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Intergenerational Mobility in Ecuador: A First Approach

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Intergenerational Mobility in Ecuador: A First Approach

Diego Del Pozo[*] Lorena Moreno[†]

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Abstract

This study provides the first comprehensive estimates of intergenerational mobility in Ecuador, combining administrative social security records, census data, and labor force surveys to measure both formal and informal labor income. Utilizing machine learning techniques to estimate informal income, we analyze both relative and absolute mobility. In terms of relative mobility, we find that a 10-percentile increase in parents' income corresponds to a 2.7-percentile increase in their children's income, indicating a moderate degree of intergenerational persistence. Regarding absolute mobility, 10.6% of children born in the lowest quintile rise to a higher quintile. Persistent inequalities are evident as 30.2% of children from low-income families and 37.4% from high-income families remain in the same economic position as their parents. The study also finds that children of parents in the 25th percentile typically advance to the 44th percentile by adulthood. Furthermore, the analysis highlights significant gender gaps, with women exhibiting lower relative mobility than men, and substantial disparities across provinces. Vulnerable areas such as the Andean Highlands exhibit lower mobility measures compared to more dynamic regions.

JEL Codes: J62, D31, I31, R23

Keywords: Intergenerational mobility, inequality, labor income, machine learning

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1 Introduction

The study of intergenerational mobility (IM) has gained significant attention since the late 1970s, with pioneering research by Becker and Tomes (1979), Loury (1981), and Solon (1992) proposing models to explain the transmission of economic outcomes between parents and children. These models emphasize the persistence of inequality through the inheritance of skills and the investments that parents make in their children's education and human capital. Piketty (2020) adds a broader ideological perspective, arguing that inequality is not only economically driven but also reinforced by narratives societies develop to justify disparities. These narratives shape policies and institutions, affecting how opportunities and resources are passed down. Consequently, measuring IM is critical for understanding both the economic mechanisms and the ideological structures that drive inequality across generations.

In Ecuador, analyzing IM is particularly crucial given the country's significant socioeconomic inequalities and the high prevalence of informal employment. Ecuador's economy is characterized by a dual labor market, with approximately 54% of the workforce engaged in the informal sector, which typically provides lower and less stable income than the formal sector (INEC), 2024). This duality not only impacts current living conditions but also has profound implications for IM and the perpetuation of inequality across generations. Understanding IM in this context sheds light on the structural barriers that hinder social mobility, especially in economies with constrained formal job opportunities.

This study is the first to measure IM in Ecuador, incorporating both formal and informal labor income through the integration of rich, granular administrative datasets and advanced machine learning (ML) techniques. While Ecuador is the second country in Latin America, after Brazil, to leverage both administrative data and ML for IM estimates, it ranks third when including Chile, which has utilized administrative data without ML methods to assess income informality. Compared to Brazil, one of the largest and most economically diversified countries in Latin America, which also benefits from relatively extensive social programs, Ecuador operates under distinct constraints. As a smaller economy with a heavy reliance on oil exports and a substantial informal labor market, Ecuador encounters unique challenges. These structural differences are crucial for understanding IM in Ecuador, where limited economic diversification and widespread informality pose significant obstacles to social mobility

Our study examines IM across a broader range of birth cohorts than previous studies in Latin America. While both this study and the Brazil study analyze income for individuals as they reach ages 25 to 31, our analysis covers a wider set of birth cohorts (1987–1998) over a longer period (2018 to 2023). This broader scope captures the socioeconomic trajectories of multiple generations as they progress through early adulthood, offering a more comprehensive view of IM under varying economic conditions. This approach provides unique insights into income persistence and variability over time, enriching the analysis of IM in Ecuador.

This study is also the first in Ecuador to utilize data from the Labor Market and Business Dynamics Laboratory (LDLE) of the National Institute of Statistics and Censuses (INEC) to estimate IM. By integrating census and survey data with social security records, we establish a linkage rate of approximately 43% for children within the selected birth cohort. This rate represents children who have at least one parent identified and include information on their labor income. This rate significantly exceeds the 15% linkage achieved in Brazil's study by Britto et al. (2022), providing a more representative dataset for analysis. Our comprehensive dataset not only captures income but also strengthens family connections across generations, adding depth to our mobility estimates.

Compared to Brazil, where intergenerational persistence is higher (with a rank-rank slope of 0.55 and a 46% probability that children from the lowest income quintile remain in the same quintile into adulthood), our findings suggest a lower coefficient of intergenerational persistence in Ecuador. We observe a rank-rank slope of 0.27, and there is a 30.2% probability that children from low-income families will remain at the same income level, and a 37.4% probability that children from high-income families will maintain the same economic position as their parents. Additionally, we find a 10.6% probability that children from families in the lowest income quintile will reach the highest quintile. Compared to Chile, where the intergenerational mobility rank-rank slope varies between 0.254 and 0.275, and 12% of children from the lowest quintile rise to the highest quintile, Ecuador presents slightly lower mobility(Díaz et al., 2021).

Additionally, this study examines heterogeneity by gender and province of birth, observing that IM for women is slightly lower than for men, suggesting a greater dependence on family income among women. Furthermore, the analysis by province of birth reveals significant geographical inequalities.

This article is structured as follows: First, we review relevant literature, focusing on studies of intergenerational mobility in developing countries. Next, we discuss the national context, specifically examining the characteristics of Ecuador's labor market and income distribution. In the data and methodology section, we detail the sources of information and the process for constructing the relational database of parents and children. We then present and discuss the national results of relative and absolute IM, examine gender and geographical disparities, and present our conclusions and recommendations for future research.

2 Literature Review

Numerous studies have analyzed IM, focusing mainly on educational, occupational, and class mobility, using household survey data where individuals report retrospective information about their parents (Neidhöfer et al., 2018). However, measuring intergenerational income mobility presents additional challenges due to the need for data that captures income information across generations. To address this, many studies—particularly in Latin America—have used a two-stage instrumental variables strategy to estimate parental income, revealing a high degree of intergenerational income association, in contrast to findings in the United States (Ferreira and Veloso, 2006; Dunn, 2007; Nunez and Miranda, 2010; Torche, 2010).

More recently, advances in data availability have enabled researchers to rely on detailed administrative records to link parents' and children's incomes, providing a more accurate measurement of IM. For instance, Chetty et al. (2014) in the United States found that mobility varies significantly with region, education, and social policies. Their study, based on detailed administrative data, showed that a 10-percentile increase in parents' income is associated with a 3.4-percentile increase in their children's income, reflecting moderate income persistence across generations. They also found that only 7.5% of children from the lowest income quintile reach the highest quintile in adulthood, while 33.7% remain in the lowest, highlighting the persistence of income inequality across generations.

Building on these insights, Chetty et al. (2016) examined the role of childhood environments and found that boys from low-income backgrounds, especially those raised in single-parent households, experienced significantly lower employment rates and were more likely to engage in crime than girls from similar backgrounds, underscoring the influence of early environments on gender disparities in adult outcomes. Expanding on the role of neighborhoods, Chetty and Hendren (2018a) demonstrated that neighborhoods exert a causal effect on IM, with each additional year of childhood spent in a higher-opportunity neighborhood improving adult outcomes by approximately 4%. Their subsequent study, Chetty and Hendren (2018b), estimated that for children from low-income families, each year spent in a county with one standard deviation higher upward mobility increased adult income by 0.5%, highlighting how neighborhood and county-level conditions directly impact long-term economic outcomes.

Beyond the United States, similar patterns of intergenerational persistence have been observed in other high-income countries, though mobility levels vary significantly due to distinct social and economic contexts. In Australia, Deutscher and Mazumder (2020) found it to be one of the more mobile advanced economies, with a rank-rank slope of 0.215, though regional disparities exist; regions affected by the mining boom, for example, saw enhanced mobility. Similarly, Connolly et al. (2019) documented higher intergenerational mobility in Canada compared to the United States, though some regions showed mobility patterns similar to low-mobility areas in the U.S. South.

Intergenerational mobility in Northern Europe and Germany generally shows higher levels of upward mobility compared to other countries. In Denmark, Eriksen and Munk (2020) reported high relative mobility, particularly in middle-income rural areas, though urban and economically disadvantaged areas displayed lower mobility rates. Sweden's IM was consistent across regions; Heidrich (2017) found that 15.7% of children born to parents in the lowest quintile were able to reach the highest income quintile. However, absolute mobility in Sweden showed regional variation, reflecting stable opportunities with differing economic outcomes across the country. Switzerland, on the other hand, has one of the highest income mobility rates among developed countries, with a rank-rank slope of 0.14, attributed partly to the country's vocational education system, which supports upward mobility (Chuard and Grassi, 2020). In Germany, Stockhausen (2021) reported that approximately 67% of sons born between 1955 and 1975 surpassed their fathers' real long-run labor income, a higher rate than in the United States, where only 60% experienced similar upward mobility. Germany's intergenerational elasticity, estimated at 0.30, also suggests moderate persistence in income across generations, although it remains higher than in Scandinavian countries.

Meanwhile, Southern European countries demonstrate more barriers to upward mobility. In Italy, Acciari et al. (2022) estimated a moderate rank-rank slope of 0.22, with only 11.2% of children from the bottom quintile reaching the top quintile, especially challenging in the less favorable labor markets of southern Italy. France shows similar patterns; Kenedi and Sirugue (2023) found that only 9.7% of children from the bottom 20% reach the top 20% in adulthood, illustrating persistent barriers to upward mobility despite extensive welfare support. Lastly, in Spain, Soria (2022) observed moderately high intergenerational mobility with a rank-rank slope of approximately 0.195, meaning that a 10-percentile increase in a parent's income rank corresponds, on average, to a 1.95 percentile increase in the child's income rank. There was significant geographic variation, with northern regions like Cataluña exhibiting mobility levels similar to Scandinavia, while southern regions like Andalucía resembled the lower mobility rates seen in the U.S. South.

While high-income countries benefit from extensive administrative data for mobility studies, developing countries like those in Latin America rely primarily on survey-based approaches, which come with unique challenges and insights. Studies in Brazil (Britto et al., 2022) and other Latin American countries have shown that labor informality and educational inequality are significant barriers to social mobility. The lack of longitudinal data and the variable quality of administrative records represent additional challenges for research in these contexts.

Ecuador is no exception to these challenges. The coexistence of formal and informal sectors in its labor market has profound implications for IM. The informal sector, which employs a large part of the workforce, offers unstable income and fewer social benefits, perpetuating inequality and limiting opportunities for social advancement (Jara and Rattenhuber, 2022). However, Ecuador has recently gathered information from interconnected administrative records that allow tracking of workers and their employment conditions in the formal sector, as well as higher education characteristics. This study takes advantage of this resource, using integrated records from the LDLE at INEC, which serve as a primary source for this research.

Intergenerational mobility studies in Latin America provide a valuable comparative perspective for understanding the Ecuadorian context. In Brazil, for instance, the rank-rank coefficient is 0.55, indicating high income persistence across generations. Additionally, Brazil's intergenerational elasticity, measuring the percentage change in children's income relative to a percentage change in their parents' income, is 0.50, further highlighting the strength of income persistence. When it comes to absolute mobility, defined as the percentage of children born into the lowest income quintile who rise to a higher quintile, Brazil has a low rate of just 2.5%, reflecting significant barriers to upward economic mobility (Britto et al., 2022).

Intergenerational mobility research in Chile sheds light on persistent economic inequality within the country, offering another comparative lens for Ecuador. Meneses (2020) reports a rank-rank coefficient of 0.21, indicating moderate income persistence, based primarily on survey data. However, more recent research by Díaz et al. (2021) using administrative records that link a child's and their parent's earnings from the formal private labor estimates that the rank-rank slope ranges between 0.254 and 0.275, while the intergenerational earnings elasticity is between 0.288 and 0.323. Furthermore, this study shows that for children whose parents are in the lowest income quintile, 27% remain in the lowest quartile as adults, while 12% ascend to the highest quintile, contrasting with children from the highest quintile where 38% remain at the top. These results highlight that Chile demonstrates relatively higher mobility than some other Latin American nations.

In Mexico, Torche (2020) analyzed intergenerational mobility across cohorts, using survey data to reveal important gender and regional patterns. Among Mexican men, mobility initially declined in earlier cohorts but showed improvement among younger cohorts, while Mexican women experienced a steady decrease in mobility, with persistence in socioeconomic status becoming more pronounced and independent of educational attainment. This reliance on survey data, as opposed to administrative data, is common in intergenerational mobility studies in developing countries, where administrative records are often limited. Such studies, including the Mexican case, provide valuable insights but underscore the need for more granular data sources, as we explore in the context of Ecuador.

In Ecuador, intergenerational income mobility has yet to be estimated using administrative records. Instead, several studies have analyzed poverty dynamics through household surveys to offer an initial view of socioeconomic mobility. Canelas (2010) used a pseudo-panel approach to study income mobility from 2000 to 2009, finding low absolute mobility and significant poverty persistence. Cuevas et al. (2016) found that although poverty decreased between 2006 and 2014, structural barriers persisted, constraining upward mobility for certain groups. Similarly, Pesántez (2014) employed synthetic panels to show that between 2007 and 2013, 23% of households exited poverty while 10% fell into it. Cano (2015) used 2004–2011 income tax records to assess mobility, finding low mobility at the top, with a 66% chance of remaining in the top 1% year-over-year. Middle-income earners showed more upward movement, though intergenerational mobility remains unaddressed.

Recent studies have extended the analysis to IM in Ecuador using survey data. Segovia and Ramos (2024) examined educational mobility across cantons, revealing marked regional disparities. They identified areas like the Galápagos as "lands of opportunity" with higher mobility, while regions such as the Central Andes exhibited persistent poverty traps. This study found that higher levels of migration, family self-employment, and schooling positively influenced mobility, whereas greater inequality and a larger Indigenous population posed challenges. Similarly, Muñoz (2022) found that upward mobility in education varied significantly across regions, with proximity to economic centers and lower reliance on agriculture as positive correlates. Doruk et al. (2024), using census data, highlighted intergenerational occupational persistence, finding that structural factors within Ecuador's labor market limit upward mobility.

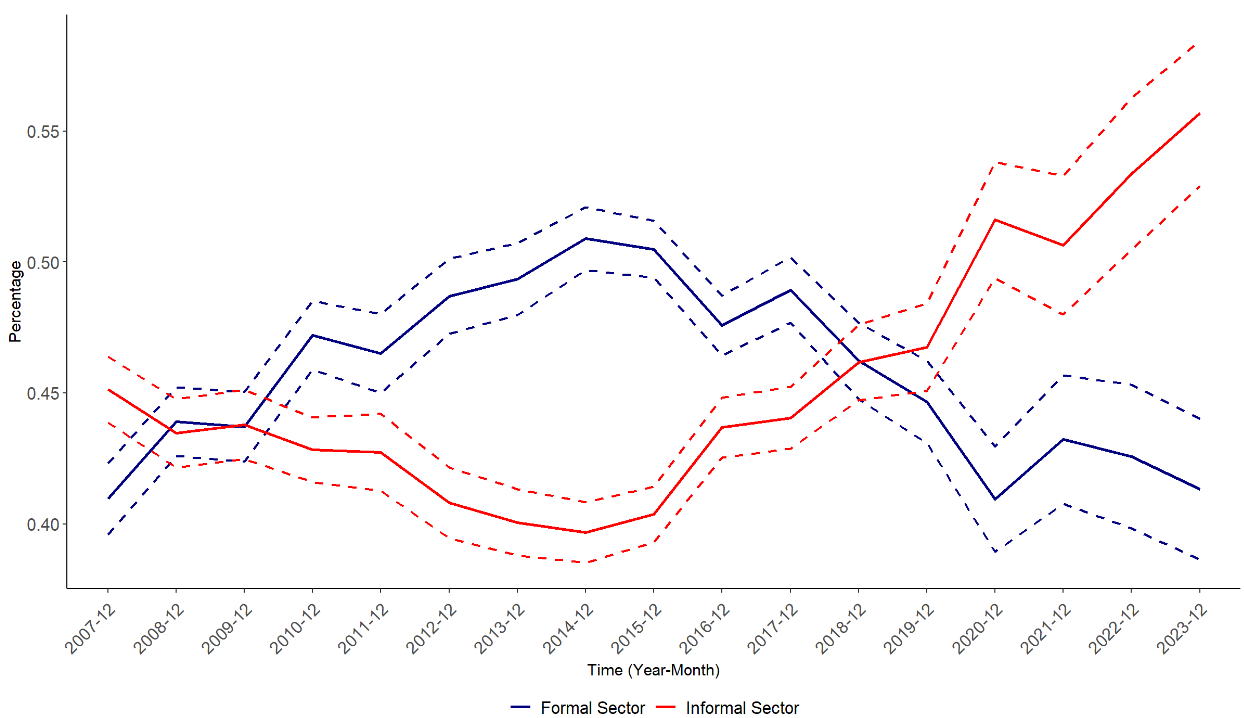
Our document aims to address these gaps by using Ecuador's newly available administrative data and advanced income imputation techniques to provide a comprehensive assessment of IM in Ecuador. By linking income records across generations and cohorts, this research will provide direct estimates of IM, offering valuable insights to inform public policies designed to promote social mobility and reduce income inequality.

3 Context

Ecuador's labor market is marked by a high level of employment in the informal sector.[1] According to data from the National Employment, Unemployment, and Underemployment Survey (ENEMDU), this trend became increasingly apparent in December 2019, when employment in the informal sector (46.75%) exceeded that in the formal sector (44.66%) by about 2 percentage points (p.p.). The COVID-19 pandemic further widened this gap, with the average difference between informal and formal sector employment reaching approximately 11 p.p. by December 2020 and continuing through 2023, favouring the informal sector.

In the most recent data from December 2023, the gap between the informal sector (55.69%) and the formal sector (41.32%) reached approximately 14 p.p., indicating a sharp increase in informality within the labor market, as shown in Figure 1.

Figure 1: Employment Distribution by Sector



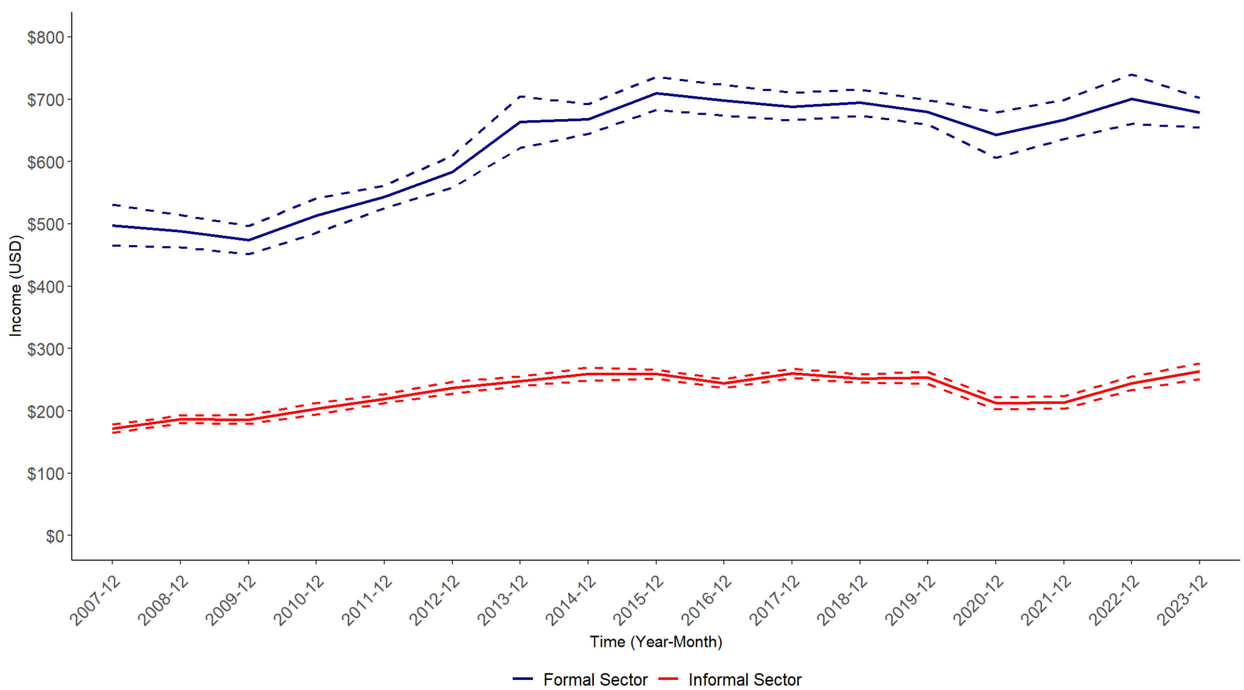
Source: ENEMDU 2007-2023

This high level of informality has significant implications for income distribution. As

[1]The operational definitions of employment in the formal and informal sectors, based on ENEMDU, are as follows (Molina et al., 2015): a) Formal sector: individuals working in establishments with a Unique Taxpayer Registry (RUC) in establishments with 100 or more employees, b) Informal sector: individuals working in productive units with fewer than 100 employees that do not have RUC.

illustrated in Figure 2, while the formal sector comprises a smaller share of the labor market, average labor income within this sector is roughly three times higher than that in the informal sector[2]. Formal sector income ranges from USD 470 to USD 710, while informal sector earnings are typically between USD 170 and USD 260. This disparity stems from national labor regulations, which mandate that formal sector workers affiliated with social security receive at least the unified basic salary (SBU). In contrast, the majority of informal sector workers earn unregulated incomes, often at or below the SBU level.

Figure 2: Current Labor Income by Employment Sector (USD)



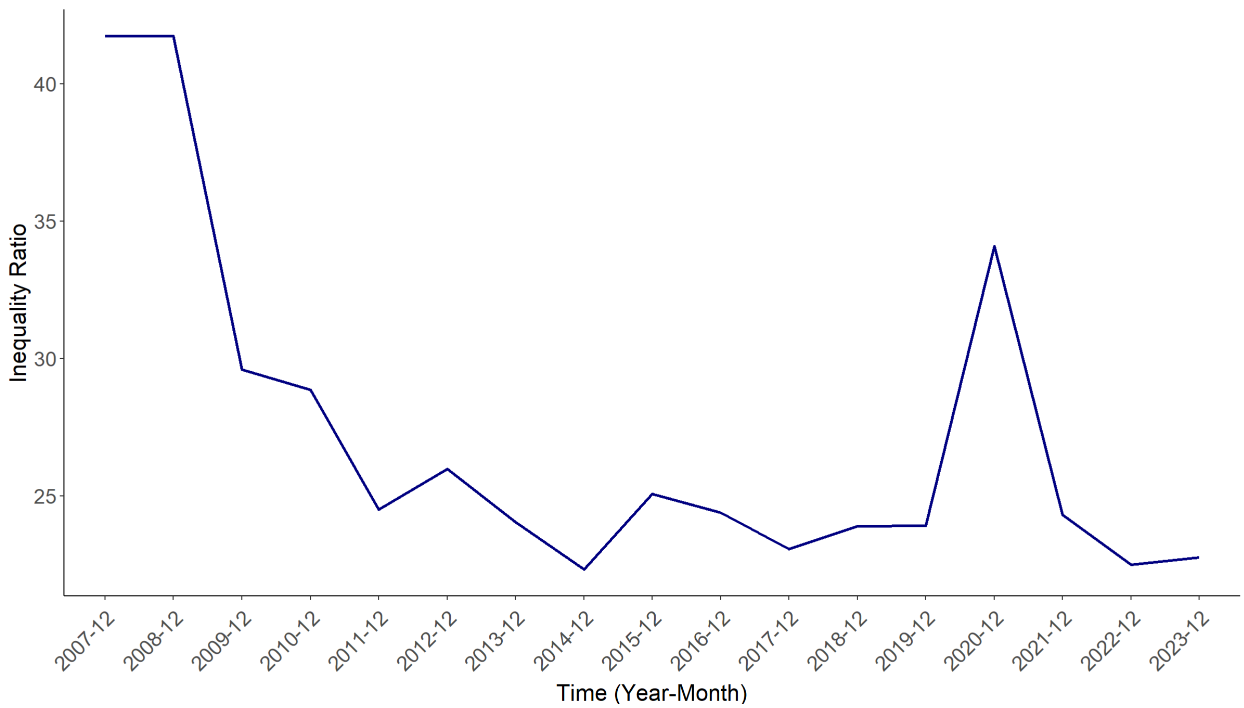
Source: ENEMDU 2007-2023

Income inequality is a prominent feature of Ecuador's economic landscape. As shown in Figure 3, the income disparity between the wealthiest 10% (decile 10) and the poorest 10% (decile 1) of the population remains substantial. In 2018, households in the top decile earned 25 times more than those in the lowest decile. This gap expanded during the COVID-19 pandemic, reaching a ratio of 34 to 1 in 2020, as the economic downturn disproportionately impacted lower-income households. By December 2021, the ratio moderated to around 24 and moderately decreased, moving to 2022. However, by the end of 2023, the gap slightly increased again, with the top decile earning 25 times more than the bottom decile. These

[2]We use data only from December months; therefore, the analysis reflects the income of the preceding month, November. This approach is chosen to avoid comparing outlier values that are usually reflected in January since the December income reported includes benefits that are typical to the last months of the year.

figures evidence the persistent economic disparity in Ecuador,[3] where a small portion of the population captures a disproportionately large share of income.

Figure 3: Income Ratio Between Decile 10 and Decile 1 (Average Household Per Capita Income)

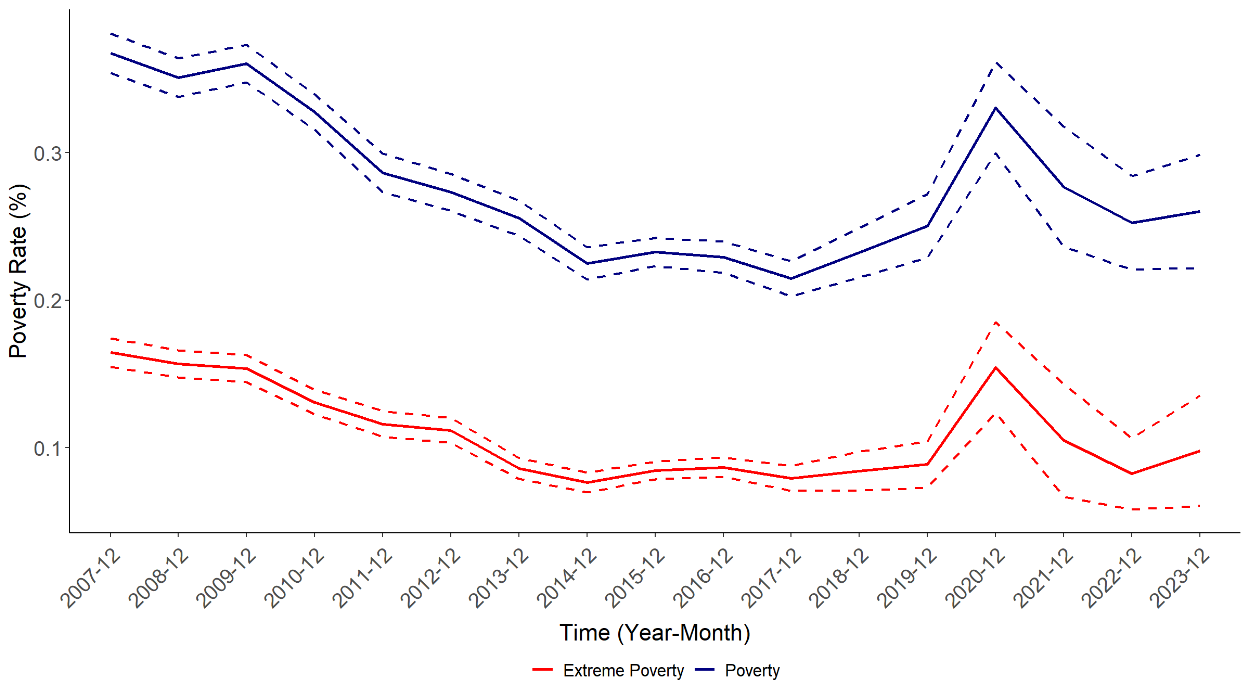


Source: ENEMDU 2007-2023

Beyond income inequality, poverty levels in Ecuador remain elevated compared to pre-pandemic years. As shown in Figure 4, poverty rates had been on a steady decline from 2007 to 2017. However, following the economic disruptions of the COVID-19 pandemic, poverty levels have plateaued, failing to return to pre-pandemic lows. As of December 2023, the general poverty rate stands at 26%, with extreme poverty affecting 9.8% of the population. This context highlights the need for an in-depth examination not only of poverty and inequality trends but also of how these dynamics have impacted different generations. The following section presents the data sources that will underpin this analysis.

[3] For a broader and more detailed analysis of income inequality in Ecuador, see Jara et al. (2024).

Figure 4: Poverty and Extreme Poverty Rates



Source: ENEMDU 2007-2023

4 Data and Methodology

4.1 Data

This study examines the relationship between parental income and the income of their children in early adulthood (ages 25–31). To achieve this, we integrate multiple data sources from Ecuador, including household surveys, population censuses, and administrative records from various governmental institutions.

In the initial phase, we construct a relational database to link parents and children. For this, we use administrative records of individuals with identification IDs from the National Civil Registry Office (DIGERCIC) as of June 2022, along with data from the 2010 and 2022 Population and Housing Censuses (CPV).

To capture formal labor income data for both children and parents, we use the Statistical Registry of Social Security (REESS), which provides monthly updated information on all workers registered with social security.[4] The digitized version of this registry is available since 2006, and for this study, we include records up to December 2023. To define informal labor

[4] The national social security office is called the Ecuadorian Institute of Social Security (IESS).

income, we train machine learning (ML) models on monthly labor force surveys (ENEMDU) available between 2007 and 2023.

By combining these data sources, we construct a comprehensive database that allows us to determine the average labor income of children over the period 2018–2023 and the average labor income of their parents during 2006–2011. Further details on the database construction process are provided in the following sections.

4.1.1 Family Links

A key objective of our study was to establish reliable relational information between children and their parents using the comprehensive administrative registry from the DIGERCIC. This registry contains the historical identification codes (ID cards) for all registered individuals in Ecuador, along with their familial connections. Nevertheless, we faced challenges from this administrative source, including issues with data accuracy—such as invalid identification codes—and gaps in recorded family ties.

To address these issues, we implemented rigorous validation procedures. Firstly, we assessed the validity of the identification codes by confirming their length [5] and consistency of the identification codes[6]. We also verified the presence of parental information within the dataset. This involved checking that each individual's record included identifiable codes for both father and mother, where available. Despite these comprehensive checks, establishing complete family linkages for the entire dataset was not possible due to missing or inconsistent data.

To enhance the robustness of the family links, we integrated supplementary data from the 2010 and 2022 CPV. These censuses include detailed household data, which was instrumental in identifying family structures. The idea behind this process was to consider, for each household, the census question about the relationship of the censused individual to the household representative, allowing for the construction of parent-child relationships. We employed two approaches for this purpose:

i) We identified children within households based on their designation as the household representative in the census data. We then confirmed the presence of household members listed as their parents. We conducted an exhaustive validation of the affiliation data to ensure accuracy. For each household, we limited parent identification to a maximum of two individuals (either a single father or a single mother, or both). This

[5] ID numbers are pseudonymized to protect privacy. Names, surnames, and exact ID numbers are replaced with anonymized codes, ensuring individual anonymity (INEC, 2022). Authentic ID numbers should contain exactly ten digits.

[6] Codes must differ from "9999999999" and must not contain letters or special characters.

approach allowed us to construct consistent and reliable family relationships throughout our dataset.

ii) We focused on households where the representatives were identified as parents and other household members as children. This approach required rigorous validation due to the potential complexity of children being registered in multiple households, such as in cases of divorced parents. We first validated the children's affiliation data to ensure accuracy. Subsequently, we integrated parental information from different households, allowing us to construct complete and accurate family relationships across the dataset.

This process was fully implemented for CPV 2022. However, replicating the same approach for CPV 2010 presented challenges due to the following limitations: (i) the relationship variable grouped parents and in-laws together, complicating the identification of biological parents; and (ii) the ID and affiliation data were more limited.[7] Consequently, for CPV 2010, family relationships were constructed primarily by evaluating household representatives identified as parents and children within the household.

After constructing three sets of family relationship records (DIGERCIC administrative records, CPV 2010, and CPV 2022), we merged them, using the validated identification registry as the primary base. This integration substantially improved parent-child linkages and added new individuals who, as of June 2022, were not included in the original identification. Additionally, we integrated data from a version of the ID records that was not historically validated but included fathers and mothers with consistent identification codes.

As a result, the total number of individuals with at least one parental relationship, which forms the core of this study, reached 15,228,850, representing 70.2% of the total registered population. Table 1 provides a detailed breakdown of the number of records and parental relationships by source.

[7] In the 2010 CPV, personal identification codes (ID numbers) were not collected. The available information was retrieved based on individuals' first and last names and the identification registry, which introduces certain limitations.

Table 1: Family Links by Information Source

Category*	Total ID Records**	Father	Mother	Both Parents††	Either Parent
ID Records V* **	21,434,120	12,667,805	13,228,433	12,046,963	13,849,275
	(100.0%)	(59.1%)	(61.7%)	(56.2%)	(64.6%)
Census 2022	13,500,082	3,120,288	2,160,267	39,414	5,241,141
	(100.0%)	(23.1%)	(16.0%)	(0.3%)	(38.8%)
Census 2010	8,464,027	2,099,367	687,110	832	2,785,645
	(100.0%)	(24.8%)	(8.1%)	(0.0%)	(32.9%)
ID Rec.s + Census 2022	21,706,924	13,678,627	13,824,911	12,275,018	15,228,520
+ Census 2010	(100.0%)	(63.0%)	(63.7%)	(56.5%)	(70.2%)
ID Rec. V + Census 2022 +	21,706,924	13,678,880	13,825,450	12,275,480	15,228,850
Census 2010 + ID Rec. NV†	(100.0%)	(63.0%)	(63.7%)	(56.6%)	(70.2%)

Notes: [*] Percentages in parentheses represent the proportion of total ID records for each category. [**] The total number of individuals corresponds to those within the information source with identification codes. [***] *ID records V* refers to information from the validated identification registry. [†] *ID records NV* refers to the information from the non-validated identification registry. [††] In census data relationships are recorded only relative to the household representative (HR), making it difficult to identify both parents. It is also rare for children living with their parents to be listed as HR.

After establishing relational information between children and parents, we defined the birth cohorts for our analysis by adapting the methodology used in the Brazil study by Britto et al. (2022), which focused on children aged 25 to 31 years. Our study extends this approach by analyzing children born between 1987 and 1998, covering a broader range of birth cohorts over an extended analysis period from 2018 to 2023. This expansion is possible due to our access to more granular and historical cohort data, enhancing our ability to capture variances in intergenerational mobility and provide new insights into economic disparities and opportunities in the region [8]. Figure 5 illustrates the selection of these cohorts for our analysis.

[8] In exploring cohort selection options, we considered several alternative approaches. Acciari et al. (2022) included individuals with formal income and at least one parental relationship, focusing on children born between 1980 and 1989, corresponding to ages 34 to 38 during each analysis period. Chetty et al. (2014) expanded the cohort to include children born between 1980 and 1991, covering ages 27 to 43 during each analysis period. Ultimately, we aligned our approach with that of Britto et al. (2022), as it provided the most comprehensive data sample for our case.

Figure 5: Ages by Birth Cohort and Year of Analysis

Birth Cohorts	Analysis Periods					
	2023	**2022**	**2021**	**2020**	**2019**	**2018**
1998	25					
1997	26	25				
1996	27	26	25			
1995	28	27	26	25		
1994	29	28	27	26	25	
1993	30	29	28	27	26	25
1992	31	30	29	28	27	26
1991		31	30	29	28	27
1990			31	30	29	28
1989				31	30	29
1988					31	30
1987						31

4.1.2 Labor income

After defining the birth cohorts to be analyzed, the subsequent step involved integrating the current income of both the children (for the periods 2018-2023) and the parents (for the periods 2006-2011) into the relational database. Our analysis focuses predominantly on labor income, informed by historical data indicating that, on average, 93% of income in Ecuador comes from labor activities, with the remaining 7% stemming from non-labor sources such as government cash transfers (INEC), 2024). This approach ensures that our study captures the majority of income channels relevant to IM.

Labor income for individuals in the formal sector encompasses the annual average of salaries for workers registered in social security, spanning public, private, and domestic[9]. Informal labor income corresponds to the average annual income of salaried, independent, and unpaid workers (have labor income from other occupations) in the informal sector. Due to the often unrecorded nature of this income, it was necessary to impute it using labor force surveys, census data, and machine learning (ML) techniques. Given Ecuador's substantial informal sector, both formal and informal labor incomes are crucial for a comprehensive understanding of economic dynamics. We include all recorded annual average salaries from

[9]For both the formal and informal sectors, labor income from all occupations/jobs is considered. The affiliation to the rural social security regime (Seguro Social Campesino) of the IESS is excluded from the analysis because it does not provide information on labor income, only indicating the contribution amount associated with the household head.

formal employment and estimate informal income for everyone in our sample. This approach involves assessing the likelihood of receiving informal income—which is typically higher than zero—and then estimating it. This methodology allows us to account for children and their parents who may derive income from formal sources, informal sources, or from a mix of both, providing a granular view of the diverse economic realities faced by Ecuadorian families.

With this brief background, Table 2 summarizes the universes of analysis for children belonging to the 1987–1998 birth cohorts and their parents, detailing the number of records for both parents and children according to the type of labor income. We are able to capture 42.5% of the total individuals in the selected birth cohorts. The following subsections will further detail the process of constructing formal and informal labor income records and their incorporation into the family relationship database.

Table 2: Linked Parent-Child Relationship Records and Labor Income

Description	**Individuals**	**% Records**
Panel A: Children of 1987-1998 cohorts		
Children	3,819,846	100.0
with only formal income	744,938	19.5
with only informal income	561,953	14.7
with mixed income	866,588	22.7
without an identified family link	1,646,367	43.1
Panel B: Fathers with children from 1987-1998 cohorts		
Fathers	1,610,945	100.0
with only formal income	191,707	11.9
with only informal income	467,944	29.1
with mixed income	457,275	28.4
without an identified family link	494,019	30.7
Panel C: Mothers with children from 1987-1998 cohorts		
Mothers	1,711,429	100.0
with only formal income	129,683	7.6
with only informal income	422,830	24.7
with mixed income	280,211	16.4
without an identified family link	878,705	51.3
Panel D: Linked and imputated children samples		
Children	3,819,846	100.0
with at least one parental relationship, both with formal income	73,369	1.9
with at least one parental relationship, both with informal income	207,364	5.4
with formal income and parents with informal income, and vice versa	222,679	5.8
and parents with mixed income*	1,118,526	29.3
without income and parents with income (formal, informal, or mixed)	905,077	23.7
with income (formal, informal, or mixed) and parents without income	551,541	14.4
without an identified family link	741,290	19.4
with at least one parental relationship with income	**1,621,938**	**42.5**

*In this category, there are children with mixed incomes matched with parents who have only formal or informal incomes, and vice versa.

4.1.2.1 Formal Labor Income Formal income was sourced from the REESS, a registry that includes the monthly wages of individuals reported in the country's social security system since January 2006, and it is updated monthly. Specifically, for the intergenerational mobility analysis, individuals from the analysis universe found in REESS were identified, and their monthly labor income from all their job positions was considered.

Subsequently, the monthly labor income from all job positions was aggregated for each child and parent, and the average monthly income per year was calculated. Finally, the average annual labor income was estimated for the period 2018-2023 for children (individuals aged 25–31) and for the period 2006-2011 for parents (when their children from the considered birth cohorts were between 8-19 years old). In total, formal labor income (either only formal or in the mixed category) was obtained for 1,611,526 children (42.4% of the total children), 648,982 fathers (40.3% of the total fathers), and 409,894 mothers (24.0% of the total mothers), as shown in Table 2.[10]

4.1.2.2 Informal Labor Income In Ecuador, we record informal labor income through national labor force surveys, starting from December 2007 to ensure historical comparability. We acknowledge that earlier surveys, using different methodologies, cannot be directly compared. Due to these surveys representing only a sample of the population, we employ a method to extrapolate the data to include the population of parents and children being analyzed. For this purpose, we applied the ML `XGBoost` technique, a supervised ensemble algorithm based on Gradient Boosting[11], which has proven highly effective in predicting labor income from such data (Del Pozo et al., 2023). We carried out the imputation of informal income in four stages:

1. **Training `XGBoost` models**, we conducted training separately for each survey available, covering parents during the period 2007–2011 and children during 2018–2023. We selected covariates for income prediction including gender, age, ethnicity (afro-ecuadorian, mestizo, and white), occupational categories (salaried, independent, and unpaid)[12], industries (agriculture, commerce, mining and quarrying, construction, manufacturing, and services), education levels (none, basic, high school, and higher), years

[10] The salary variable is corrected for outliers, which are identified based on the analysis of the lower and upper tails. In the first case, the unified SBU is used as a reference, since by regulation an employee cannot be earning a salary lower than this (only daily salaries greater than or equal to the daily SBU are considered). In the second case, we work with an outlier identification threshold set at 10 times the 99th percentile of the daily salary.

[11] The technique consists of generating a predictive model in the form of an ensemble of simpler models (decision trees). The Gradient Boosting process is carried out sequentially, where each new model seeks to correct the residual errors of the previous models (Aydin and Ozturk, 2021).

[12] There are workers who reported being unpaid in their primary activity but have a secondary activity where they are salaried or independent, from which they report labor income.

of schooling, and region of study (a variable grouping the five main cities represented in the survey: Quito, Guayaquil, Cuenca, Machala, and Ambato, along with other geographic areas). To improve model performance, we also applied oversampling techniques to balance key variables such as education level, occupational category, and industry.

2. **Integrating information for predicting informal labor income**, we included the same covariates from labor force surveys in the family relationships database, sourced from the CPVs. For parents, we utilized information from CPV 2010, and where not available, from CPV 2022. For children, we used only CPV 2022 data. We assumed that individuals maintained the same occupational category over the years, which is essential for efficient prediction[13].

3. **Prediction of Monthly Labor Income for Children and Parents and Estimation of Annual Average Income:** [14]. Using the information gathered from the CPVs and the trained models, we predicted monthly incomes. We then estimated the annual average labor income. As an example of the imputation results, Table 2 indicates that we successfully imputed solely informal labor income for 561,953 children (14.7% of the total children), 467,944 fathers (29.1% of the total fathers), and 422,830 mothers (24.71% of the total mothers).

4. **Consolidation of Formal and Informal Labor Income:** In the relational database, we integrated both formal and informal income sources for parents and children into a single database. The average labor income of the parents was calculated based on both parents' annual labor incomes. Finally, the analysis sub-universe for intergenerational mobility of the cohort of children born between 1987 and 1998 included 1,621,938 individuals, representing 42.5% of the total cohort.

4.1.3 Descriptive Analysis of the intergenerational mobiity sample

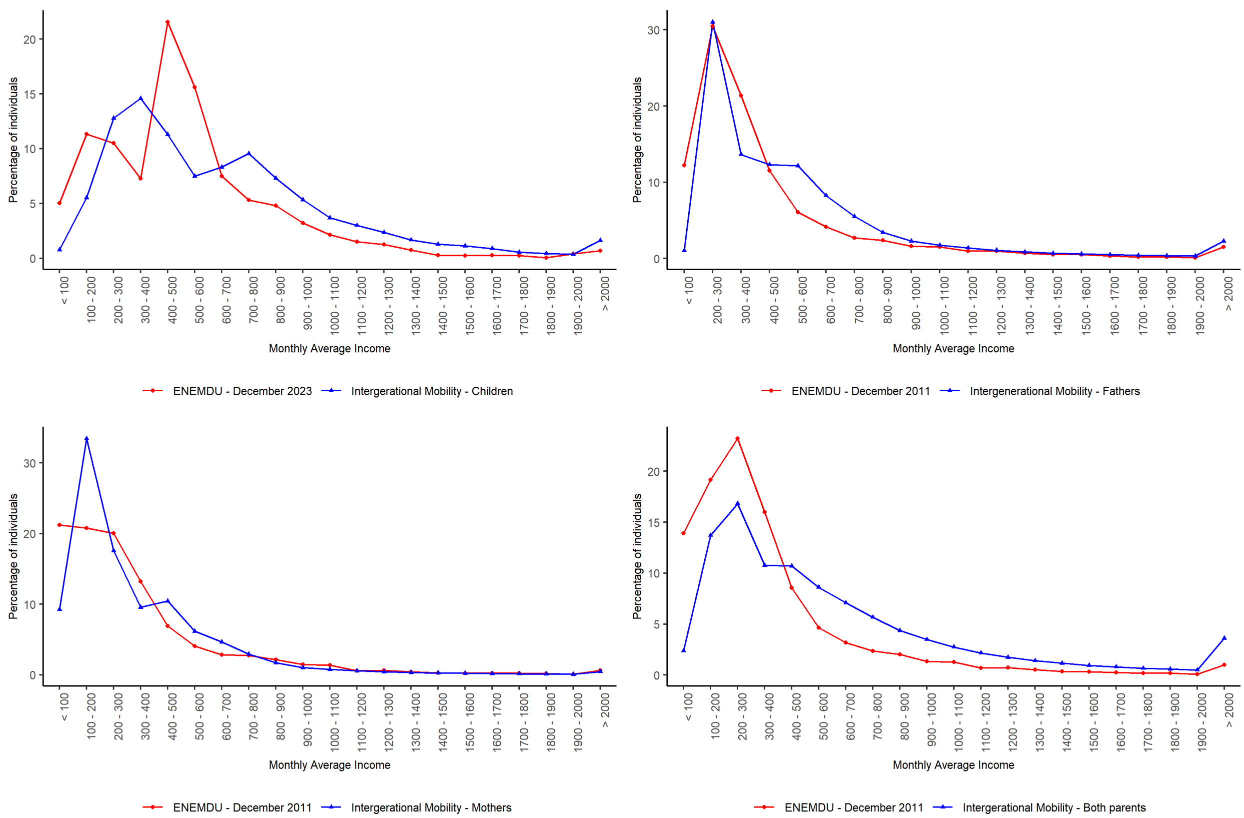
To verify the consistency of the labor income data we generated for both parents and children, we compared the distribution of the population by income level between the IM complete sample and the national labor force survey (ENEMDU). We used the December 2011 survey data for the parents and the December 2023 survey for the children.

[13]Table A1 presents the performance metrics aligned with the models for the training and test groups, in addition to the hyperparameters selected for the model training.

[14]To maintain consistency in the generated models, the age of individuals was calculated, and the variables for schooling and education level were adjusted for each period of the labor force survey, based on the information from the CPVs. Figure B1 provides a comparison between the distributions of labor income from the national survey and labor income predicted by the `XGBoost` models.

The goal of this comparison was to ensure that our constructed sample and the survey align in terms of population composition across different income levels. Figure **??** shows that the income distribution for both parents and children are generally consistent. Even though we observe more pronounced peaks around the SBU [15] for both fathers and mothers in the complete sample, the results confirm that the labor income data we generated, is similar to the official national survey and does not overestimate labor income for any population group.

Figure 6: Distribution of Average Monthly Labor Income for Parents and Children (IM Sample and ENEMDU)



Source: ENEMDU 2011, 2023 and IM Sample
Notes: 1) The ENEMDU survey corresponds to the period of December 2023 for children and December 2011 for parents. 2) The labor income compared between both sources corresponds to current income.

Once we validated the constructed sample, we proceeded with a descriptive analysis of the labor income for parents and children, presented both globally and disaggregated by sex. Additionally, children's income is analyzed across different birth cohorts. According

[15]The SBU, as defined by law, was USD 264 in 2011 and USD 450 in 2023.

to Table 3, children's average income surpasses that of their parents. Specifically, the median income for parents is USD 457.17, while for children it exceeds the SBU, recorded at USD 566.75. There is also significant dispersion observed at the upper end of the income distribution for both groups.

In terms of gender differences, male parents typically earn higher incomes than female parents, with median incomes of USD 370.58 and USD 232.82, respectively. A similar pattern is evident among children, where males have a median income of USD 575.20 compared to USD 554.79 for females. Interestingly, this trend reverses in the highest income percentile (95th), where female children earn more than their male counterparts.

Analyzing children's income by birth cohorts reveals that both median and mean incomes tend to decrease incrementally over time. Despite this general trend, there is considerable variation at the distribution's extremes: in the lower tail (5th percentile), incomes for more recent cohorts are higher than those for older cohorts, whereas in the upper tail (95th percentile), the situation is reversed.

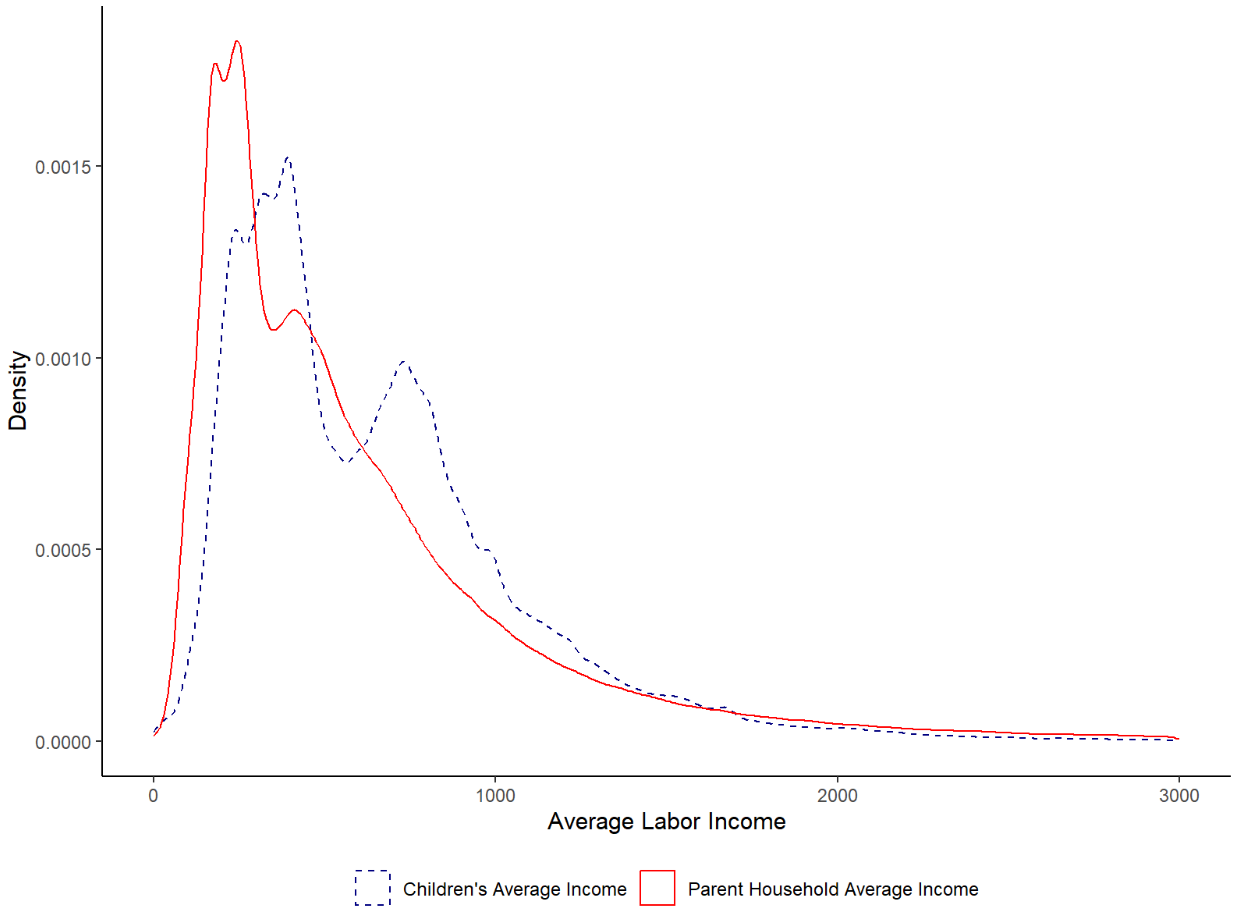
Table 3: Descriptive Statistics of Income Distribution (USD)

Category	5%	50%	95%	Mean
Parents	130.06	457.17	1750.85	635.81
Men	159.61	370.58	1333.01	515.99
Women	85.06	232.82	855.84	339.38
Children	187.00	566.75	1500.73	664.60
Men	227.13	575.20	1464.66	671.00
Women	161.81	554.79	1537.55	655.78
Children: birth cohort				
1987	184.97	613.27	2024.51	785.43
1988	188.45	633.83	1896.15	778.51
1989	186.30	616.76	1758.14	740.83
1990	183.45	615.93	1669.11	720.21
1991	192.83	612.05	1579.40	701.60
1992	191.65	607.50	1500.35	685.53
1993	185.26	583.09	1395.65	652.29
1994	185.35	555.57	1312.46	626.11
1995	182.66	534.83	1260.86	605.36
1996	187.21	518.97	1218.05	588.28
1997	183.24	497.96	1200.00	576.36
1998	190.83	458.23	1124.82	548.79

Notes: 1) The descriptive information for parents corresponds to fathers for men and to mothers for women. 2) The labor income analyzed corresponds to current income.

Additionally, to examine the distribution of labor income among children and parents, Figure 7 employs kernel density functions to illustrate their respective income distributions. The figure reveals distinct differences between the two groups, particularly noticeable in the lower tail of the distribution. Here, parents' incomes are concentrated at lower values, whereas children's incomes are distributed further to the right, indicating an improvement in their average labor income relative to their parents. These findings align with those reported by Stockhausen (2021) in Germany, highlighting similar trends in intergenerational income mobility.

Figure 7: Distribution of Average Monthly Labor Income for Parents and Children (complete Sample-USD)



Notes: 1) Incomes above USD 3,000 are excluded to ensure the scale of the figure. 2) The labor income corresponds to current income.

4.1.4 Robustness Check

Due to data quality concerns, particularly the incomplete identification of family links between parents and children, we sought to verify that the income distributions for both groups in our sample corresponded with data from the National Employment, Unemployment, and Underemployment Survey (ENEMDU) for the respective years and cohorts. To do this, we compared the income distributions of parents and children in our sample against the national-level data provided by ENEMDU. We used survey data from 2006–2011 for parents and from 2018–2023 for children.

Figure B2 illustrates the income distributions across percentiles for both our complete sample and the corresponding ENEMDU data. The left panel of the figure details the comparison for children, covering the years 2018 to 2023, while the right panel focuses on parents from 2006 to 2011. In both panels, the complete sample is shown in red and the ENEMDU data in blue. The similarity in shapes and trends across most percentiles indicates a strong alignment between our sample and the national survey data. Particularly at the lower percentiles, both distributions start similarly, showing that our sample effectively represents lower-income groups and corresponds well with the survey data.

However, as we examine higher percentiles, particularly beyond the 95th percentile, we notice that the income levels in our sample start to deviate from the ENEMDU data. The higher income levels in our sample, especially in the upper tail of the distribution, are likely due to underreporting in the ENEMDU survey, where individuals often underreport their true income. In contrast, our REESS data, based on formal records, capture these high incomes more accurately and are less affected by underreporting. This discrepancy suggests that high-income parents are disproportionately represented in the formal sector. Despite their children's incomes not fully catching up—potentially due to younger age or different career paths—we chose to include the full income range in our analysis. This decision ensures our analysis comprehensively reflects all income dynamics, despite the challenges of comparing formal recorded income with survey data.

4.2 Intergenerational Mobility Measurement Methodology

Intergenerational mobility, as discussed by Chetty et al. (2014) and Acciari et al. (2022), can be understood through two main measures: relative mobility and absolute mobility. Relative mobility examines the outcomes of children from low-income families relative to those from high-income families, emphasizing the differences in economic advancement opportunities. Absolute mobility assesses the outcomes of children from families with a specific income or rank in the parental income distribution.

Following the methodology proposed by Chetty et al. (2014) and adapted by Britto et al. (2022), this study estimates the relationship between the income ranks of children and their parents. We relate the percentile ranks of children's income (y_i) and their parents' income (p_i) on a national scale from 1 to 100 using linear regression as shown:

$$y_i = \alpha + \beta_{RRS} p_i + \epsilon_i \tag{1}$$

This method allows us to measure children's economic positioning relative to their peers and their parents' standing compared to other parents within the same cohorts. The coefficients obtained, particularly β_{RRS} (the rank-rank slope), quantify the inverse of relative mobility, indicating how much parental income rank affects child income rank. A higher β suggests lower mobility, with $\beta = 0$ indicating perfect mobility. The intercept α provides an expected rank for children at the lowest parental income ranks.

To further explore social mobility, we focus on absolute upward mobility (AUM), specifically analyzing the average rank of children whose parents are at the 25th percentile of national labor income. This percentile is chosen for its significance in assessing the mobility of children from below-median income families, highlighting shifts in social positioning among the more economically vulnerable. Additionally, selecting this specific income percentile aligns our study with similar metrics used in other developing countries, enhancing the comparability of our results. This comparative approach provides a standardized basis for evaluating and understanding intergenerational progress in different socio-economic contexts.

Moreover, we employ transition matrices that divide parental and children's incomes into quintiles to examine the likelihood of economic advancement relative to their parents. This method provides a tangible view of intergenerational mobility.

Finally, we estimate the intergenerational income elasticity (EMI), which captures the influence of high versus low parental income on children's income:

$$\log(y_i) = \alpha + \beta_{EMI} \log(p_i) + \epsilon_i \tag{2}$$

Here, β_{EMI} represents the elasticity of intergenerational mobility, a critical measure for comparing the impact of parental income on children's economic outcomes across different contexts.

4.2.1 Measurement of Gender and Geographical Mobility

After providing a general overview of the national estimates for the main indicators discussed, we further analyze IM by segmenting the data according to the sex of the children. This step allows us to compare economic outcomes specifically by gender, providing insights into how opportunities for economic advancement differ between male and female children.

Following the gender-based analysis, we explore within-country variations. In Ecuador, regional disparities are significant, particularly in historically vulnerable areas such as the remote highlands and the Amazon regions. To understand these geographic differences in mobility across Ecuador's provinces, we employ the same rank-rank regression approach used at the national level but adapt it to consider the geographic origins of children. Highly detailed birthplace data provided by DIGERCIC, the national authority responsible for identity records, allows for precise geospatial analysis of intergenerational mobility. The model is specified as follows:

$$G_{ig} = \alpha_g + \beta_g p_i + \epsilon_{ig} \tag{3}$$

Where G_{ig} represents the mean percentile rank in the national distribution for a child i growing up in province g, and P_i denotes the parental rank in the national income distribution. Both children and parents are ranked based on their positions in the national income distribution, rather than within their specific province. This methodology presupposes the linearity of the relationship between parental and child ranks across different geographic areas. While this assumption simplifies the estimation and interpretation of mobility metrics, it may not fully capture non-linear dynamics that could vary by region. Nonetheless, as long as linearity is a reasonable approximation, relative and absolute mobility at different geographical levels can be estimated using the Rank-Rank Slope (β_g) and the Absolute Upward Mobility (G_{25g}) measures:

$$G_{25g} = \alpha_g + 25 * \beta_g \tag{4}$$

Finally, to quantify geographical gender disparities in economic mobility, we use the following gap estimation function:

$$\Delta Y = \beta_{\text{male}} - \beta_{\text{female}} \tag{5}$$

where ΔY represents the estimated gap in outcomes between male and female children, and β_{male} and β_{female} are the coefficients from gender-specific regressions of children's economic outcomes on parental income. This measure helps identify the extent to which gender impacts economic mobility.

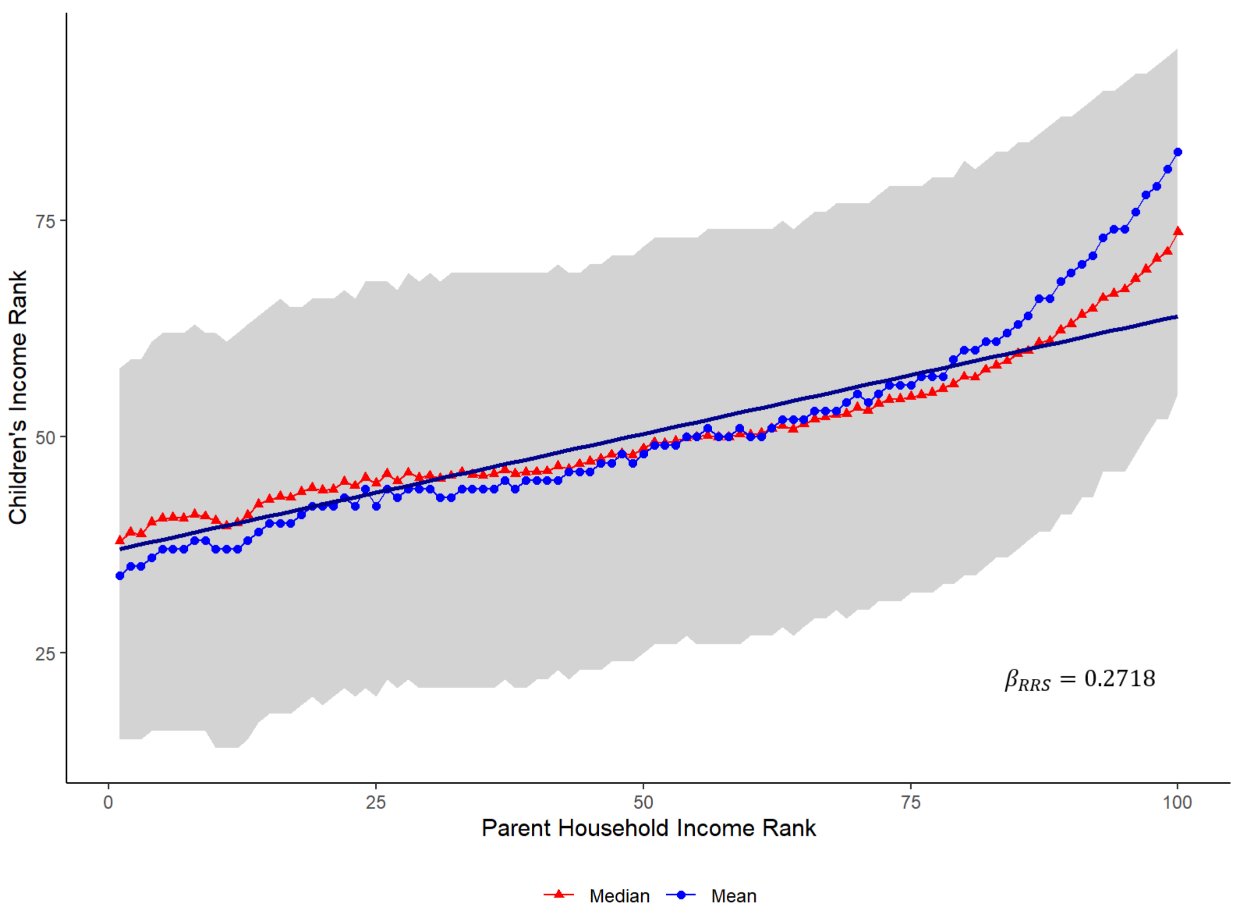
5 Results

5.1 Intergenerational Mobility Estimates

The analysis of intergenerational mobility began by evaluating the relationship between the mean and median rankings of children's labor income in adulthood and the percentile rankings of parental labor income. Parents' income was segmented into 100 groups, and the average income percentiles of the children were calculated for each group, as illustrated in Figure 8. This scatter plot provides a visual representation of the relationship.

We observe a stable evolution of the mobility curve, indicating a generally consistent relationship across most income percentiles. However, the curve exhibits some non-linear characteristics at specific points, notably just before the 20th percentile, where there is a decrease in the β coefficient (lower persistence), and around the 75th percentile, where the β increases significantly (higher persistence). Such dynamics suggest localized deviations from the overall trend. These findings indicate that while there is a broadly stable relationship between parental and children's income ranks, contributing to a reliable measure of intergenerational mobility, certain income thresholds exhibit distinct mobility dynamics. For a detailed view on the evolution of the IM curve by source (administrative records or full sample), see Figure B3.

Figure 8: Labor Income Mobility Curve in Ecuador



Note: The figure shows the relationship between the mean and median of the labor income percentiles of the children (birth cohorts 1987–1998) for each labor income percentile of the parents.

Tables 4 and 5 present the regression output from Equation (1) for both the full sample, which proxies all labor income, and administrative records sample, which proxies the formal labor income, including a detailed analysis across parental income quintiles. We determined the rank-rank slope (β) to be **0.27** for the all labor income sample and **0.24** for the formal labor income sample. This relationship suggests that a 10-percentile increase in parental income corresponds to a 2.7 and 2.4-percentile rise in children's adult income, respectively. Smaller β values indicate narrower income percentile gaps between generations, suggesting enhanced intergenerational mobility.

Interestingly, the second quintile in the full sample shows the lowest persistence (β), indicating lesser dependency of children's income on their parents' economic status. This quintile is pivotal as it aligns with the poverty threshold commonly used in Ecuador and other developing countries to identify beneficiaries for social programs, such as the Bono de Desarrollo Humano, which is a major cash transfer program. On the other hand, negative coefficients in the second and third quintiles of the administrative records point to a divergent relationship where higher parental income correlates with lower children's income. These variances elucidate the complex landscape of intergenerational mobility, emphasizing the unique economic challenges and opportunities within various income strata.

Table 4: Relative IM regression results: Parental Income Rank on Children's Income Rank (Full sample)

Variable	Full Sample	Q1	Q2	Q3	Q4	Q5
Rank-rank slope	0.2718***	0.2735***	0.08051***	0.2406***	0.3148***	0.8314***
	(0.0008)	(0.0083)	(0.0085)	(0.0085)	(0.0085)	(0.0083)
Constant	36.7711***	38.2796***	42.92196***	36.4394***	31.1497***	-11.2041***
	(0.0440)	(0.0999)	(0.2635)	(0.4309)	(0.6007)	(0.7545)
Observations	1,621,938	324,388	324,388	324,388	324,387	324,387
R-squared	0.0739	0.003303	0.0002741	0.002474	0.004214	0.02986

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are in parentheses.

Table 5: Relative IM regression results: Parental Income Rank on Children's Income Rank (Records sample)

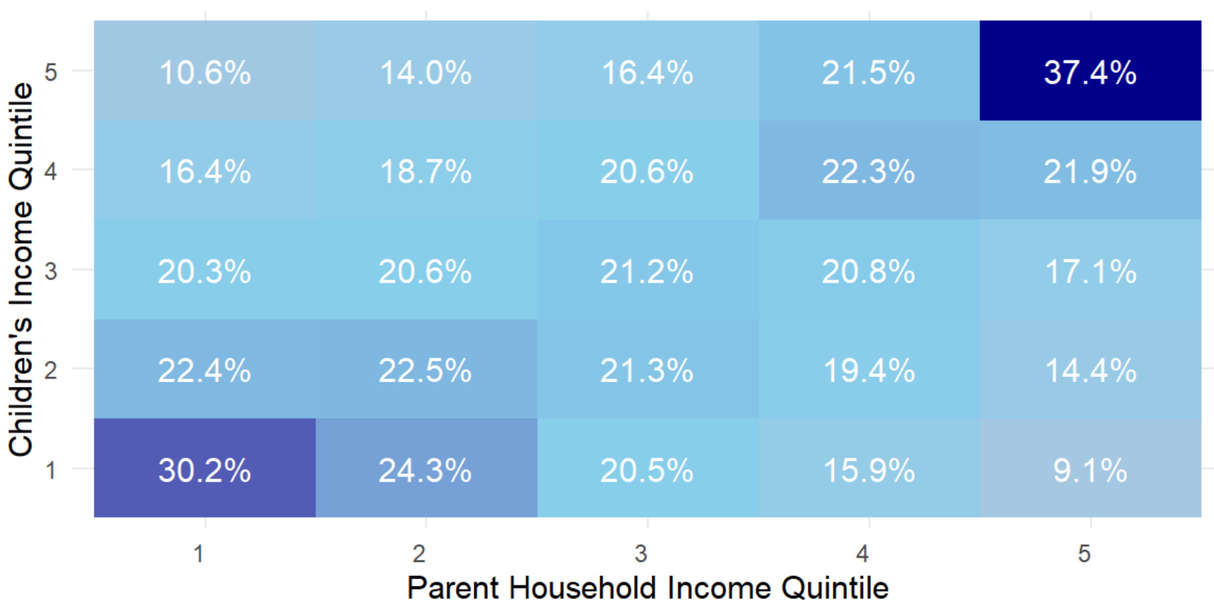
Variable	Records sample	Q1	Q2	Q3	Q4	Q5
Rank-rank slope	0.237***	0.3749***	-0.2224***	-0.1491***	0.3214***	0.5716***
	(0.0011)	(0.0116)	(0.0119)	(0.0120)	(0.0124)	(0.0125)
Constant	38.529***	38.4897***	51.2744***	57.5179***	31.2932***	9.9103***
	(0.0628)	(0.1389)	(0.3680)	(0.6091)	(0.8742)	(1.1338)
Observations	807,281	161,457	161,456	161,456	161,456	161,456
R-squared	0.05618	0.006423	0.002168	0.0009519	0.004164	0.01277

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are in parentheses.

Regarding absolute upward mobility we observe that children of parents in the 25th percentile typically advance to the **44th** percentile by adulthood, consistently across both the complete sample and the administrative records sample.

Supplementing these findings, Figure 9 illustrates the transition matrix for labor income quintiles between parents and children in Ecuador. The matrix shows a **10.6%** chance of children advancing to a higher quintile from the lowest one, compared to a **9.1%** likelihood of remaining in the lowest quintile despite their parents being in the highest. Additionally, the probability that children retain their position in the lower and upper quintiles from their parents is **30.2%** and **37.4%**, respectively[16]. Additionally, these matrices are calculated using dollars adjusted for inflation as of December 2023. We found no important differences when comparing the results (see Figures B5 and B6).

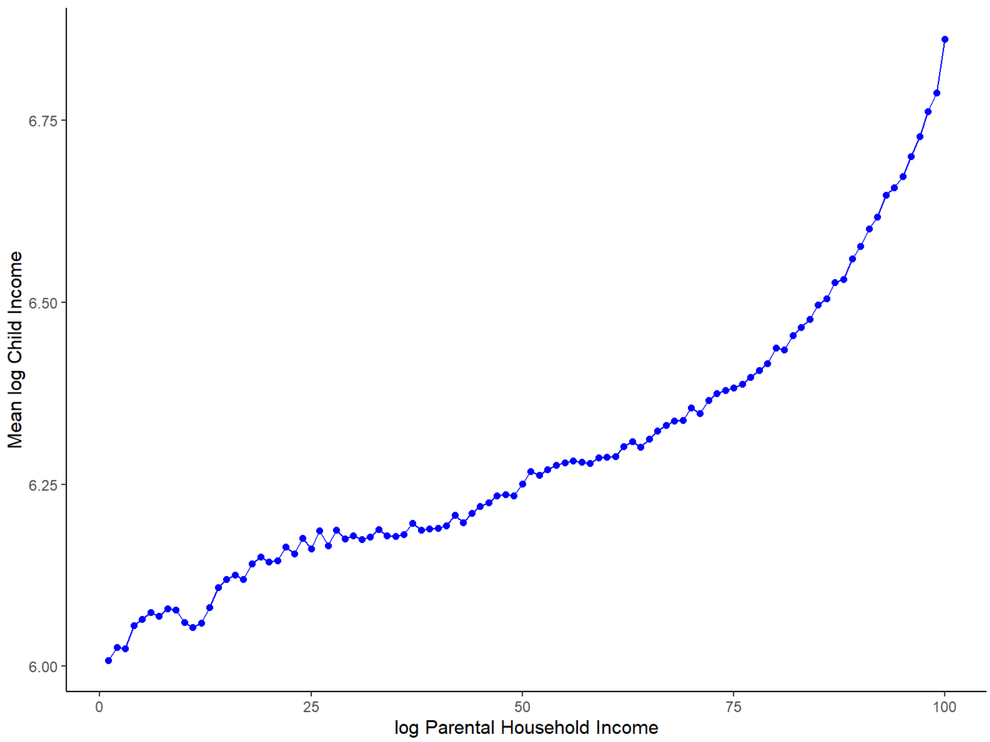
Figure 9: Transition Probability Matrix by Labor Income Quintile



The intergenerational income elasticity (EMI) was estimated by analyzing the elasticity coefficient (β_{EMI}). In Ecuador, the β_{EMI} was found to be **0.23** in the complete sample and 0.21 in the administrative records sample. These values suggest that a 10% increase in parents' income is associated with a 2.3% increase in their children's income in adulthood for the complete sample, and a 2.1% increase for the administrative records sample, as depicted in Figure 10.

[16]Figure B4 presents a similar matrix but is limited to the formal labor income sample

Figure 10: Intergenerational Income Elasticity

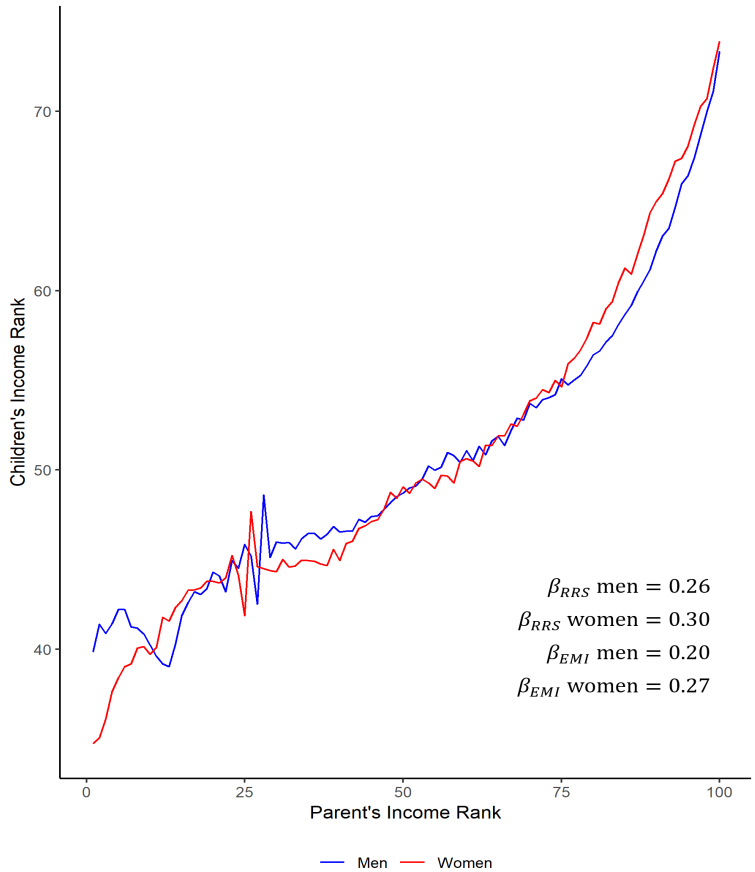


Note: The figure illustrates the relationship between the logarithmic income of children and that of their parents. For each level of parents' logarithmic income (divided into 100 intervals), the average logarithmic income of children is calculated during the period from 2018 to 2023, at the age of 25 to 31 years.

5.2 Intergenerational Mobility by Gender

Children's labor and economic outcomes are influenced by their parents' labor income and sociodemographic factors such as gender. Figure 11 illustrates the relationship between children's income and the classification of parental labor income by gender for both the complete sample and the administrative records sample. In both samples, we observe a general consistency in the income classification between parents and children by gender. Notably, the income mobility curve for men is slightly flatter than that for women, particularly at the lower and upper tails of the distribution. In the percentile range of 1 to 25, there is an average gap of 1.02 percentiles in favor of men, indicating that sons tend to rank higher in the income distribution than daughters, given the same level of parental income. Conversely, starting from the 60th percentile, women surpass men by 1.17 percentiles, and from the 75th to the 100th percentile, the gap widens to 1.77 percentiles in favor of women, suggesting greater upward mobility for women in these higher income ranges.

Figure 11: Intergenerational Mobility by Gender



Note: The vertical axis presents the combined income ranking of both parents, while the horizontal axis reflects the labor income of children by gender.

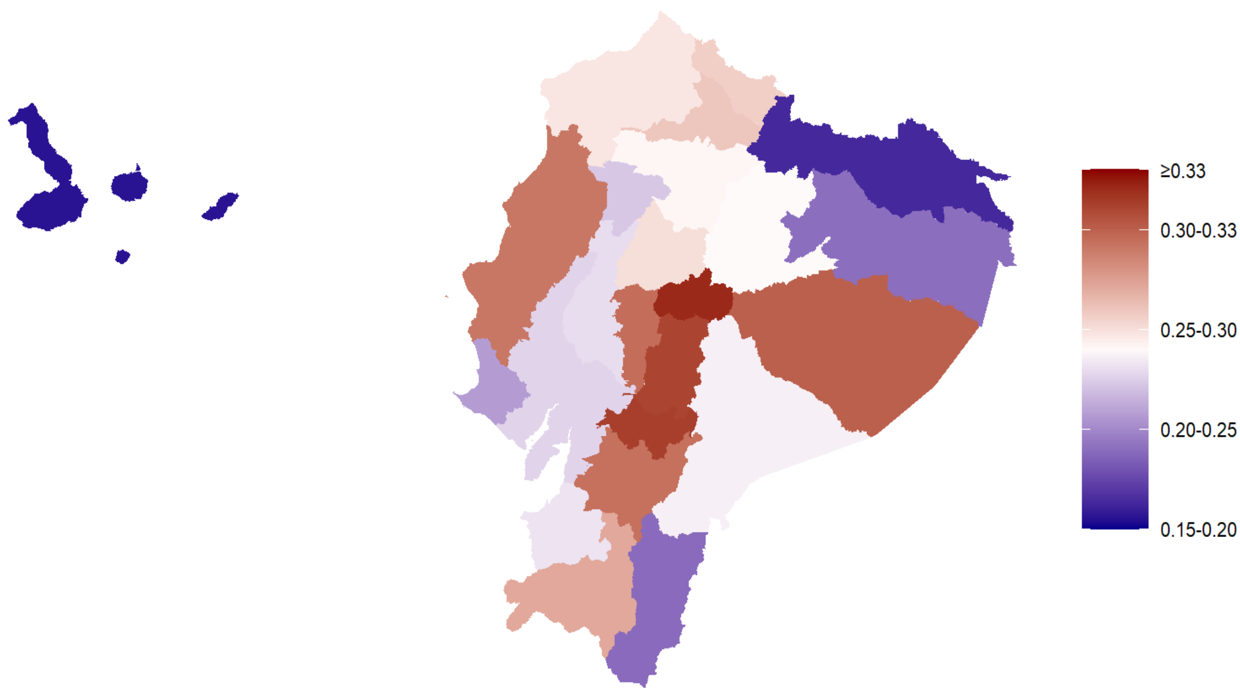
Regarding the rank-rank slope, the coefficient β is slightly higher for women at 0.30 compared to 0.26 for men. This higher value for women indicates that their economic positions are more closely tied to their parents', suggesting less relative intergenerational mobility for women in response to changes in parental income. Furthermore, analysis of the intergenerational income elasticity (EMI) reveals that elasticity is higher for women, with a β_{EMI} of 0.27, compared to 0.20 for men. This suggests that women's incomes are more sensitive to variations in parental income, reflecting a greater degree of economic influence from one generation to the next.

5.3 Geographic Disparities in Intergenerational Mobility

Geographical disparities often play a significant role in shaping the economic trajectories of individuals within a country. To explore how intergenerational mobility varies across different regions, we conducted an analysis that maps the rank-rank slope across the provinces of

Ecuador. This approach allows us to visualize and quantify the extent of mobility, reflecting the influence of parental income rank on children's income outcomes in each province, keeping the national level as a reference. Among the provinces, Tungurahua exhibited the highest rank-rank slope at 0.3209, suggesting lower mobility, whereas Galápagos showed the lowest at 0.1557, indicating higher mobility. Pichincha, which includes the capital city of Quito, recorded a moderate rank-rank slope of 0.2415, placing it near the middle range of mobility among the provinces. Figure 12 presents a heatmap of the rank-rank slope across provinces, offering a visual representation of these disparities.

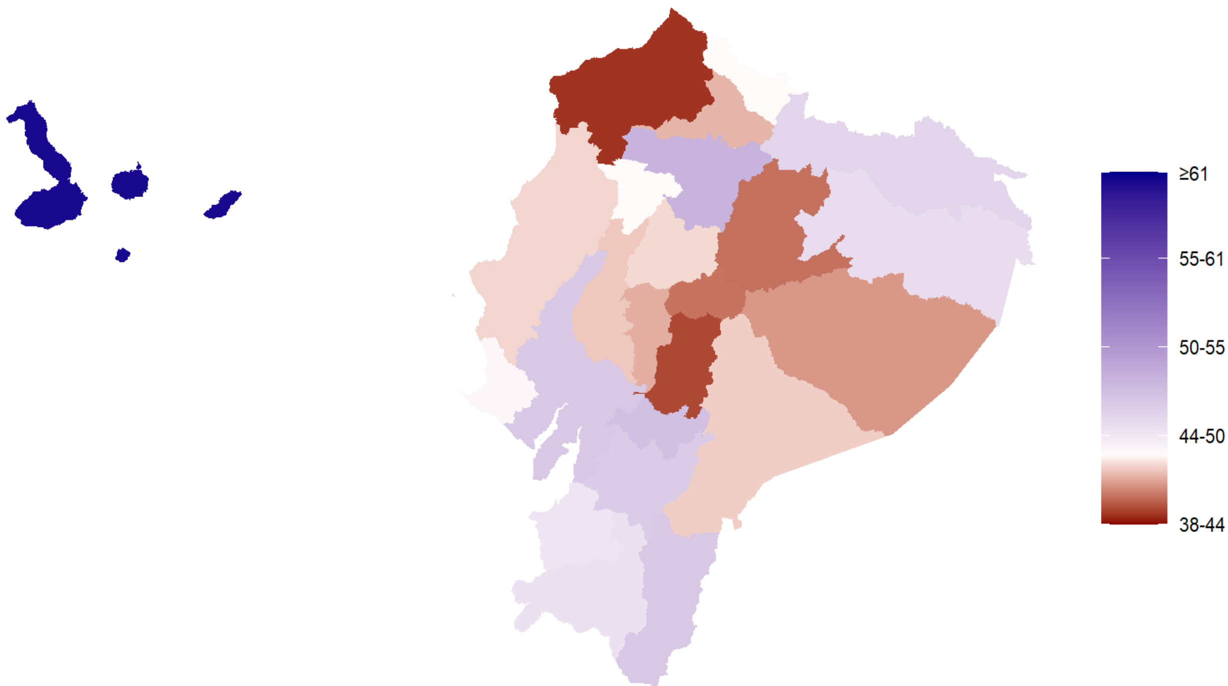
Figure 12: Province Heatmap of the Rank-Rank Slope



Note: This figure demonstrates the rank-rank slope for income mobility analysis.

Exploring trends in absolute upward mobility, Figure 13 visually depicts the average ranks achieved by children across each province, whose parents are situated at the 25th percentile of the national labor income distribution. This heatmap reveals, for instance, that the province of Galápagos shows the highest upward mobility with an average percentile increase to 60.48, suggesting significant economic advancement from one generation to the next. Conversely, Esmeraldas exhibits the lowest mobility, with an average increase to only 38.62, indicating less generational progress. Pichincha, also ranks high for mobility, with children advancing to an average of 47.58, reflecting potentially greater opportunities or better socioeconomic conditions.

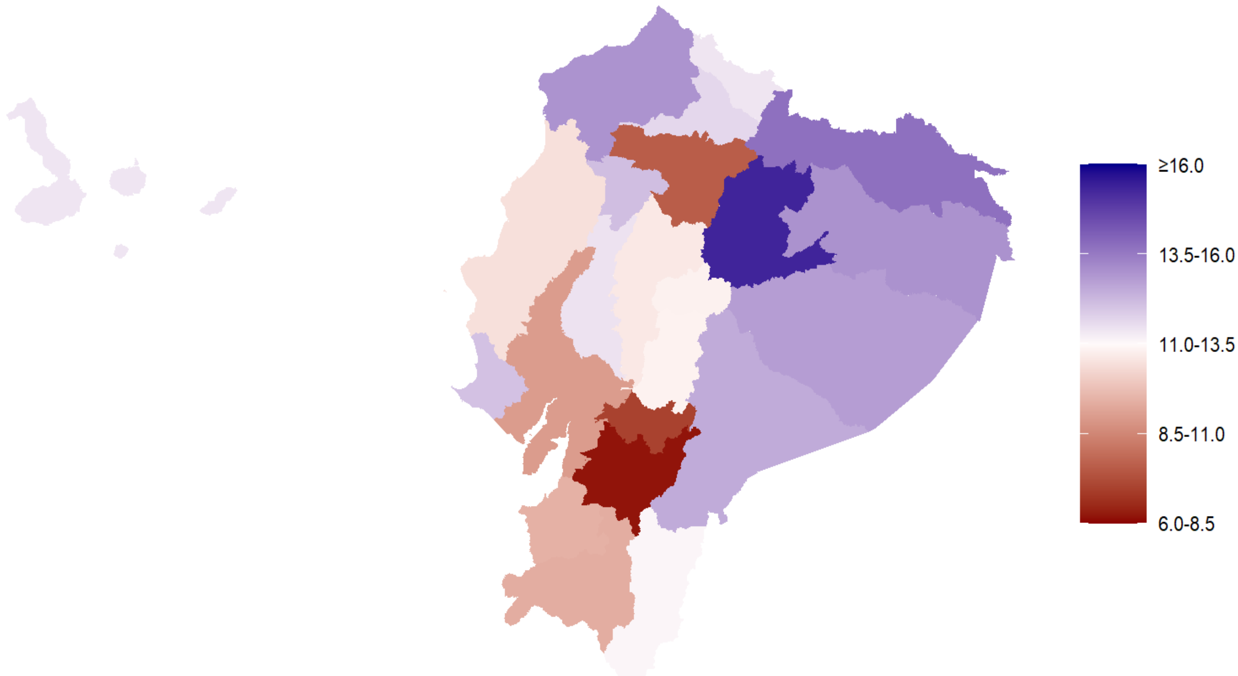
Figure 13: Province Heatmap of the Absolute Upward Mobility



Note: The figure represents absolute upward mobility trends over time.

Figure 14 demonstrates the probability of individuals in each province ascending from the bottom quintile (Q1) to the top quintile (Q5) of the income distribution. This heatmap offers a granular view of upward mobility across Ecuador. For instance, Napo exhibits a notably high potential for upward mobility, with a probability of 15.34%, in stark contrast to Cañar, which has the lowest at just 5.99%. Interestingly, despite its generally favorable performance in other mobility metrics like the rank-rank slope and absolute upward mobility, Pichincha records a lower likelihood of 7.57% for such upward mobility. These findings highlight the importance of employing multiple measures to fully understand economic mobility, thus enabling targeted interventions to mitigate regional disparities effectively. Table A2 presents detailed results of the province disparities analysis.

Figure 14: Province Heatmap of $P(Q5 \mid Q1)$



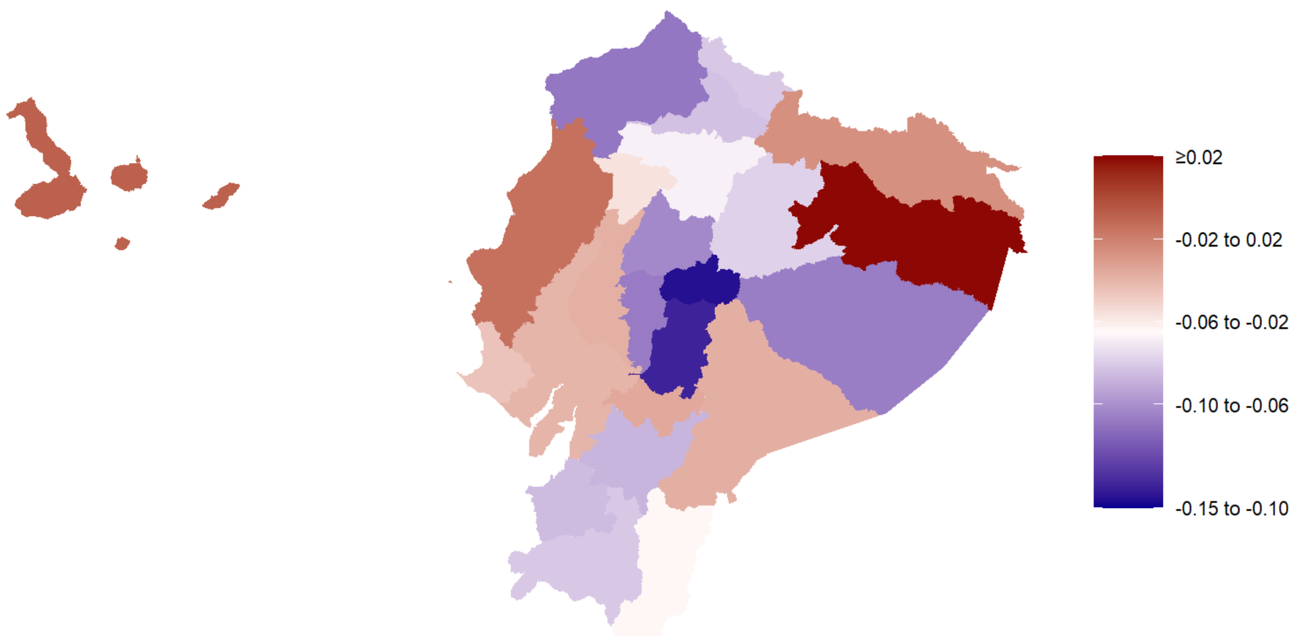
Note: The figure shows the probability of getting to the highest quintile coming from the lowest quintile.

Figure 15 illustrates the rank-rank slope gender gaps across provinces, reflecting differences in intergenerational mobility between genders. We find that Tungurahua and Pichincha have significant gender gaps in economic mobility, with gaps of -0.145 and -0.068, respectively. This disparity might indicate that women in these regions face more challenges in improving their economic status relative to their male counterparts. In contrast, Orellana exhibits minimal gender differences in mobility, with a gap of only 0.019, indicating more equitable economic opportunities between genders.

In Figure 16, we explore the disparities in absolute upward mobility by gender across provinces. Sucumbíos presents one of the largest disparities, at 10.235, indicating that one gender significantly outperforms the other in moving up the economic ladder. Conversely, Manabi shows almost negligible gender disparity, with a gap of only 0.863, suggesting a more balanced environment for economic improvement across genders.

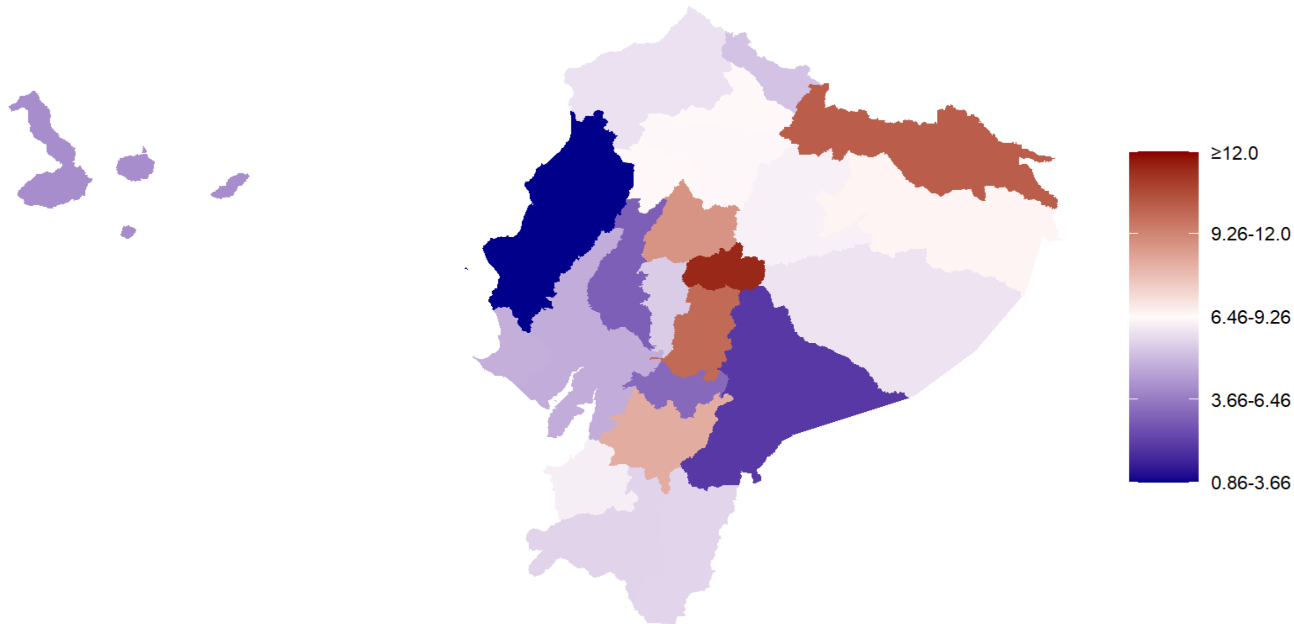
Figure 17 shows the gender differences in the probability of transitioning from the lowest to the highest income quintile across provinces. Interestingly, despite province variances, women consistently exhibit a higher probability than men of ascending to the top quintile from the bottom, reflecting a notable trend in favor of women's economic mobility. The two provinces in the Amazon region, Sucumbíos and Napo, exhibit pronounced gender disparities in economic mobility, uniquely favoring women over men. In Sucumbíos, the likelihood of women reaching the top income quintile is 21.28%, significantly higher than the 8.61% for men, resulting in a notable gender gap of −12.67 percentage points. Similarly, in Napo, women have a 20.26% probability of ascending to the top quintile, compared to 11.08% for men, with a gender gap of −9.18 percentage points. These statistics highlight the intricate influence of both regional and gender factors on economic outcomes. Comprehensive data on these gender disparities, assessed through the rank-rank slope, absolute upward mobility, and transitions between quintiles, is detailed in Table A3.

Figure 15: Province Heatmap of the Rank-Rank Slope Gender Gap



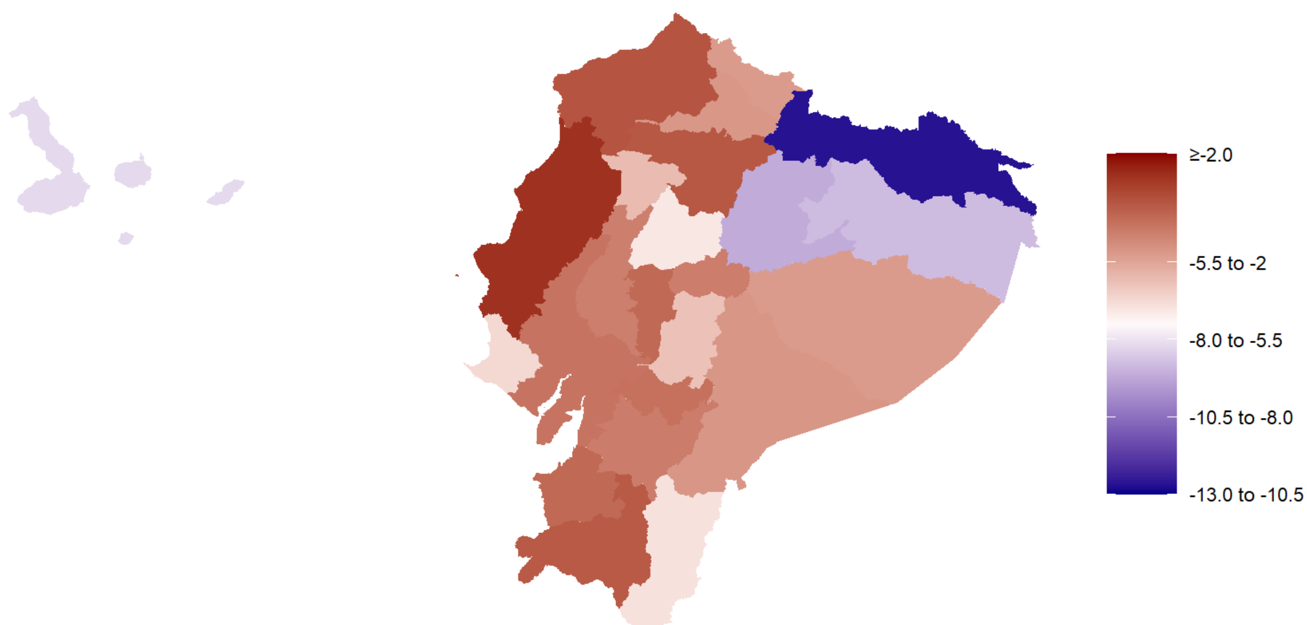
Note: This figure shows the rank-rank slope gender gaps.

Figure 16: Province Heatmap of Absolute Upward Mobility Gender Gap



Note: The figure shows the absolute upward mobility gender gaps.

Figure 17: Province Heatmap $P(Q5 \mid Q1)$ Gender Gap



Note: This figure shows the P(Q5|Q1) gender gaps.

6 Conclusions

This study presents the first estimates of intergenerational mobility for Ecuador, adding to the short list of developing countries with such estimates, by combining administrative records, surveys, and census data, and leveraging detailed individual matching alongside machine learning techniques to estimate labor income.

We began by constructing a relational database to link parents and children. Specifically, we validated and consolidated the ID holder registry with family relationships derived from the ID records and the 2010 and 2022 population censuses. Initially, we recorded 21,434,120 ID holders, which increased to 21,706,924 by incorporating census data. This enhancement also increased the probability of finding records with links to either parent, rising from 13,849,275 to 15,228,850, thus increasing from 64.6% to 70.2% of the total corresponding population. While this data covers individuals of all ages, our focus on analyzing intergenerational mobility led us to narrow our data to individuals in birth cohorts 25 to 31 during the 2018–2023 period, along with their parents from the 2006–2011 period.

To estimate labor income, we directly extracted formal income from social security records. For informal labor income, we utilized the XGBoost machine learning technique, integrating labor force surveys (ENEMDU) from 2007 to 2023 with census data, ensuring a comprehensive representation of both formal and informal labor markets. Within our dataset, which comprises 3,819,846 individuals in the birth cohort aged 25 to 31, we identified 1,621,938 individuals who had at least one parental relationship with recorded income, constituting our full IM sample. This subset represents 42.5% of the total cohort.

Our results reveal that Ecuador exhibits moderate intergenerational mobility in both absolute and relative terms. The rank-rank coefficient of 0.27, tells us that a 10-percentile increase in parental income is associated with a 2.7 percentile increase in children's adult income. When compared to other countries, Ecuador's mobility coefficient suggests a somewhat looser connection between parental and child economic status compared to Brazil, where the coefficient is 0.55, and the United States, with a coefficient of 0.34. However, Ecuador still lags behind Chile and Italy, with coefficients between 0.25 and 0.27 for the former and 0.22 for the latter. Continuing with our assessment of relative IM measures, we observe that Ecuador's intergenerational income elasticity is estimated at 0.24. This indicates that a 10% increase in parental income corresponds to a 2.4% increase in children's income. Such findings highlight the substantial role that improvements in Ecuador's labor market conditions and educational access could have potentially played in facilitating upward mobility.

Interestingly, when analyzing the rank-rank slope by labor income quintiles, we find notable differences. The first quintile has a coefficient of 0.2735, close to the national average, indicating moderate persistence of children's income relative to their parents'. This figure drops sharply to 0.0805 in the second quintile, the lowest among all. This quintile is closely aligned with the national poverty threshold, which is a critical target for government interventions such as cash transfers. These transfers, categorized as non-labor income sources, are added to household total income and might contribute to the remarkably low labor income dependency seen in this quintile. The dependency rate rises again in the third quintile to 0.2406, underscoring the intricate dynamics of intergenerational mobility in Ecuador.

Regarding absolute upward mobility we observe that children of parents in the 25th percentile typically advance to the 44th percentile by adulthood. Additionally, based on the transition probability matrix, We find that 10.6% of children advance to higher income quintiles compared to their parents. While this percentage exceeds Brazil's absolute mobility (2.5%), it remains lower than Chile (12,0%), Italy's (11.2%) and Sweden's (15.7%). Furthermore, persistent inequalities remain: 30.2% of children from low-income families and 37.4% from high-income families remain in the same economic position as their parents.

The gender analysis reveals critical disparities in intergenerational mobility. Women exhibit greater sensitivity to parental income, with a rank-rank slope of 0.30 compared to 0.26 for men. Similarly, the elasticity for women is 0.27, while it stands at 0.20 for men. This suggests that daughters' incomes are more dependent on family economic background than sons' incomes. These disparities may reflect lifecycle biases, particularly career interruptions experienced by women due to caregiving roles such as maternity. Addressing these gendered barriers requires complementary measures that account for women's unique challenges and provide more accurate comparisons of intergenerational mobility.

We also identified significant geographical variation in intergenerational mobility across Ecuador. Provinces like Galápagos stand out with a rank-rank slope of 0.16, indicating high upward mobility, driven perhaps by economic diversification and a dynamic tourism industry. In contrast, regions such as Tungurahua (0.32) and Chimborazo (0.31) display lower mobility, reflecting persistent reliance on traditional economic sectors. An analysis of absolute upward mobility reveals that Galápagos (60.48) achieves the highest levels, consistent with its favorable rank-rank slope. In contrast, Esmeraldas (38.62) records the lowest levels, highlighting a pronounced disparity between regions with dynamic income growth and those facing generational labor income stagnation.

In conclusion, Ecuador demonstrates moderate intergenerational mobility, outperforming countries like Brazil while showing room for improvement compared to Chile, Italy and Sweden. Our results highlight the importance of education, labor market conditions, and regional economic opportunities in driving upward mobility. However, persistent gender and regional disparities remain challenges that require tailored policy responses. Future research should explore non-labor income dynamics, incorporate more administrative records, and employ advanced methodologies like network analysis to create a more comprehensive dataset. This approach will allow for a more nuanced assessment of the long-term impacts of social policies on intergenerational mobility. By addressing these areas, Ecuador can enhance economic opportunities for all its citizens and further reduce income persistence across generations.

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Appendix

A Supplementary Tables

Table A1: XGBoost Model Performance: RMSE for Training and Testing Groups

Year-Month	rmse_train	rmse_test	Year-Month	rmse_train	rmse_test
2007-12	101.97	102.27	2021-05	39.01	57.10
2008-06	48.53	51.75	2021-06	31.50	39.58
2008-12	67.37	66.87	2021-07	37.16	40.09
2009-12	92.82	104.18	2021-08	49.21	53.71
2010-06	73.90	82.35	2021-09	51.77	61.98
2010-12	64.23	72.04	2021-10	45.19	58.33
2011-06	77.75	79.75	2021-11	42.58	52.39
2011-12	145.99	154.96	2021-12	46.07	56.42
2012-06	107.22	120.07	2022-01	37.91	42.58
2012-12	96.33	123.25	2022-02	60.94	74.97
2013-06	78.84	87.33	2022-03	56.11	54.70
2013-12	80.27	83.80	2022-04	62.53	57.59
2014-03	60.21	64.03	2022-05	48.10	53.52
2014-06	85.89	86.58	2022-06	60.09	61.06
2014-09	62.38	78.70	2022-07	40.70	46.21
2014-12	109.91	103.71	2022-08	38.79	53.94
2018-03	71.08	76.21	2022-09	47.49	54.13
2018-06	79.14	85.49	2022-10	50.34	65.70
2018-09	81.13	83.58	2022-11	80.75	76.71
2018-12	72.34	84.21	2022-12	45.84	56.11
2019-03	61.77	65.91	2023-01	51.75	54.93
2019-06	102.57	104.52	2023-02	49.90	131.35
2019-09	73.00	71.83	2023-03	47.81	60.36
2019-12	179.18	111.18	2023-04	42.39	55.37
2020-07	36.80	39.79	2023-05	58.43	57.57
2020-08	35.97	43.29	2023-06	44.48	54.73
2020-09	43.38	46.28	2023-07	67.33	76.10
2020-11	40.65	48.76	2023-08	51.05	56.55
2020-12	37.73	41.19	2023-09	59.04	61.33
2021-01	37.23	42.53	2023-10	46.39	50.53
2021-02	39.98	51.28	2023-11	39.63	49.05
2021-03	44.57	63.41	2023-12	56.00	61.66
2021-04	38.11	42.60			

Notes: i) The selected model had the lowest RMSE for both training and testing groups. ii) The final model was tested on both balanced and unbalanced samples. iii) Model selection involved evaluating hyperparameter grids, cross-validation, and random parameter selection to achieve high performance. The established hyperparameters for the final model are: a) Nrounds (number of training iterations): 50, b) Max_depth (maximum tree depth): 3; 6; 9, c) Eta (learning rate): 0; 0.1; 0.2, d) Gamma (minimum loss reduction required to split a tree node): 0; 0.1; 0.2, e) Colsample_bytree (subsample of columns analyzed in each tree): 0.6; 0.8; 1, f) Min_child_weight (minimum weight required to create a new tree node): 1; 3; 5, g) Subsample (subsample of rows when building each tree): 0.6; 0.8; 1

Table A2: Geographic Disparities in Intergenerational Mobility across Provinces

Province	**Rank-rank slope**	**Absolute Upward Mobility**	**P(Q5|Q1)**
Azuay	0.294	45.83	6.19
Bolivar	0.295	41.04	10.62
Cañar	0.313	46.63	6.99
Carchi	0.257	42.53	11.40
Cotopaxi	0.251	41.88	10.63
Chimborazo	0.311	39.01	10.83
El Oro	0.232	43.99	9.43
Esmeraldas	0.248	38.62	13.00
Guayas	0.227	46.07	8.97
Imbabura	0.260	41.19	11.66
Loja	0.272	44.29	9.35
Los Rios	0.230	41.54	11.45
Manabi	0.291	41.83	10.44
Morona Santiago	0.236	41.66	12.52
Napo	0.240	39.82	15.34
Pastaza	0.300	40.59	12.80
Pichincha	0.241	47.58	7.57
Tungurahua	0.321	39.86	10.81
Zamora Chinchipe	0.189	46.04	11.10
Galapagos	0.156	60.48	11.39
Sucumbios	0.163	45.17	13.72
Orellana	0.190	44.60	13.02
Santo Domingo	0.222	42.54	12.15
Santa Elena	0.207	42.83	12.08

Notes: The number of records of children with information about their geographic birth location is 1,615,829.

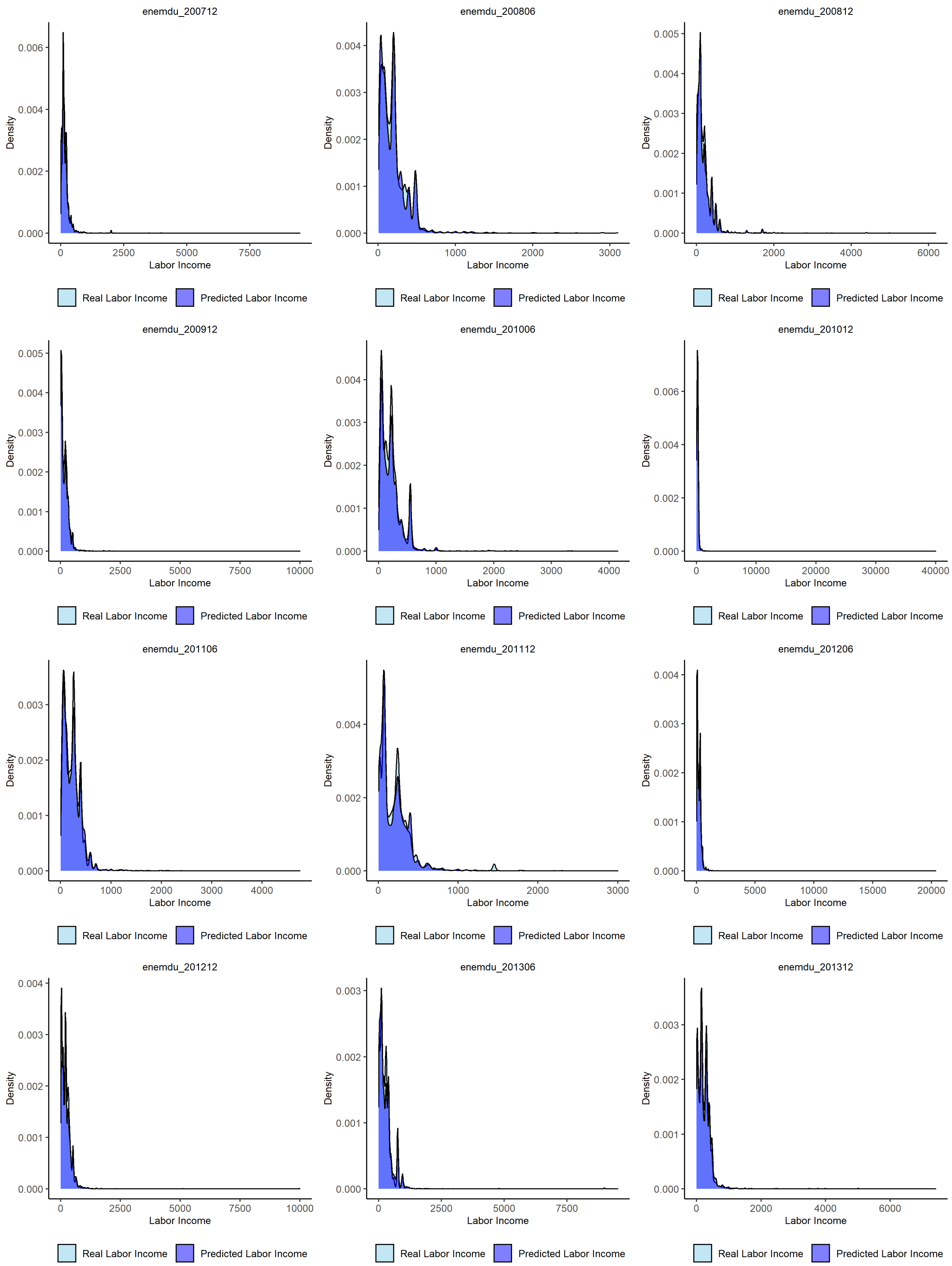
Table A3: Intergenerational Mobility Gender Gaps across Provinces

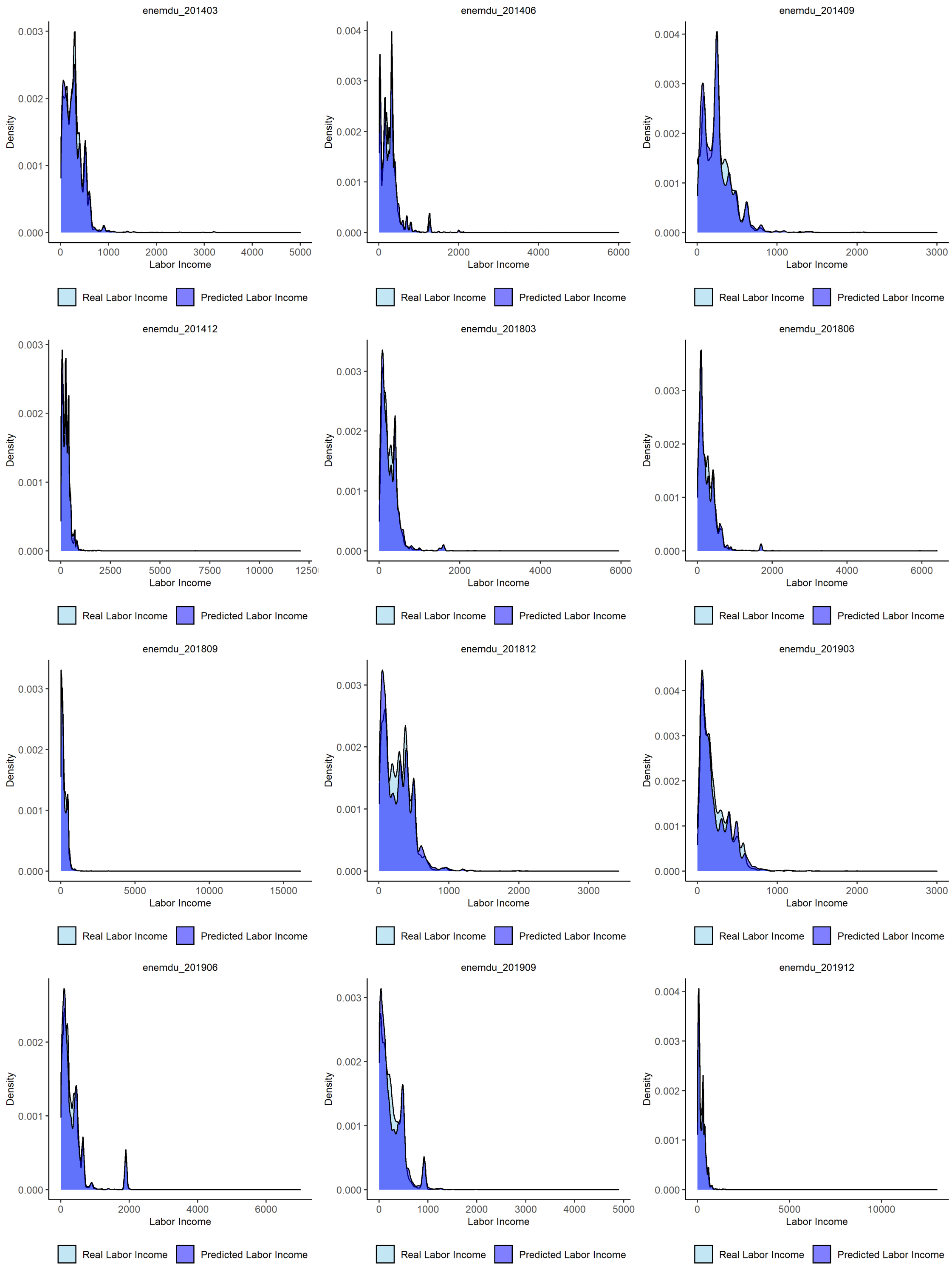
Province	**RRS m**	**RRS w**	**RRS gap**	**AUM m**	**AUM w**	**AUM gap**	**P(Q5|Q1) m**	**P(Q5|Q1) w**	**P(Q5|Q1) gap**
Azuay	0.254	0.342	-0.088	49.65	41.36	8.29	3.98	8.47	-4.49
Bolivar	0.253	0.360	-0.107	43.14	37.70	5.44	8.63	12.65	-4.02
Cañar	0.299	0.334	-0.035	48.05	44.82	3.23	4.94	9.15	-4.21
Carchi	0.223	0.304	-0.081	44.73	39.49	5.24	8.82	14.06	-5.24
Cotopaxi	0.210	0.312	-0.103	45.68	36.76	8.92	7.22	14.28	-7.06
Chimborazo	0.253	0.393	-0.139	43.27	33.33	9.93	7.72	13.89	-6.17
El Oro	0.200	0.286	-0.085	46.41	40.23	6.19	7.58	11.60	-4.02
Esmeraldas	0.211	0.320	-0.109	40.58	34.68	5.89	11.43	14.97	-3.54
Guayas	0.215	0.255	-0.040	47.84	43.06	4.78	7.03	11.31	-4.28
Imbabura	0.226	0.309	-0.083	43.94	37.47	6.47	9.17	14.33	-5.16
Loja	0.241	0.322	-0.081	46.49	40.89	5.60	7.58	11.24	-3.66
Los Rios	0.220	0.258	-0.038	42.48	39.48	3.00	9.39	13.96	-4.57
Manabi	0.287	0.301	-0.014	42.11	41.25	0.86	9.18	11.90	-2.72
Morona Santiago	0.222	0.260	-0.038	42.45	40.37	2.08	10.17	15.29	-5.12
Napo	0.212	0.290	-0.078	42.15	35.93	6.22	11.08	20.26	-9.18
Pastaza	0.257	0.364	-0.107	42.99	37.04	5.95	10.36	15.60	-5.24
Pichincha	0.212	0.280	-0.068	50.45	44.08	6.37	5.81	9.43	-3.62
Tungurahua	0.256	0.401	-0.145	45.11	33.64	11.47	8.63	13.15	-4.52
Zamora Chinchipe	0.164	0.228	-0.064	48.34	42.69	5.65	7.91	14.83	-6.92
Galapagos	0.152	0.160	-0.008	62.28	58.21	4.07	7.58	15.77	-8.19
Sucumbios	0.159	0.185	-0.026	48.80	38.56	10.24	8.61	21.28	-12.67
Orellana	0.203	0.184	0.019	46.79	40.22	6.57	9.46	18.28	-8.82
Santo Domingo	0.204	0.261	-0.056	45.04	38.56	6.48	9.38	15.40	-6.02
Santa Elena	0.199	0.244	-0.045	44.20	39.37	4.82	9.24	15.94	-6.70

Note: m=men, w=women.

B Additional Figures

Figure B1: Comparison between labor income from the ENEMDU survey and the XGBoost models





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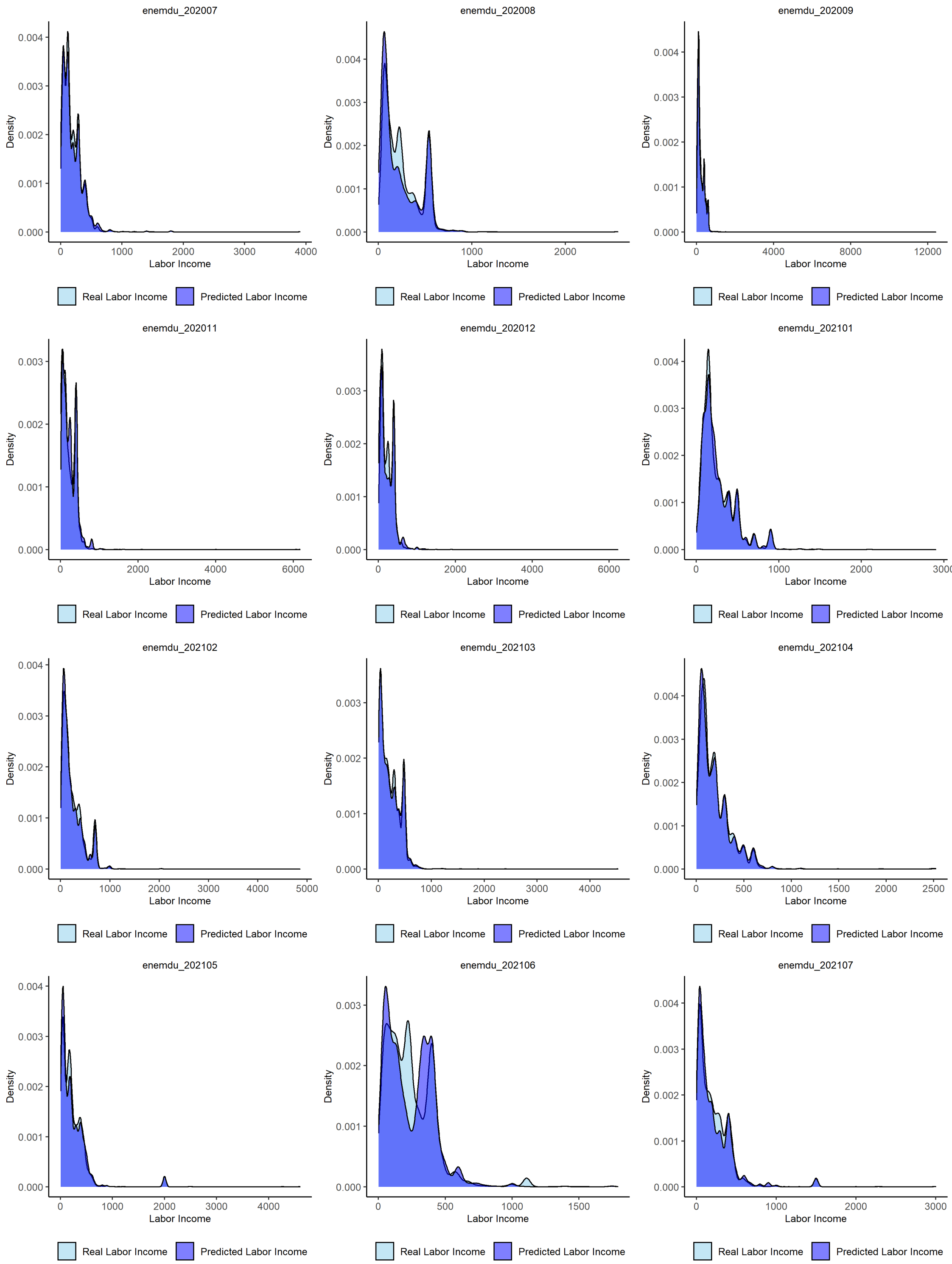
Labor Income
Real Labor Income
Predicted Labor Income



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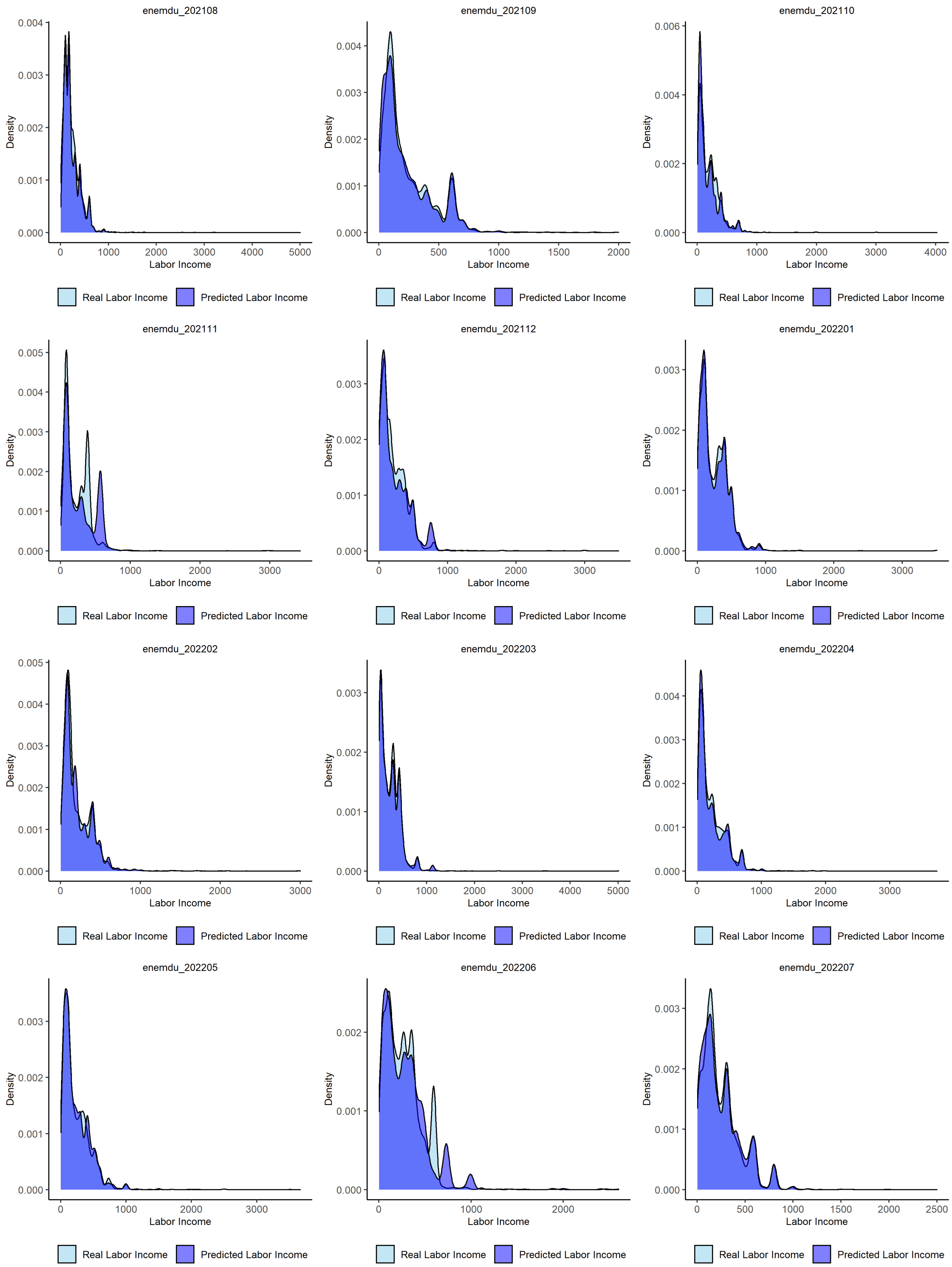
Density
Labor Income
Real Labor Income
Predicted Labor Income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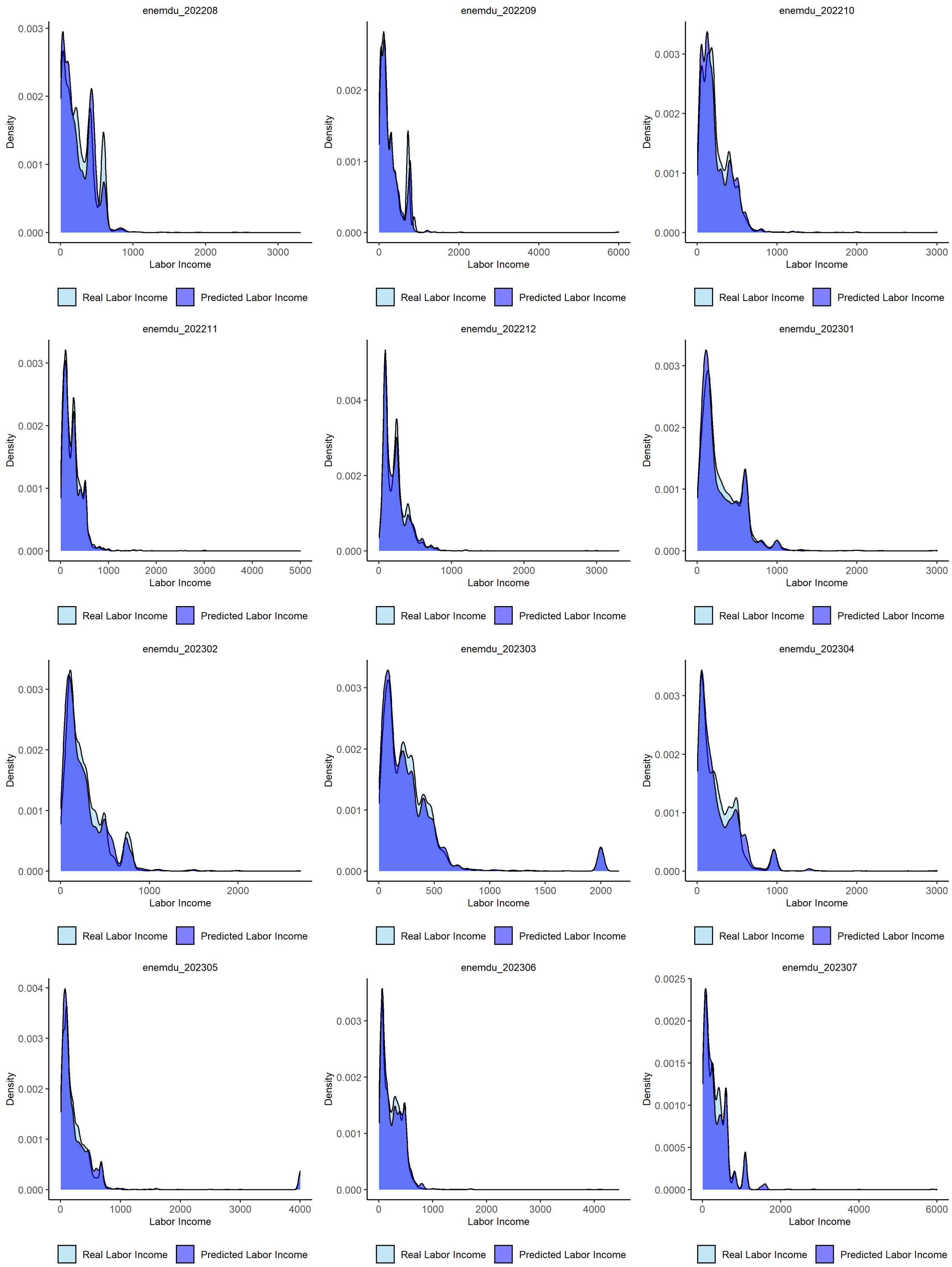
Density
Labor Income
Real Labor Income
Predicted Labor Income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Density
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Predicted Labor Income

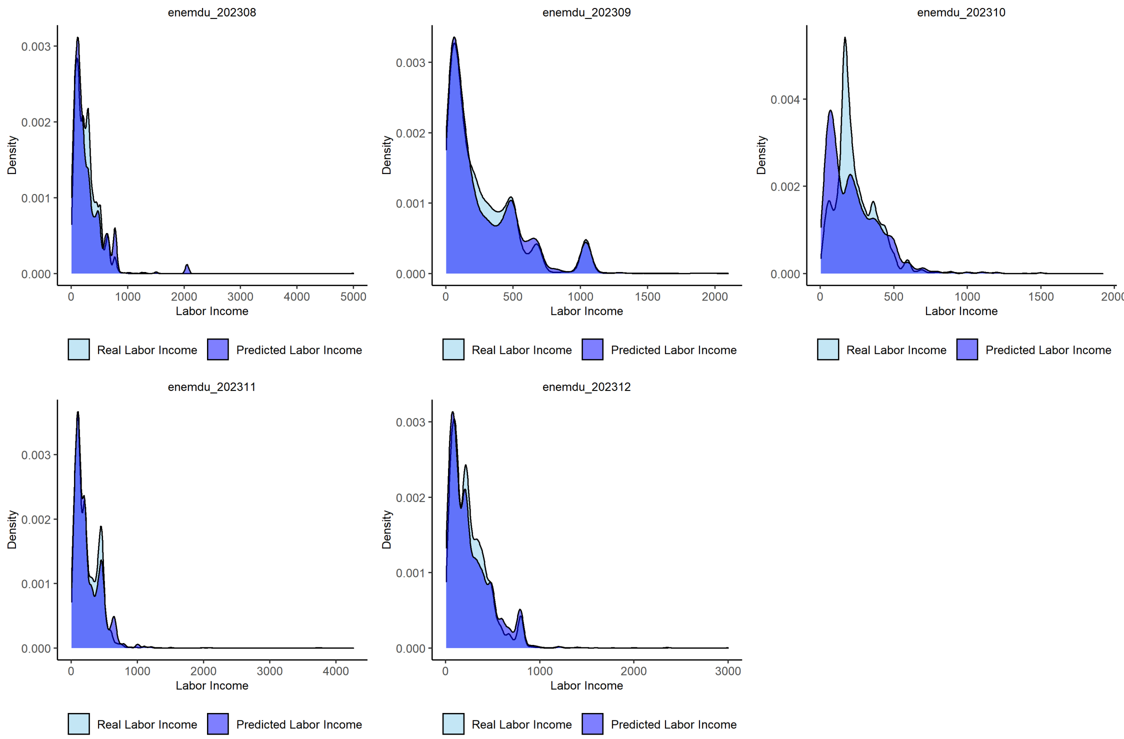


Figure B2: Income Distribution Percentiles: Full Sample vs. ENEMDU

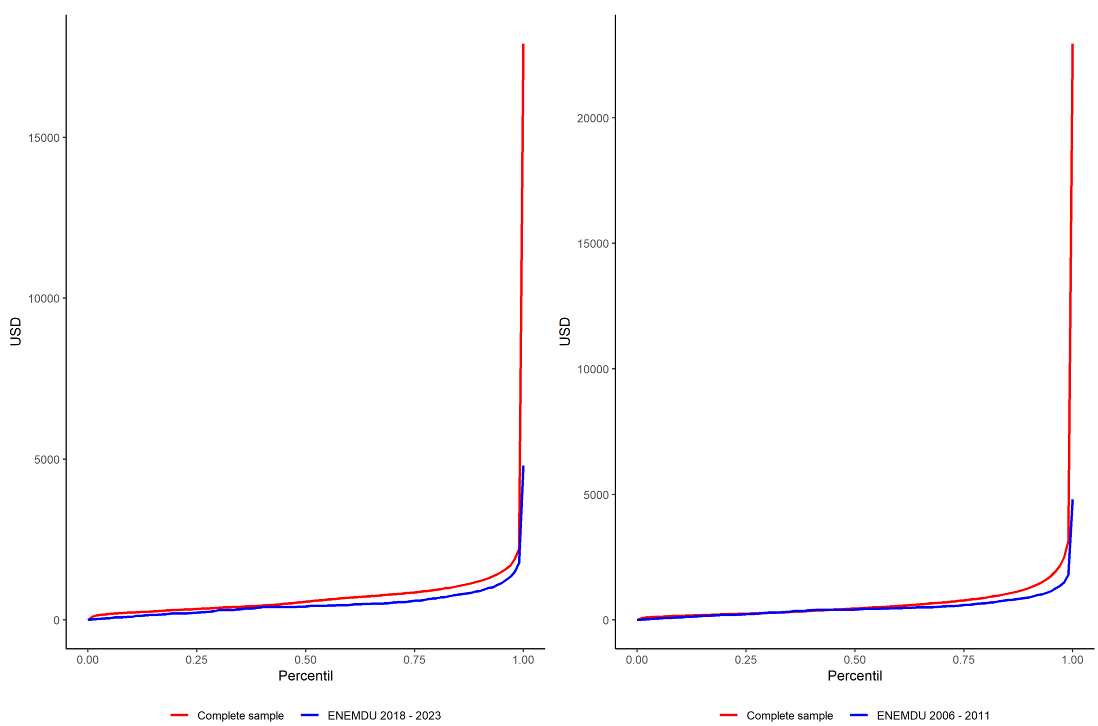


Figure B3: Intergenerational Mobility curve by data source: Full Sample vs. ENEMDU

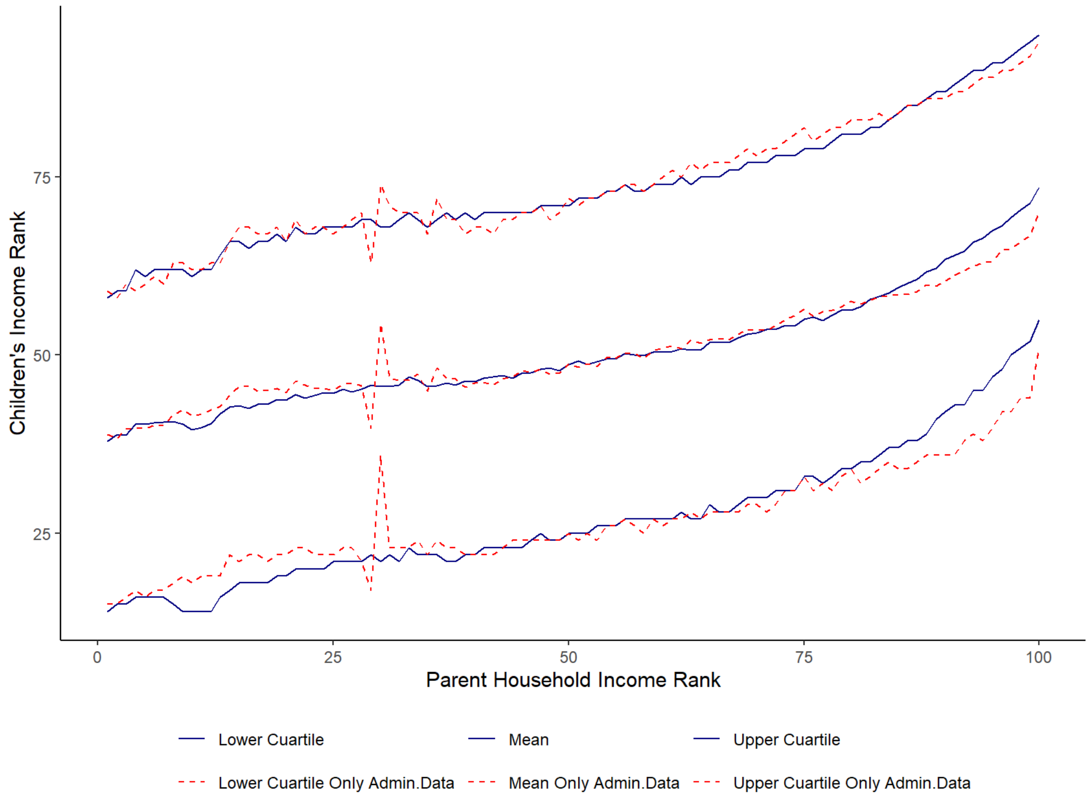


Figure B4: Transition Probability Matrix by Labor Income Quintile (Administrative records sample)

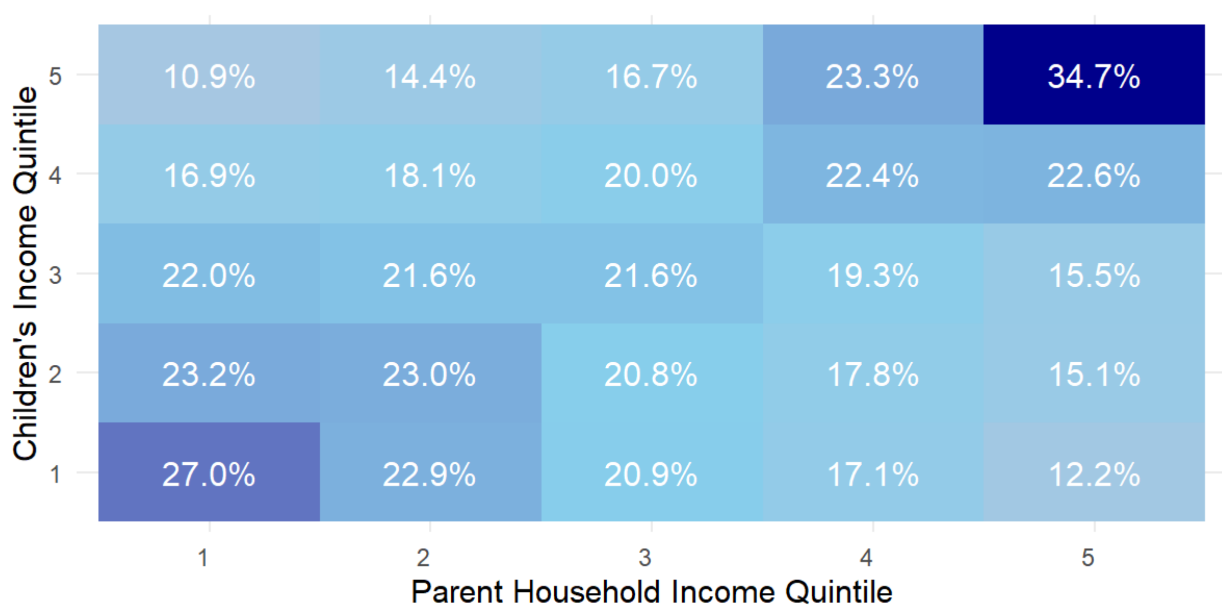
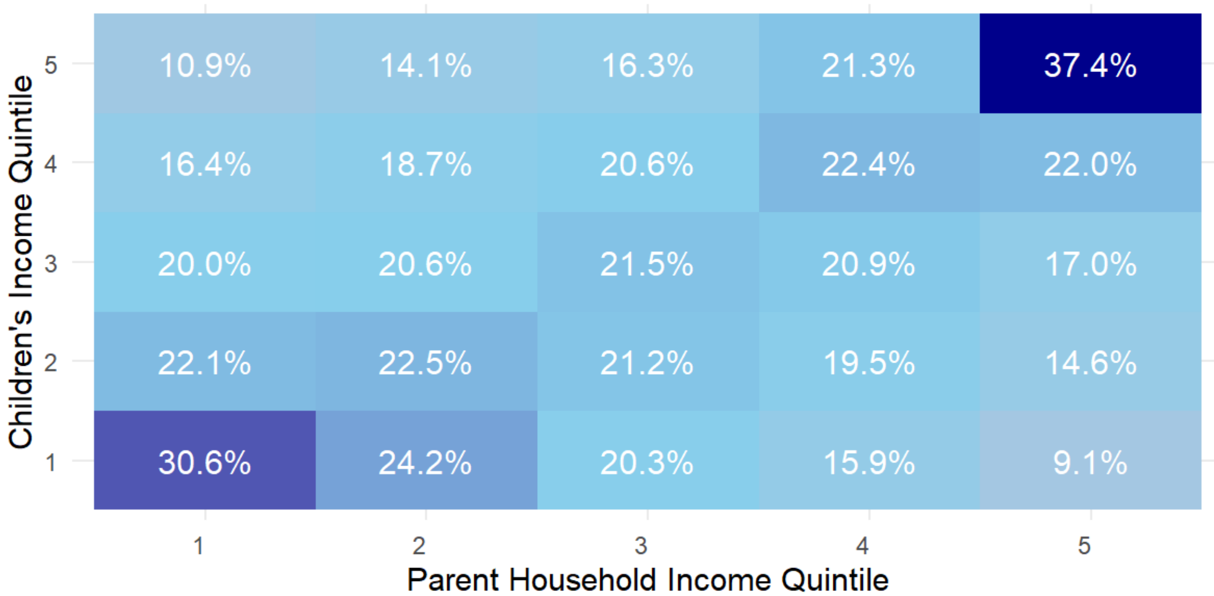
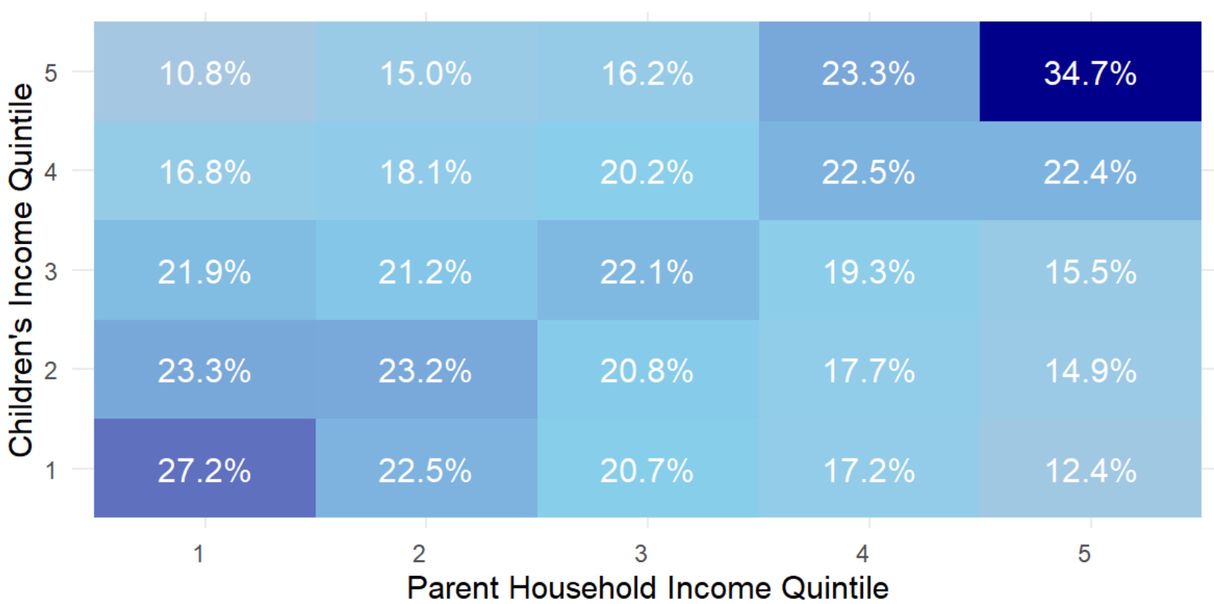


Figure B5: Transition Probability Matrix by Labor Income Quintile (real dollars)



Notes: This matrix presents values that are adjusted for inflation as of December 2023

Figure B6: Transition Probability Matrix by Labor Income Quintile for the Administrative records sample (real dollars)



Notes: This matrix presents values that are adjusted for inflation as of December 2023

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