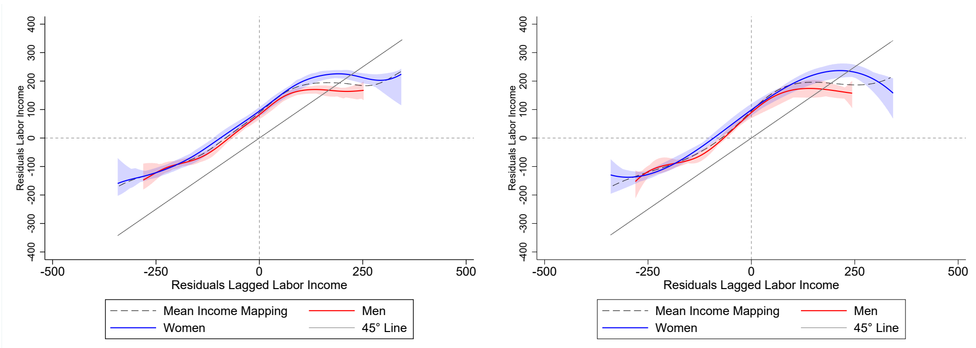
Panel 4: Ten years lag

Figure 6: **Estimations Results**: This figure presents the outcome of semi-parametric estimations comparing current with lagged labor income across different numbers of lags. Each figure is centered around zero and illustrates the intersection between the 45° line and the labor income mapping.

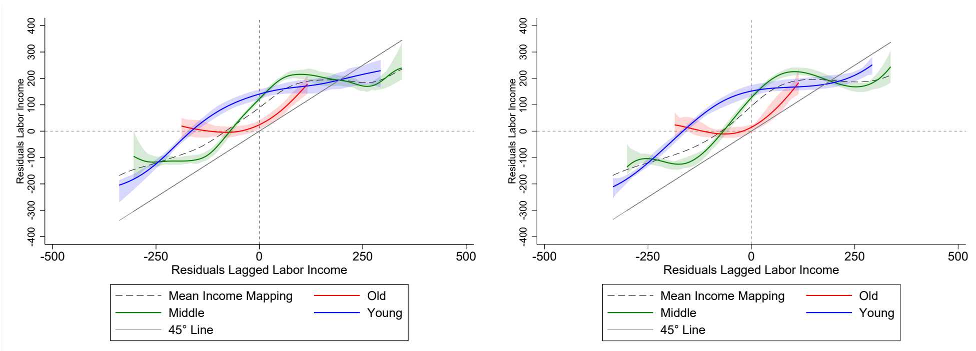
10.3. Appendix C: Non-labor Heterogeneous Effects



Panel A: Education



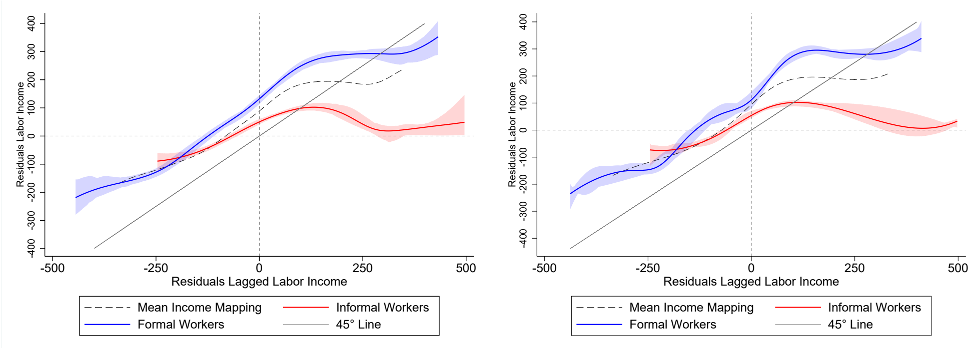
Panel B: Gender



Panel C: Age Groups

Figure 7: **Non-labor Heterogeneous Effects**: This figure illustrates the varying income mapping between current and 5-year lag labor income for each heterogeneity test related to non-labor status. *Panel A* shows the results by education level: above 13 years of education and up to 13 years of education. On *Panel B* I show the mean labor income mapping for both men and women across all generations. *Panel C* depicts the mean labor income mapping for cohorts of men and women born between 1925 and 1949 as the oldest, from 1950 to 1979 as middle-aged, and from 1980 to 2004 as the youngest.

10.4. Appendix D: Labor Heterogeneous Effects



Panel D: Status in labor market

Figure 8: **Labor Heterogeneous Effects**: This figure illustrates the varying labor income mapping between current and 5-year lag labor income for each heterogeneity test related to labor status. Panel D shows the mean labor income mapping for all formal and informal workers, formal workers are identified by their contributions to the IESS, ISSFA, or ISSPOL.

10.5. Appendix E: Results of B-spline Estimations

Spline Estimations				
Number of lags	*Crossing point*	*Income*	*Derivative*	*Elasticity*
1	218.35	\$423.67	0.44	0.92 (0.01)
3	208.09	\$413.41	−0.01	0.78 (0.02)
5	211.57	\$416.89	−0.19	0.76 (0.03)
10	–	\$205.32	–	0.64 (0.05)

Table 5: **Results of Spline Estimations**: This table presents the outcomes from spline estimations comparing current and lagged income. Each *Crossing Point* indicates where $\bar{y}_{i,t} = \bar{y}_{i,t-p}$. The *Income Level* is determined by adding the crossing point with the average cohort effect (205.32). The *Elasticity* is the estimate of time-dependent income mobility. Bootstrap Standard errors are reported in parentheses.

10.6. Appendix F: Income Mobility

Income Mobility				
	Crossing point	*Income*	*Derivative*	*Elasticity*
Panel A: Education				
Above 13 years of education	360.18	\$565.50	-0.15	0.82 (0.03)
Up to 13 years of education	161.70	\$367.02	0.01	0.76 (0.03)
Panel B: Gender				
Men	186.33	\$391.64	-0.19	0.75 (0.04)
Women	263.26	\$468.57	-0.25	0.68 (0.04)
Panel C: Age Groups				
Old (1925 - 1949)	-	-	-	0.54 (0.07)
Middle Aged (1950 - 1979)	210.22	\$415.54	-0.68	0.65 (0.03)
Young (1980 - 2004)	181.31	\$386.63	0.12	0.83 (0.04)
Panel D: Status in labor market				
Informal Worker	147.54	\$352.86	0.43	0.66 (0.03)
Formal Worker	308.70	\$514.02	-0.02	0.80 (0.03)

Table 6: **Income Mobility**: This table displays the outcomes of semi-parametric B-spline estimations for current and five-year lag labor income. Results are presented based on different demographic and labor market statuses. Each *Crossing point* is where $\bar{y}_{i,t} = \bar{y}_{i,t-p}$, and the *Income level* is determined by adding the crossing point with the average cohort effect (205.32). The *Elasticity* is the estimate of time-dependent labor income mobility. Bootstrap standard errors are reported in parentheses.

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