INTERGENERATIONAL MOBILITY IN SPAIN: GEOGRAPHIC ANALYSIS AND CAUSAL NEIGHBORHOOD EFFECTS

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Intergenerational Mobility in Spain: Geographic Analysis and Causal Neighborhood Effects*

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Abstract

This paper provides new evidence on intergenerational income mobility in Spain using rich administrative data linking millions of parents and children over 25 years. We find that Spain ranks in the middle-to-lower tier of intergenerational mobility: a 10 percentile point increase in parental income rank is associated with a 2.74 percentile point increase in a child's adult income rank, and the probability of rising from the bottom to the top income quintile is 10.4%. Notably, income persistence is particularly strong at the top of the distribution, exceeding levels in the United States. Our analysis also indicates a deterioration in intergenerational mobility among cohorts born in the last two decades of the twentieth century, especially those entering the labor market during the Great Recession. Methodologically, we introduce a Bayesian hierarchical modeling approach that yields more precise and robust estimates of mobility at granular geographic levels by borrowing strength across units, which is crucial for overcoming spatial data sparsity. Using these estimates, we show that variation in upward mobility in Spain exhibits a strong regional dimension alongside neighborhood-level differences. Finally, by exploiting variation in the age at which children move with their families, we document large causal effects of growing up in a better neighborhood, which explain around 60% of the observed geographic variation in upward mobility rates.

Keywords: intergenerational mobility, inequality, neighborhood effects

JEL codes: E24, J16, J31, J61, J62, R1

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1 Introduction

At the heart of a thriving society lies the principle of equal opportunity: the idea that one's background should not preordain one's future. However, the increase in income inequality over the last decades has raised public concern about the deterioration of this principle (Alvaredo et al., 2018; Piketty, 2020). An excellent indicator of equality of opportunities is the intergenerational mobility of income, since it measures the extent to which the income of parents influences the income of their children as adults. Hence, a society with high levels of intergenerational mobility is one where an individual's economic success is less dependent on the socioeconomic status of their parents and which, consequently, provides more opportunities to its members.

Intergenerational mobility is important for several reasons. Firstly, it is a matter of fairness. Families from the highest deciles of the income distribution can transmit a wide range of benefits such as better education and childhood environments (Chetty and Hendren, 2018b; Chetty et al., 2020), appropriate health practices (Abel, 2008; Chetty et al., 2016; Matthew and Brodersen, 2018), large economic inheritances (Korom, 2016; Fessler and Schürz, 2018) and high levels of social and cultural capital (Bourdieu, 1987, 2011) that families at the lowest deciles cannot. These disparities tend to linger over time and, consequently, opportunities remain substantially different for the children growing up in top-income families in comparison to those growing up in low-income families. Secondly, a high level of intergenerational mobility is not only desirable in terms of fairness, but also in terms of economic efficiency: the loss of talent due to fewer opportunities of disadvantaged backgrounds children is detrimental to innovation (Aghion et al., 2017; Bell et al., 2019) and growth (Van der Weide and Milanovic, 2018).

Although the traditional studies of intergenerational income mobility provided the best estimates available at the time, they often relied on small samples and survey data and were vulnerable to lifecycle bias and attenuation bias (Blanden, 2013; Black and Devereux, 2010; Solon, 1999, 2002). The seminal work of Chetty et al. (2014a) marked a turning point by exploiting large-scale administrative tax records for millions of families and adopting a rank–rank specification, thereby eliminating reliance on self-reported income, mitigating biases from life-cycle and extreme values, and delivering distribution-free measures of intergenerational mobility. This innovation, and together with an increased availability of similar large-scale administrative datasets, has catalyzed a new wave of studies in Australia, Canada, Brazil, Denmark, Italy, Sweden, Switzerland, and beyond (Deutscher and Mazumder, 2020a; Connolly et al., 2019; Britton et al., 2023; Eriksen and Munk, 2020; Acciari et al., 2022; Heidrich, 2017; Chuard and Grassi, 2020; Pozo and Moreno, 2025), yielding more precise, geographically detailed, and informative estimates of intergenerational income mobility.

Nevertheless, the range of country studies using this new framework remains limited. To the best of our knowledge, no prior study has investigated income mobility across generations in Spain using this new approach and large-scale administrative data. This country is an interesting scenario to study intergenerational mobility that can help to improve our understanding of the factors shaping it: Spain is a very decentralized state formed by autonomous communities (the equivalent of regions) that have a high degree of independence in very relevant areas of public policy such as health, education, transports or housing policies. Also, this is a very particular institutional structure that could help to clarify the effects of local policies on intergenerational mobility in quasi-experimental settings. Furthermore, only a handful of European countries, chiefly the Nordic countries, along with Italy (Acciari et al., 2022) and Switzerland (Chuard and Grassi, 2020), have been examined using big administrative data and none of them have been able to establish causal effects on upward mobility.

The existing literature on intergenerational mobility in Spain is limited in time span and geographical coverage and survey data. Several studies carry out historical analyses (focused on the 18th and 19th centuries) that examine social mobility in some Spanish regions (namely Madrid, Valencia and Guadalajara) and use archive data on literacy, education or family occupation (Santiago-Caballero, 2011; Santiago Caballero et al., 2018; Beltran Tapia and de Miguel Salanova, 2021). Next, other studies develop innovative methodologies to analyze income mobility exploiting the socio-economic information conveyed in surnames. Collado et al. (2012) analyzes two regions, Cantabria and Murcia, focusing on the long-run intergenerational mobility of occupation and education over the 20th century. Güell et al. (2015) also take advantage of surnames information exploiting the 2001 census data of Cataluña to analyze educational mobility over generations. Regarding the analysis of intergenerational mobility of education, De Pablos Escobar and Gil Izquierdo (2016) explore the 2005 Spanish Intergenerational Transmission of Poverty survey and show a huge improvement in the access to education and completion rates for women over the past century but it does not translate to significant gains in the labor market. There are very few studies that examine income mobility (and not other outcome variables) across generations. In this sense, Cervini-Plá (2015) analyzes the intergenerational elasticity of income for children cohorts born between the 1950s and the 1970s exploiting survey data from the Spanish Income and Living Conditions survey. She shows that Spain is located between high and low mobility countries. In companion papers, the author provides potential explanations for this fact such as social referral to fill jobs, intergenerational persistence of occupation or a more intense process of assortative mating (Cervini-Plá, 2012; Cervini Plá and Ramos, 2013). Yet, these works are based on a small sample for children cohorts way before the 1980s. In sum, the limitations of these studies render the intergenerational mobility estimates for Spain limited in scope and, importantly, not comparable to the country studies circumscribed in the so-called new wave of literature on intergenerational mobility.

This paper provides new detailed evidence of intergenerational income mobility in Spain using rich administrative data that link millions of parents and children across more than 25 years. Our findings position Spain in the middle-to-lower end of the global picture of intergenerational mobility: a 10 percentile increase in parental income rank predicts a 2.7 percentile gain in a child's income rank, and the probability of a child born in the bottom quintile reaching the top quintile is just 10.4%. The main distinctive fact in international perspective is that intergenerational persistence is especially stark at the top: a child born into the top 1% is 51.4 times more likely to reach the top 1% in adulthood than a child born into the bottom 10%, higher than in countries like the United States, Canada or Italy. Regarding the evolution of intergenerational mobility, our cohort-specific analysis for those born between 1980 and 1990, measuring children's income at age 31, reveals a U-shaped evolution in intergenerational persistence. Between the 1980 and 1983 cohorts, the rank–rank slope fell by 13.1%, reflecting a temporary increase in intergenerational mobility. Later, persistence rose sharply: by the 1990 cohort the slope reached 0.265, a 42.5% increase over the 1983 level, approaching the intergenerational income mobility level of the United States (?). This reversal aligns almost exactly with the entry of the 1982–1983 cohorts into the labor market at the start of Spain's Great Recession, when youth unemployment exceeded 50%. Early-career scarring from high unemployment and reduced first-job opportunities in large firms, among other factors, likely drove this rise in persistence, limiting skill development and long-term wage growth for children from low-income families (Arellano-Bover, 2022, 2024).

Methodologically, a key contribution of this paper is the development of a novel Bayesian hierarchical framework to generate local-level estimates of intergenerational mobility at the municipality and ZIP code level. This method allows for information to be shared across clusters, leading to improved precision and robustness in low-population areas, overcoming sparse data constraints to enable more robust causal inference. Using these expanded local-level estimates, we document substantial geographic variation in upward mobility at various geographic levels. Children born into similar socioeconomic backgrounds face significantly different trajectories depending on where they grow up. The most socially mobile areas tend to be located in the North/North-East of the country whereas the less mobile ones are mainly located in the South/South-West. The region with the highest level of both absolute and relative mobility is Catalonia, with mobility rates on the levels of Scandinavian countries. The regions with the lowest levels of absolute and relative mobility are Andalucia, Extremadura and the Canary Islands, with mobility estimates similar to Southern United States ones.

We present the first estimates of the causal effects of neighborhood exposure on long-term economic outcomes using a movers' design in a European context (Chetty and Hendren, 2018b; G.C. Britto et al., 2022). By comparing children from similar family backgrounds who move to the same destination municipality at different ages, we exploit variation in exposure to place that is plausibly exogenous to long-term outcomes. This design enables us to estimate how the timing of a move affects adult income and to quantify the causal impact of growing up in a better destination. We document large causal effects of growing up in a better neighbor- hood, which explain around 60% of the observed geographic variation in upward mobility rates. Once we identify the magnitude and heterogeneity of causal effects of growing up in a high-opportunity place in Spain, we analyze the main geographic correlates of mobility across municipalities. Consistent with international evidence (Chetty et al., 2014a; G.C. Britto et al., 2022; Kenedi and Sirugue, 2022; Acciari et al., 2019), we find that higher upward mobility is associated with lower unemployment, stronger presence of the industrial sector, and higher rates of post-secondary education. Additionally, places with more affordable housing, smaller average household size and more stable family structures tend to exhibit greater intergenerational mobility.

We also uncover two novel empirical facts that distinguish the Spanish case from that of the United States and other countries and that are informative for the literature analyzing the drivers of intergenerational mobility. First, beyond the well-documented influence of childhood environments—such as school quality, family structure, and neighborhood socioeconomic composition—we find that labor market conditions at the time of entry into adulthood seem to play a central role in shaping both generational trends and regional disparities in mobility. Areas with persistently high youth unemployment not only exhibit lower mobility but also show sharper declines across cohorts. Importantly, the effect of unemployment in Spain has a "double hit effect", since high unemployment in parental cohorts is one of the strongest correlates of upward mobility, something in line with the causal effect of parental employment rates on changes in intergenerational mobility documented by Chetty et al. (2024). These results suggest that late-teen and early-adult labor market frictions are an essential, and often overlooked, dimension in the analysis of factors shaping intergenerational mobility.

Second, unlike in the United States (Chetty et al., 2014a; Chetty and Hendren, 2018b) we find that Spain's biggest metropolitan areas, notably Madrid and Barcelona, actually serve as engines of upward mobility for children from low-income families. Ewing et al. (2016) shows that int he United States sprawling, car-dependent commuting zones actually depress upward mobility: compact urban areas facilitate better job access and yield significantly higher mobility, whereas sprawl's isolation and income segregation weaken both direct and indirect pathways to advancement. Similarly, Barza et al. (2024) examine the Brazilian context and find that southern cities, where unskilled and skilled workers routinely interact within diversified industrial and vocational ecosystems, generate stronger upward mobility than their more segregated northern counterparts. Together, these findings imply that cities only become engines of opportunity when their built environments promote accessibility and social integration. This suggests that the high-mobility performance of Madrid or Barcelona may stem not merely from their size but from their compact form, mixed-use neighborhoods as we show that in these major Spanish urban areas young people benefit from dense networks of universities and vocational schools, extensive metropolitan public transport, and stronger social services.

The rest of the paper is organized as follows: Section 2 defines the measures of intergenerational mobility used int he paper. Section 3 describes the administrative dataset, explains the reasons behind the selection of the analysis sample and shows some descriptive statistics. Section 4 presents the main results at the national level, describe their evolution across generations and puts them in an international context. Section 5 focuses on the geographic analysis of intergenerational mobility. Section 6 studies the causal effects of neighborhoods in Spain on intergenerational mobility. Section 7 concludes.

2 Measures of Intergenerational Mobility

We follow the seminal work of Dahl et al. (2008) and Chetty et al. (2014a) and the new wave of intergenerational income mobility studies using large-scale administrative data (Britton et al., 2023; Acciari et al., 2022; Deutscher and Mazumder, 2020b; Heidrich, 2017; Chuard, 2021; Pozo and Moreno, 2025) and express both parent and child income as percentiles within their respective income distributions rather than using income levels or logarithms. There are several important reasons for this choice. First, income levels and even log income are sensitive to changes in the marginal distribution of income over time. For example, if the overall level of inequality rises or the income distribution becomes more skewed, a fixed income level will not carry the same relative meaning across generations. In contrast, percentile ranks are invariant to such changes, as they only capture relative position within each generation's distribution. Second, using percentiles allows us to avoid problems related to extreme values or measurement error in the tails of the distribution, which can strongly influence log income measures. Ranks provide a robust and interpretable measure that is particularly well-suited for comparing across time periods, countries, or subgroups. Finally, expressing income as a percentile facilitates direct interpretation of mobility as movement *across* the income ladder, rather than focusing on monetary gains or losses.

Therefore, we estimate some of the most common measures of relative and absolute mobility in this strand of the literature using income percentiles ranks. Relative mobility captures the extent to which children's income positions depend on those of their parents, typically summarized by the rank-rank slope when using percentiles. In contrast, absolute mobility measures the average economic outcomes of children from a given parental background, reflecting whether living standards improve across generations. Both dimensions are relevant: relative mobility informs us about equality of opportunity and the strength of inherited advantage, while absolute mobility speaks to whether economic growth is broadly shared.

2.1 Relative Mobility Measures

Rank-rank slope (RRS). It is defined as the coefficient β in a linear regression of child income rank (y_i) on parent income rank (p_i), both measured as percentiles on the $[0, 100]$ scale. Intuitively, it captures the average change in a child's rank associated with a one-point increase in the parent's rank. Formally, β is the estimated slope in the following equation:

$$y_i = \alpha + \beta p_i + \varepsilon_i \tag{1}$$

The coefficient β captures the linear association between parent (p_i) and child (y_i) income ranks. A slope of $\beta = 0$ implies perfect relative mobility: no relationship between parental and child rank. A slope of

$\beta = 1$ indicates complete immobility, where children exactly replicate their parents' rank in the distribution. Because both y_i and p_i are bounded in the $[0, 100]$ interval and approximately uniformly distributed, the rank-rank slope is scale-invariant and directly interpretable as a measure of dependence. It allows for meaningful comparisons across time, geography, or demographic groups, without being affected by changes in income inequality or growth.

Top-Tail Relative Mobility. Traditional mobility measures tend to focus on average trends and the middle or lower parts of the distribution. However, they may mask important non-linear dynamics at both tails of the distribution, a featured share by many of the country-level studies of intergenerational mobility beyond the United States (Britton et al., 2023; Acciari et al., 2022; Deutscher and Mazumder, 2020b; Heidrich, 2017; Chuard, 2021; Corak, 2020). Increasing inequality in many countries has raised interest in the question of whether top incomes are especially persistent across generations (DiPrete, 2020; Berman). To address this, we introduce a new simple measure that captures top-tail persistence. We compute the relative likelihood that a child reaches the top 1% of the income distribution depending on whether their parents were also in the top 1%, versus the bottom 10%:

$$\text{TTRPR} = \frac{\Pr(y_i \in \text{Top1} \mid p_i \in \text{Top1})}{\Pr(y_i \in \text{Top1} \mid p_i \in \text{Bottom10})} \tag{2}$$

We refer to this metric as the *Top-Tail Relative Persistence Ratio (TTRPR)*. A value greater than 1 indicates that children of top-income parents are more likely to remain at the top than those from low-income families. A value equal to 1 would imply perfect equality of opportunity at the top, with no advantage from parental background. This measure complements the rank-rank slope and absolute upward mobility by shining a light on elite reproduction and the entrenchment of privilege, which may be driven by mechanisms such as access to elite education, wealth transfers, or social networks.

2.2 Absolute Mobility Measures

Absolute upward mobility (AUM). A measure also introduced by Chetty et al. (2014b), is to compute the expected income percentile of children whose parents were at the 25th percentile of the income distribution.

$$\mu_{25} = \mathbb{E}[y_i \mid p_i = 25] \tag{3}$$

This measure, denoted μ_{25}, indicates how far children from a typical low-income family (i.e., at the median of the bottom half of the income distribution) climb on average. Higher values of μ_{25} imply greater upward mobility for children born into poverty, capturing whether the bottom of the income distribution experiences improvement across generations[1]. In practice, AUM is computed using the fitted values from the rank-rank regression: AUM $= \alpha + 25 \times \beta$, where α and β are the intercept and slope from Equation (1). Both dimensions are essential: relative mobility informs us about equality of opportunity and the degree of positional persistence, while absolute mobility captures whether living standards are improving across generations. Taken together, they provide a richer understanding of how inequality is transmitted and transformed over time.

Rags-to-riches probability. In addition to absolute upward mobility, we compute a full quintile-to-quintile transition matrix that describes the joint distribution of parent and child income ranks grouped into population quintiles. Each cell in this matrix represents the probability that a child born to parents in a given income quintile attains a specific quintile in adulthood. Of particular interest is the probability of "rags-to-riches" mobility, denoted $p_{1,5}$, which captures the share of children who move from the bottom 20% of the parental income distribution to the top 20% in adulthood. High values of $p_{1,5}$ signal a society where even those from the poorest backgrounds have a meaningful chance of reaching the top, while low values indicate strong barriers to upward mobility.

3 Data

3.1 Institutional Background

Spain, a parliamentary monarchy and member of the European Union, is characterized by a significant degree of decentralization in its political and administrative organization. The country is divided into 17 *comunidades autónomas* (autonomous communities or regions) and the two autonomous cities of Ceuta and Melilla. These autonomous communities have considerable legislative and executive power, with substantial independence in key areas of public policy such as health, education, and transportation, which can contribute to regional variations in opportunities and socioeconomic outcomes. These communities are further subdivided into a total of 50 provinces, plus Ceuta and Melilla. A provincial map highlighting these regions can be found in Appendix Figure A1. Provinces, in turn, consist of municipalities, which are the smallest administrative units and total 8,131 across Spain. Each municipality is further divided into ZIP codes, known locally as *códigos postales*, with a total of approximately 11,752 ZIP codes nationwide[2]. A municipality-level map colored by regions is presented in Appendix Figure A2, offering a detailed geographical representation of these subdivisions.

In comparative terms within the European Union, Spain presents distinct economic characteristics, marked by relatively high levels of inequality, persistent unemployment, and moderate GDP per capita. According to traditional measures, Spain's income inequality—captured by the Gini coefficient—is higher (31.5) than the

[1]While it focuses on a specific percentile, the approach can be generalized to other points in the parental distribution (e.g., 10th, 50th, 75th percentiles. We compute this measure of AUM to make our estimates comparable with other countries using the same data and methodology) to paint a more complete picture of upward or downward mobility.

[2]In rural areas, the vast majority of municipalities have only one ZIP code.

EU average (29.6), similar to Italy and higher than France and Germany (Eurostat, 2024). In terms of distributional inequality, the last World Inequality ReportChetty et al. (2018b) shows that Spain's top 10% income share stands at approximately 34%, exceeding the EU average of around 30%, yet remaining below the U.S. level of approximately 45% (Chancel et al., 2022). Wealth inequality is more pronounced: the top 10% in Spain own roughly 58% of total wealth, above the EU average of about 55% but again lower than the concentration observed in the United States, where the top 10% control about 70% of all wealth (Chancel et al., 2022). Regarding national income, Spain's GDP per capita, approximately €34,500 in purchasing power standards, is below the EU average (€39,700) and considerably lower than the United States (approximately $82,800, or €74,500 in purchasing power parity terms), highlighting substantial differences in economic conditions and opportunities (Eurostat, 2025a; The World Bank, 2025). One of the most particular characteristics of the Spanish economy is its persistently high unemployment, at approximately 12.2% in 2023, significantly exceeding the EU average (6.1%) and markedly higher than the U.S. unemployment rate (3.6%) (Eurostat, 2025b; U.S. Bureau of Labor Statistics, 2025). Although sharing similarities with many of its neighbors in Western and Southern Europe, the Spanish labor market has unique features that influence intergenerational mobility analyses. For example, the high incidence of temporary contracts, elevated youth unemployment rates, and regional differences in labor market outcomes (shared with Italy, as covered in Acciari et al. (2022)) affect key outcomes such as income trajectories and job stability, which are central to intergenerational mobility analyses.

Finally, it is important to note that the Basque Country and Navarra have special fiscal regimes (*régimen foral*), derived from historical rights and longstanding agreements recognized and preserved in the Spanish Constitution of 1978. These regions operate under a distinct fiscal arrangement known as the *Concierto Económico* (Economic Agreement) in the Basque Country and the *Convenio Económico* in Navarra. Under these agreements, the regional governments have the authority to administer and collect most taxes independently, subsequently making annual financial contributions to the central government to cover shared national services. While this arrangement grants substantial fiscal autonomy, the regions remain integrated into Spain's broader fiscal framework and contribute financially to the central administration. Nevertheless, due to this decentralized administration of taxes, individual-level administrative data from these two communities are not systematically included within the centralized records managed by Spain's national tax authority, the *Agencia Estatal de Administración Tributaria* (AEAT), which provides the primary data source for this study. Consequently, this dataset covers only the 15 autonomous communities and 46 provinces under the general fiscal regime, comprising approximately 93.6% of the Spanish population.

3.2 Description of the Administrative Data

The primary source of income data for this study comes from administrative tax records. In Spain, personal income tax (*Impuesto sobre la Renta de las Personas Físicas* - IRPF) is levied by the central government, although autonomous communities have some normative capacity. Tax filing is mandatory for individuals whose income from various sources (labor, capital, economic activities) exceeds certain thresholds, or who meet other specific criteria. For instance, in 1998, the minimum personal income threshold for mandatory filing was approximately €3,300 per year. The tax system distinguishes between different types of income, captured in forms such as *Modelo 100* (primarily for labor income) and *Modelo 190* (often related to self-employment and professional activities). Building upon this administrative foundation, we develop and exploit the Spanish Opportunity Atlas 2.0, a new version of the *Atlas de Oportunidades* originally analyzed in Soria-Espin (2022). Inspired by the work of Chetty et al. (2014b), the original database focused on the cohort of individuals born during the 1980s. Specifically, it combined economic information from parents whose children were born from 1980 to 1990 with the economic information of those children 18 years later. This linkage was achieved by combining the income tax returns of parents in 1998 and the income tax returns of their offspring in 2016, when they were adults.

The Spanish Opportunity Atlas 2.0 significantly improves this dataset by adding two critical pieces of information. First, it expands the sample to include children born in the 1990s, allowing us to observe younger siblings from the same households originally characterized in Atlas 1.0. Second, whereas the original Atlas was cross-sectional (observing parents in 1998 and children in 2016), the new Atlas is a continuous panel. This allows us to track households (both children and parents) continuously from 1998 through 2022. The database provides detailed income and demographic characteristics derived from the main types of tax declarations in Spain: *Modelo 100* (personal income tax for labor activities) and *Modelo 190* (mainly for self-employment activities). From 1998 to 2008, the dataset includes total gross and net income, as well as its components (e.g., labor income, capital income, real estate income) at the individual and household levels, along with age, residence, and filing status. Starting in 2008, the dataset is enhanced by having additional data on non-filers, as well as on individual and household wealth.

To the best of our knowledge, there are no other existing databases for Spain combining administrative economic information for millions of parents and their children to analyze intergenerational mobility. Consequently, this rich administrative data allows us to estimate relative and absolute mobility measures at various geographical levels (national, regional, provincial, municipal, and ZIP code), providing a detailed picture of geographic differences in income mobility. However, this database has some limitations. Firstly, Spain has two distinct fiscal regimes: the special one (for Basque Country and Navarra, as mentioned in the previous section) and the general one (for the rest of Spain)[3]. As the data originates from the general Spanish Tax Agency, it only covers households under the general regime. That is, it includes households living in Spain outside of the Basque Country and Navarra regions who filed tax returns in 1998 and listed a child born between 1980 and 1990 as a dependent. Secondly, the raw database does not include information on the children

[3]To obtain more information on the origins, legal implementation and economic consequences of the special Basque regime see this and this.

of parents who did not file income tax returns in 1998. These households were probably among the poorest in Spain, likely below the minimum filing threshold discussed earlier.

To analyze the geographic variation in mobility, we utilize ZIP code data from parent and child tax returns. Parental location is determined using the ZIP code reported in the 1998 tax return, from which we derive parental municipality, urban area, province, and region for the main sample. Children are assigned the ZIP code their parents reported in 1998 to represent their childhood location. For their adult location, we use ZIP code data available in their tax returns from 2008 onwards, allowing us to track their geographic location annually.

3.3 Sample Definitions

For our main analysis, we define parental income by averaging data from three years: 1998, 1999, and 2000. Using multiple years helps minimize attenuation bias in our intergenerational mobility estimates by reducing the impact of temporary income fluctuations and measurement error in any single year. Our approach to attenuation bias is further discussed in Section 4.5.

As discussed in the intergenerational mobility literature (G.C. Britto et al., 2022), measurement error in income remains a significant challenge when using administrative or survey data. To minimize the impact of such error on our sample, particularly concerning potential underreporting or volatility in both parental and child income data, we apply a series of three filtering decisions. The first two filters target potential issues with parental income, while the third addresses child income. Firstly, following standard practice in the field (Chetty et al., 2014b), we remove parental households reporting negative income during the sample period. Households with negative income, often stemming from business losses, significant capital deductions, or temporary reporting anomalies, are typically not representative of persistently low-income households and can distort estimates of mobility at the bottom of the distribution. Therefore, we exclude any parental household that reported negative annual income in any of the three years used for calculating average parental income (1998, 1999, or 2000). Secondly, we utilize imputed real estate data from 1998 to identify parental households that appear to be underreporting their income. These are households that report negligible overall income despite possessing substantial real estate wealth, suggesting potential income misreporting rather than genuine low income. To identify such cases, we remove households that meet two simultaneous criteria: they reported imputed real estate income above the national 60th percentile and their overall reported income was below the national 10th percentile. These households are unlikely to represent the true low-income population and could bias mobility estimates.

The third and final filter addresses potential underreporting or measurement issues at the very bottom of the child income distribution. We remove the bottom 5% of children based on their reported income.

This specific threshold was chosen empirically based on the observation that the relationship between child income percentile and average parental income exhibits an implausible negative slope for the lowest few percentiles. This pattern suggests that children reporting extremely low incomes are often not from the poorest backgrounds but may have significant unobserved income, be reporting zero income for reasons unrelated to poverty (e.g., early career stages, focus on education), or have other data anomalies. Removing this bottom tail helps ensure our estimates of mobility at the lower end of the distribution are based on more reliable income data. Figure A3 in the appendix illustrates the cumulative effect of each of these filtering decisions on the final sample used in our analysis.

3.4 Variables Definitions

Parental Income: Parental economic status is captured by total household gross income, which encompasses income from all taxable sources reported to the AEAT, including labor earnings, self-employment income, capital income, and taxable public transfers. To mitigate transitory income fluctuations and better approximate permanent income, we average this household income over a three-year period (1998-2000). For our baseline 1980-1986 child birth cohorts, parental income is typically measured when the children were aged 12-18. This period is chosen to reflect resources available during crucial formative years of childhood. As detailed in Section 3.3, households with zero or negative average income over this three-year window are excluded from our primary analysis sample. Parents are then ranked nationally based on this average household income relative to other parents of children within the same child birth cohort group.

Child Income: For the children's generation, our primary measure is individual gross income, again encompassing all taxable sources reported to the AEAT. For the baseline 1980-1986 birth cohorts, child income is averaged over the two-year period from 2021 to 2022. During these years, children in these cohorts are aged between 36 and 42 for cohort-age structure). This window is selected to capture earnings in early to mid-career, generally after the completion of higher education and the characteristic longer school-to-work transitions prevalent in Spain and other Mediterranean countries (Pastore et al., 2021). We apply filters to the left side of children income distribution to reduce misclassification, as discussed in section 3.3.

The use of individual income for children is a deliberate choice to isolate the direct intergenerational transmission of economic status, minimizing the confounding influence of assortative mating. Incorporating a spouse's income into the child's outcome measure would entangle the impact of parental background with the partner's economic contribution to the new household, thereby obscuring the clarity of the intergenerational income link. Existing research highlights that a substantial fraction of the covariance between parental income and child family income can be attributed to spousal income, reinforcing the methodological rationale for using individual income to measure mobility (Cervini-Pla; Cervini-Plá, 2015). Children are ranked based on their average individual gross income relative to other children in the same birth cohort group nationally.

Income Percentile Ranks: For both parents and children, income ranks are constructed by ordering individuals (or parental households) based on their respective smoothed income measures and then assigning a percentile rank ranging from 1 to 100 within their relevant national reference cohort. This rank-based approach is standard in contemporary intergenerational mobility research as it provides a scale-invariant measure of position within the income distribution and is less sensitive to extreme income values or changes in the shape of the income distribution over time (Chetty et al., 2014a).

3.5 Descriptive Statistics

Appendix Table A1 presents descriptive statistics for the baseline sample, which includes over 1.5 million parent-child pairs observed in Spanish tax records. Average individual income for children is €29,231, while household income for parents is nearly identical at €29,247, though with a slightly smaller interquartile range, reflecting differences in life-cycle stages and income composition. Most parents were born in the early 1950s, and children in the early 1980s, implying that outcomes are measured in adulthood. The sample is balanced by gender for children, while most primary tax filers (Parent 1) are male. Nearly all primary parents are registered as married or in long-term partnerships during the child's upbringing. These rich administrative data provide a uniquely comprehensive and demographically representative foundation to estimate intergenerational income mobility in Spain.

Appendix Figure A5 displays the income distributions for parents and their children in our baseline sample, excluding the top 1% of the income distribution to mitigate the influence of extreme outliers. Both panels reveal highly skewed distributions with long right tails, characteristic of income data. While parental household income (left) is more concentrated around lower income brackets, children's individual income (right) shows slightly greater dispersion, reflecting life-cycle variation and the individual nature of earnings. In addition, Appendix Figure A5 presents the raw income profiles across the parental and child income distributions. The left panel plots mean child income in adulthood by parental income percentile, while the right panel reverses the axes to show mean parental income by child income percentile. Both graphs reveal a pronounced convex shape, with a sharp increase in average income at the top percentiles. This curvature reflects growing income dispersion among top earners and underscores the importance of modeling nonlinearities at the very top in our subsequent intergenerational mobility analysis.

4 National Results

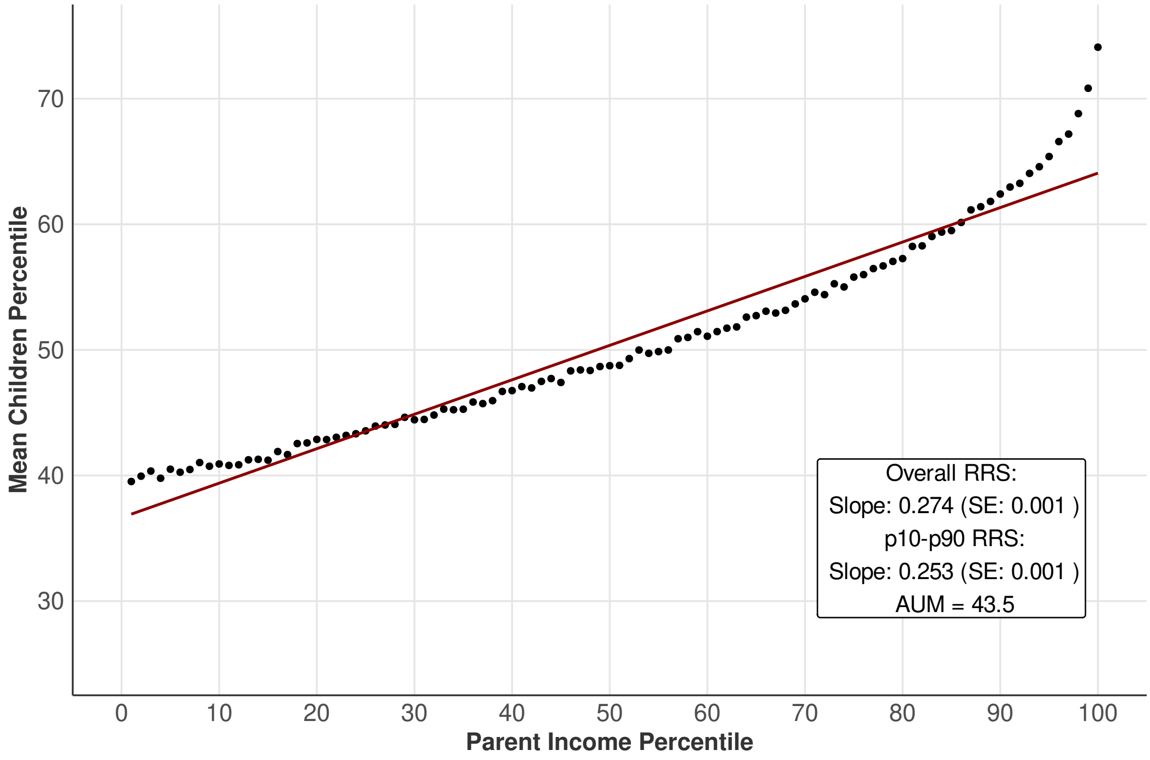
We begin our analysis presenting the national-level estimates of our main measures of intergenerational mobility on the baseline sample described in the previous section, chosen to minimize the conventional biases in intergenerational mobility studies (see Section 4.5). It includes individuals born in the 1980–1986 cohorts; parental household income is measured as the three-year average over 1998–2000, while children's individual income is measured as the two-year average over 2021–2022, when they are aged 36–42. We use total household income for the parent generation and individual total income for the children.

4.1 Main Results

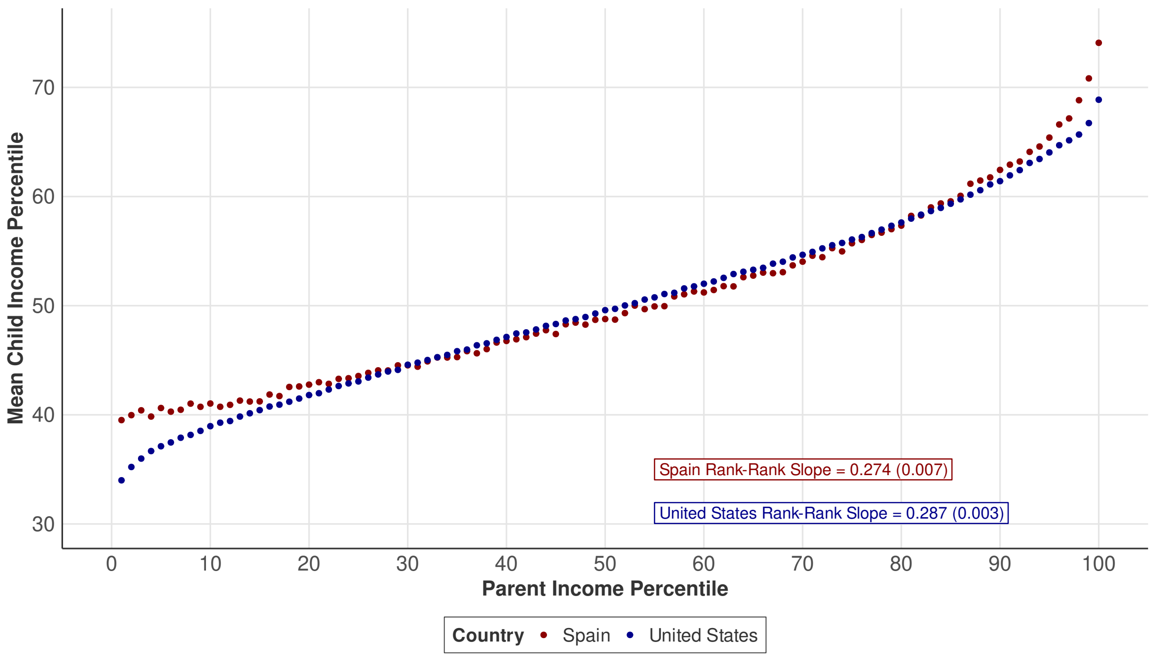
Figure 1 jointly illustrates the relationship between parental and child income percentiles: Figure 1a focuses on the national rank–rank profile for Spain, while Figure 1b compares Spain's profile against that of the United States. Figure 1a plots the mean child income percentile against parent income percentiles for Spain. The baseline rank-rank slope corresponds to 0.274, which means that a 10 percentile increase in parental income is associated on average with a 2.74 percentile increase in children's income in adulthood. The overall rank–rank slope (0.274) and the restricted 10th–90th slope (0.253) both show a similar level of relative mobility, while absolute upward mobility shows that children born to 25th percentile families on average reach the 43th percentile, which corresponds approximately to 21,080 euros. This rank–rank relationship is largely linear throughout most of the distribution but shows pronounced upward curvature at the top, meaning extra persistence among the top 10%. This pattern is consistently observed in comparable studies (Britton et al., 2023; Acciari et al., 2022; Deutscher and Mazumder, 2020b; Chuard, 2021; Corak, 2020; Kenedi and Sirugue, 2022) with the exception of the United States (Chetty et al., 2014a), which shows a exceptionally linear relationship all over the distribution.

Figure 1b overlays Spain's rank–rank relationship (red) on that of the United States (blue) from (Chetty et al., 2018a), with child individual income measured in 2014–15 (ages 31–37) and parent family income averaged over 1996–2000. Although the United States exhibits substantially greater income and wealth inequality—and under the Great Gatsby Curve framework (Corak, 2013) one would therefore expect a steeper rank–rank slope (indicating lower mobility)—the estimated slopes are nearly identical (0.274 for Spain versus 0.287 for the U.S.), revealing a surprising similarity in intergenerational persistence across these two very different economic contexts using the same definition of income and same cohorts.

Figure 1: Mean Child Income Rank vs. Parent Income Rank at the National Level



(a) Mean Child Income Rank vs. Parent Income Rank in Spain with Income Reference

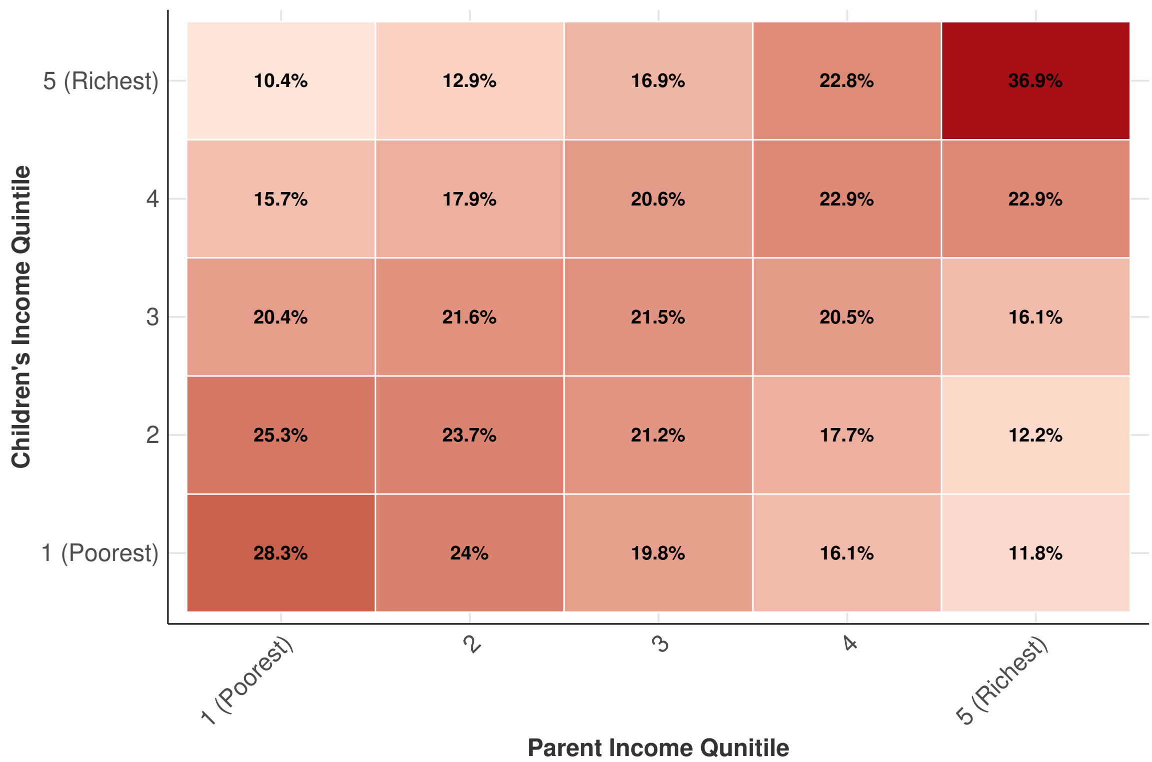


(b) Mean Child Income Rank vs. Parent Income Rank in Spain and the United States

Notes: **Figure 1a** presents the mean child income percentile by parental income percentile at the national level for Spain. The figure also includes the rank-rank slope (RRS) for the whole distribution, as well as a restricted range between percentiles 10 and 90 (P10–P90) and the national-level absolute upward mobility (AUM). **Figure 1b** presents nonparametric binned scatter plots of the relationship between children's and parents' percentile income ranks at the national level in the United States and Spain. The red line corresponds to Spain, where income definitions follow those used in the baseline results sample. The blue line corresponds to the United States (Chetty et al., 2018a), where child income is the mean of individual income in 2014–2015 (when the child is between 31 and 37 years old), and parent income is the mean family income from 1996 to 2000. Standard errors are reported in parentheses. Incomes in both countries are defined as total gross income following the IRS definition.

Figure 2 presents the national-level quintile transition matrix, showing the probabilities that children born into each parental income quintile will land in each quintile in adulthood. Of primary interest is the *rags-to-riches* probability—the likelihood that a child from the bottom quintile climbs to the top—which is only 10.4%, highlighting the enduring barriers to upward mobility for those starting at the bottom. By contrast, 36.9% of children raised in the richest quintile remain there, while just 11.8% descend to the lowest quintile, demonstrating a pronounced *glass floor* effect that insulates top-income families from downward mobility (Gugushvili et al., 2017). The matrix also reveals more fluid movement among the middle three quintiles, where children's transitions are more evenly distributed, suggesting that the central segments of the income distribution exhibit higher intergenerational mobility. A comparable transition matrix using income deciles is provided in Appendix Figure A6.

Figure 2: National Quintile Transition Matrix



Notes: This figure presents the national-level quintile transition matrix in the form of a heatmap, illustrating the probability of children transitioning across income quantiles based on their parents' household income quintile. Each row represents the children's individual income quintile in adulthood, while each column corresponds to the parental household income quintile. The percentages inside each cell indicate the probability that a child born into a specific parental income quintile reaches a given quintile in adulthood. The color intensity reflects the probability magnitude: darker shades indicate higher probabilities, highlighting the persistence of income across generations. A strong diagonal pattern suggests low intergenerational mobility, meaning children are likely to remain in the same income quintile as their parents. In contrast, more even shading across rows suggests higher mobility, where children's income is less dependent on their parents' income. Income definitions follow those used in the baseline results sample.

Subgroup analysis Appendix Table A2 disaggregated the national rank–rank slope, the absolute upward mobility (AUM) and the rags-to-riches probability (PQ5Q1) measures by relevant subgroups. Column 1 reports the overall relative and absolute mobility estimates shown in Figures 1 and 2. Beyond gender, subgroup comparisons reveal only modest variation: second-generation migrants exhibit a slope of 0.276 (first-generation

0.251), first-born children 0.277 (not-first-born 0.279), and children of married parents 0.280 (unmarried 0.242; divorced 0.247). Even extending the birth cohort to 1980–1990 leaves the slope virtually unchanged (0.277)[4]. By contrast, the largest heterogeneity arises by child gender. Sons face a slope of 0.260 versus 0.285 for daughters, indicating stronger intergenerational income persistence for female children. This gender gap also manifests in terms of absolute upward mobility: sons from families at the 25th percentile reach on average the percentile 47.8 but daughters only climb up to percentile 39.3, which translate to an approximate income gap of €3,091 (See Appendix Figure A8). Regarding the probability of reaching the top quintile from the bottom quintile, we also observe a substantial gender gap, with a probability of 12.7% for sons compared to 8.2% for daughters[5]. Further examining the very top of the children's income distribution reveals dramatic gender disparities: in the top percentile (average income of €213,858), male children are overrepresented by roughly 40% relative to their national share, while female children are mechanically underrepresented by a 60%, underscoring that sons are much more likely than daughters to attain economic elite income status in Spain (see Appendix Figure A7).

Top-tail intergenerational mobility As shown in Figure 1, the rank-rank relationship is mostly linear for most of the distribution but there is a marked upward curvature at the top, indicating an extra persistence among top 10% families. This suggests that average slope estimates may understate the strength of top-tail immobility. To better capture intergenerational mobility dynamics at the very top of the income distribution, we introduce the Top-Tail Relative Persistence Ratio (TTRPR). This metric compares two probabilities: the likelihood that a child reaches the top 1% of the income distribution if their parents were in the top 1%, versus the likelihood that a child reaches the top 1% as an adult if their parents were in the bottom 10%. Formally, it is the ratio of these two conditional probabilities. A TTRPR above 1 thus indicates that children of top-income parents have a relatively higher chance of attaining elite status than those from low-income families.

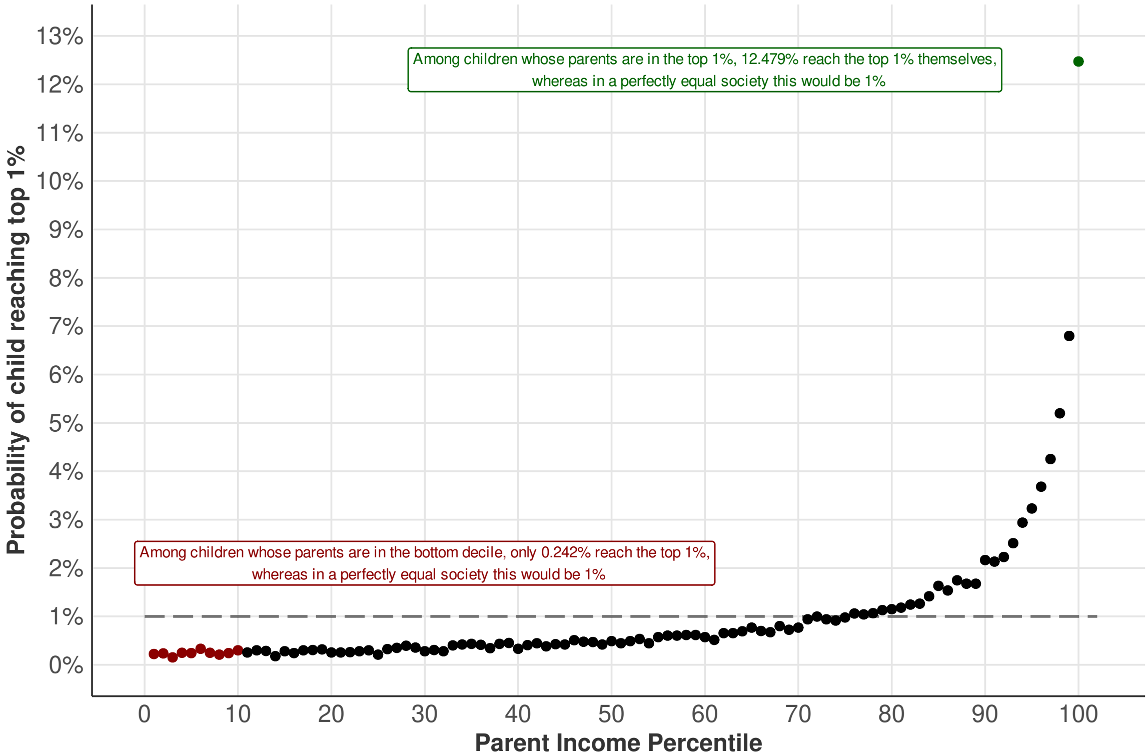
To illustrate this ratio, we firstly show in Figure 3 the probability of a child reaching the top 1% of the income distribution as an adult, conditional on their parental income percentile. A perfectly equal society would imply that 1% of children from every parental income group reach the top 1% (represented by the dashed horizontal gray line), but the figure shows significant deviations from this benchmark. In particular, we see that the probability of a child to end up in the top percentile coming from a top percentile household is 12.479% whereas this figure is only 0.242% for a child growing up in a bottom-decile household. Dividing these two conditional probabilities yields a Top-Tail Relative Persistence Ratio (TTRPR) of approximately 51.4, which means that a child born into the top 1% is 51.4 times more likely to reach the economic elite than a child born into the bottom 10%[6].

[4]For a detailed analysis of the differences in intergenerational mobility between migrants and natives in Spain and international perspective see Abramitzky et al. (2019) and Boustan et al. (2025).

[5]See Appendix Figure A8 for the full quintile transition matrix by child gender.

[6]See calculations details in Appendix A.1

Figure 3: Conditional Probability of Reaching the Top 1% by Parental Income Percentile



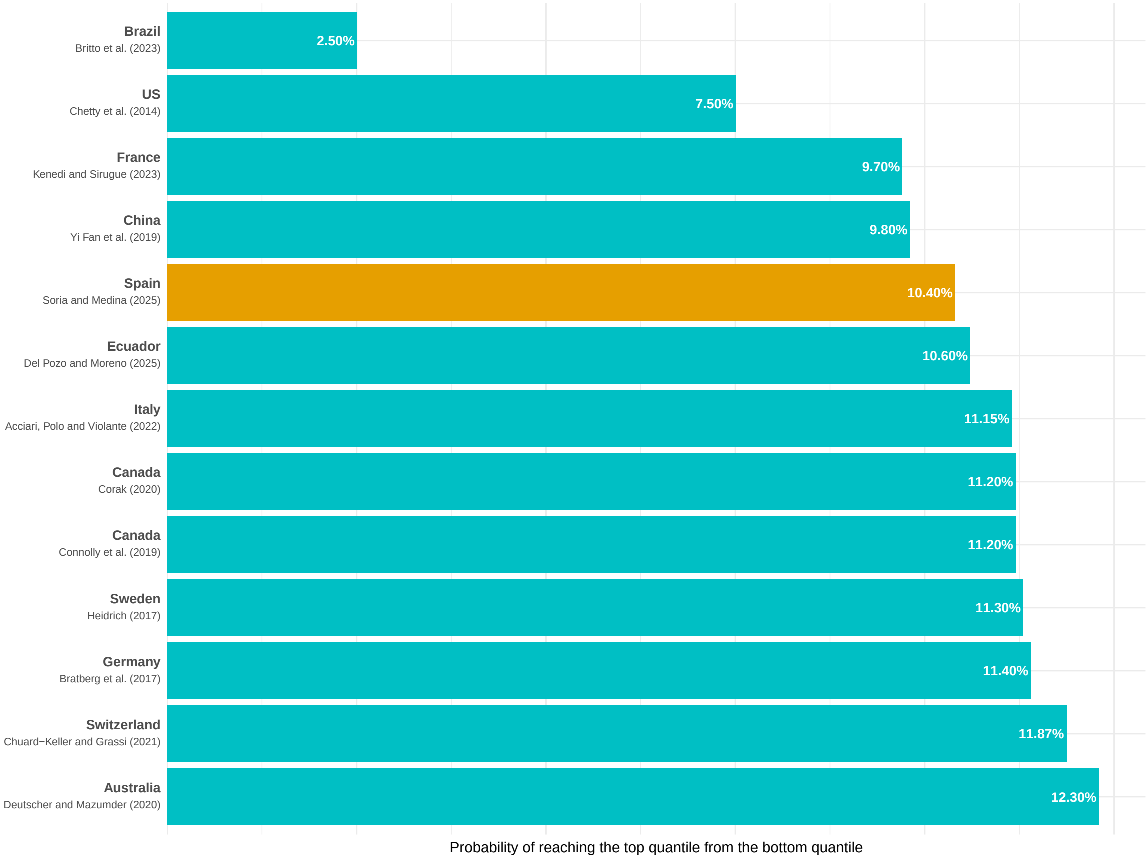
Notes: In this figure each point shows the probability that a child reaches the top 1% of the adult income distribution, conditional on the parent's household income percentile. Probabilities are computed as the number of children with parents in percentile i who themselves fall in the top 1%, divided by the total number of children with parents in percentile i. Points are color–coded by two groups: bottom decile (red) and top 1% (dark green). The dashed horizontal line at 1% denotes the benchmark of perfect equality. The dark green annotation reports $\mathrm{P}(\text{child} \in \text{Top1} \mid p \in \text{Top1}) = 12.48\%$, and the red annotation reports $\mathrm{P}(\text{child} \in \text{Top1} \mid p \in \text{Bottom10}) = 0.24\%$.

4.2 International Comparisons

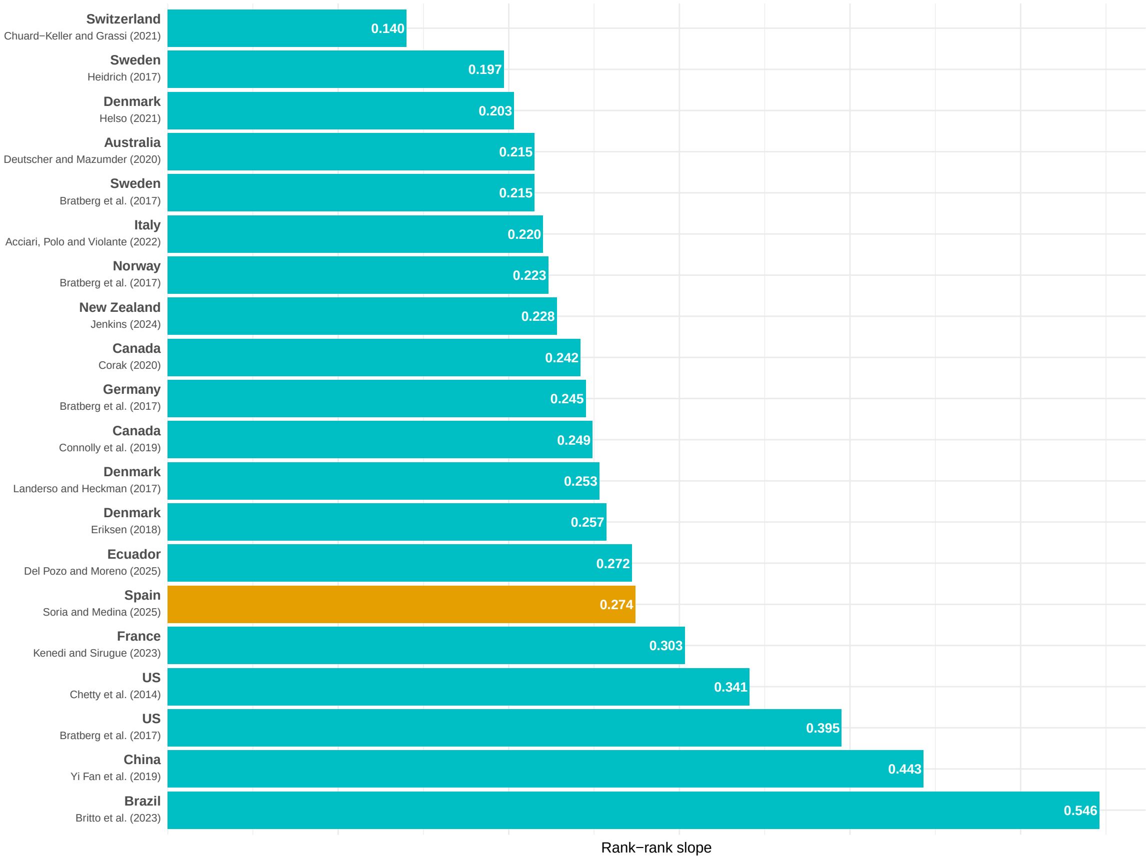
Where does Spain stand in the global picture of intergenerational mobility? To better understand the extent of intergenerational mobility in Spain, Figure 4 puts our national-level rank-rank slope and *rags-to-riches* probability in international perspective[7]. Panel A ranks countries by the probability that a child from the bottom income quintile will reach the top quintile as an adult. We observe wide variation: Brazil's *rags-to-riches* probability is very low (2.5%), while Ecuador, Italy, Canada, and Spain cluster around 10–11%. At the high end, Australia and Switzerland exceed 12%. Panel B orders the same set of studies by the rank–rank slope, where lower values denote greater overall mobility. Denmark and Sweden exhibit the flattest slopes (0.14–0.20), whereas persistence is strongest in Brazil (0.55) and China (0.44). Both international comparisons place Spain in a lower-middle position in the new literature of intergenerational income mobility: its 10.4% chance of rising from the bottom to the top quintile falls short of high-mobility countries like Australia and Switzerland yet exceeds that of low-mobility settings such as Brazil and the U.S., is only slightly above the global average. A detailed international comparison table can be found in Appendix Table A3

[7]An important caveat is that we restrict our international comparison to those country studies using (i) similar children cohorts, (ii) the rank-rank approach and (iii) income data coming from tax records.

Figure 4: Relative and Absolute Mobility in International Perspective



(a) Probability of reaching the top quintile from the bottom quintile

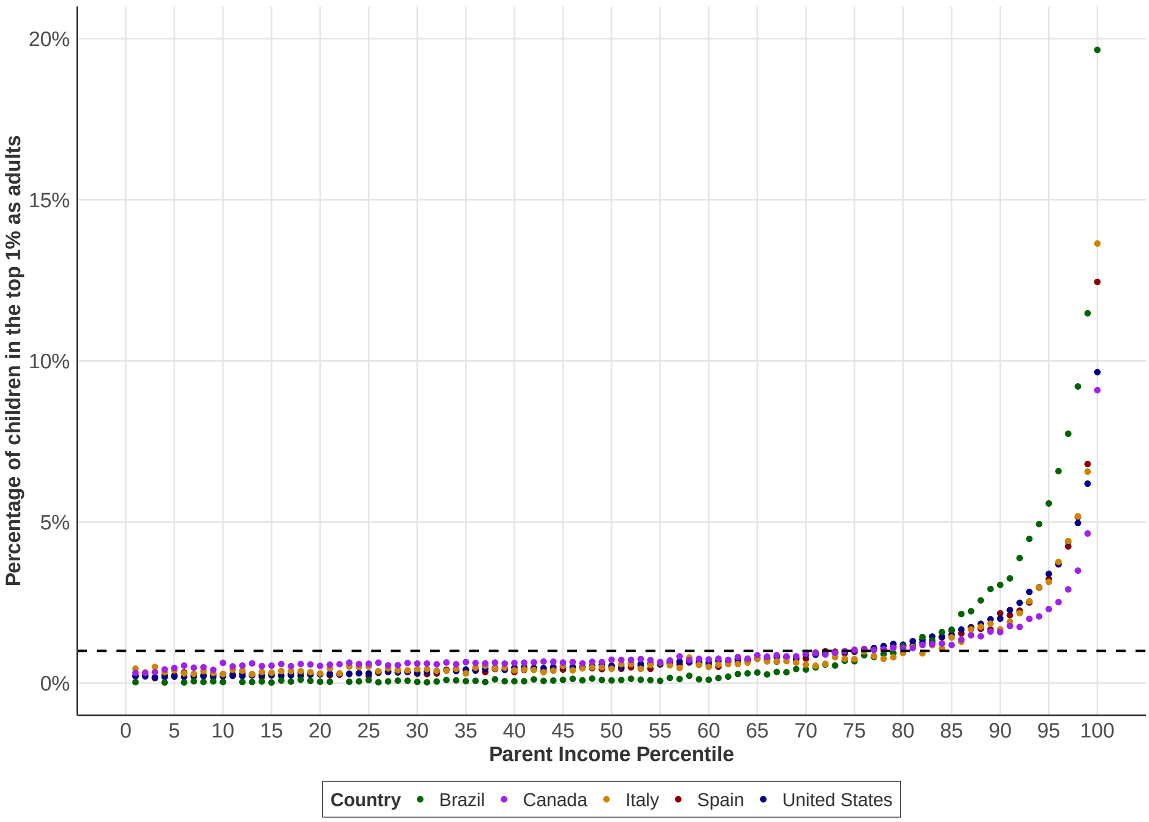


(b) Rank-rank slope

Notes: **Panel A (top)** shows the probability that a child born into the bottom income quintile reaches the top quintile across countries. **Panel B (bottom)** displays the rank–rank slope—estimated as the coefficient in a linear regression of child income rank on parental rank across countries.

Following the structure of our main results (Section 4.1), we now turn to an international comparison of top-tail intergenerational mobility dynamics. Figure 5 plots the conditional probability that a child reaches the top 1% of the income distribution for each parental percentile in five countries with comparable studies, namely Brazil (G.C. Britto et al., 2022), Canada (Connolly et al.), Italy (Acciari et al., 2022) and the United States (Chetty et al., 2014a). In this top-tail comparison, Spain occupies a central position in terms of the raw probability of top-percentile persistence: children born to parents in the top 1% have a higher chance of staying at the top than in Canada and the United States, but a lower chance than in Italy and Brazil[8].

Figure 5: Conditional Probability of Reaching the Top 1% by Parental Income Percentile Across Countries



Notes: This figure shows the probability that a child reaches the top 1% of the adult income distribution, conditional on the parent's household income percentile in some countries, namely Brazil (G.C. Britto et al., 2022), Canada (Connolly et al.), Italy (Acciari et al., 2022) and the United States (Chetty et al., 2014a). Probabilities are computed as the number of children with parents in percentile i who themselves fall in the top 1%, divided by the total number of children with parents in percentile i. The dashed horizontal line at 1% denotes the benchmark of perfect equality.

However, what sets Spain apart is a combination a low upward mobility from the bottom decile (similar with the United States) with a higher success rate for children of top-1% parents. Because the probability of climbing from the bottom 10% to the top 1% is very small in Spain, yet the probability of remaining in the top 1% when born to top 1% parents exceeds the U.S. level, its Top-Tail Relative Persistence Ratio is the highest among our peer countries (see Figure 6).

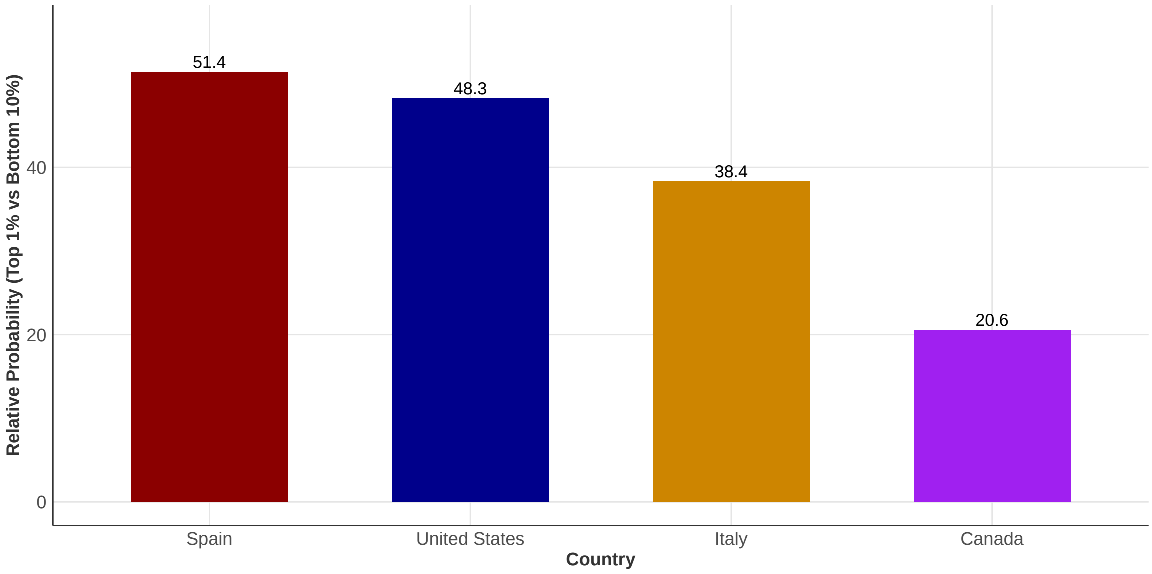
Among the general mechanisms of social reproduction highlighted in the literature, certain economic conditions, social structures, and historical legacies, especially pronounced in Spain, may help explain why

[8]See Appendix Figure A10 for a detailed figure of this international comparison

intergenerational persistence is so strong among the country's top earners. Firstly, Spain's elevated structural unemployment, persistent productivity stagnation, and an absence of *superstar* innovation sectors jointly constrain the creation and turnover of high-earning positions, thereby reinforcing intergenerational persistence at the top. Secondly, some features of the decentralized tax system in Spain may reinforce the observed top-tail persistence. On one hand, higher regional inheritance and gift taxes sharply reduce upward mobility for heirs at the bottom of the distribution: less-wealthy beneficiaries must liquidate financial assets at unfavorable prices or incur personal debt to pay tax bills, while illiquid real estate delays deleveraging and blocks investment, effectively trapping bottom-decile families in low-wealth positions (Mico-Millan, 2023). On the other hand, wealthy families exploit family-firm structures to reclassify private wealth as tax-favored corporate equity, shifting inheritances into entities that escape full inheritance tax (Micó-Millán, 2024). By simultaneously constraining liquidity for less-wealthy heirs and enabling sophisticated avoidance for the wealthy, Spain's tax regime both reduces the upward mobility prospects of low-income children and prevents downward mobility of high-income children, reinforcing the exceptionally high intergenerational persistence observed among the top 1%.

A final historical contributor could be the fact that the transition to democracy after Franco preserved much of the pre-existing economic elite. Unlike other democratizing countries where economic elites faced significant restructuring, Spain's transition from Franco's dictatorship left economic elites largely intact. Padilla et al. (2025) show a positive relationship between the individual's position during the dictatorship and the democracy: business and economic elites remained dominant across generations. This historical continuity likely reinforced social reproduction at the very top, maintaining privileged access to high-income positions for families already in power before democracy. The absence of major structural reforms during the transition allowed economic networks, corporate leadership, and inherited wealth to persist, further solidifying intergenerational income persistence.

Figure 6: Top-Tail Relative Persistence Ratio (TTRPR) Across Countries



Notes: This figure shows the The Top-Tail Relative Persistence Ratio (TTRPR) in Spain, Brazil (G.C. Britto et al., 2022), Canada (Connolly et al.), Italy (Acciari et al., 2022) and the United States (Chetty et al., 2014a). This ratio is defined as the ratio of (i) the probability that a child reaches the top 1% of the adult income distribution given that their parents are in the top 1%, to (ii) the probability that a child reaches the top 1% given that their parents are in the bottom 10%.

4.3 Evolution of Intergenerational Mobility in Spain

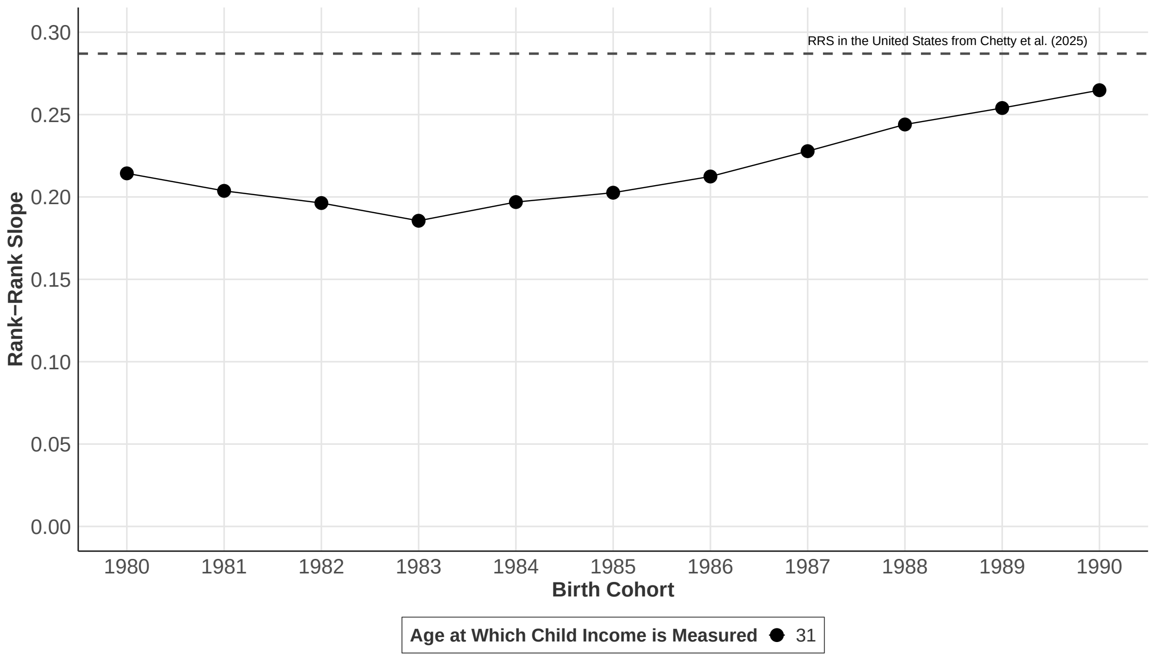
We examine how intergenerational mobility has evolved for the 1980–1990 birth cohorts by computing cohort-specific rank–rank slopes, with children's income consistently measured at age 31 (the oldest age our data window permits). As shown in Panel A of Figure 7, the slope declined a 13.1% from 0.214 for the 1980 cohort to 0.186 by 1983, before rising steadily to 0.265 for the 1990 cohort, an increase of 42.5% over the 1983 level. This U-shaped pattern indicates that intergenerational persistence weakened (hence, intergenerational mobility increased) for those born in the early 1980s but then intensified sharply for later cohorts. As a consequence, by the late 1980s, Spain's slope is approaching the U.S. benchmark of 0.287 (dashed line in Figure 7). Furthermore, as shown in Appendix Figure A16, this evolution of the rank-rank slope is both driven by the deterioration of upward mobility for children from low-income backgrounds (i.e. children from 25th percentile families) and the improvement of the prospects of high-income children (i.e. children from 75th percentile families).

Interestingly, this U-shaped pattern aligns almost perfectly with the years in which these cohorts first entered the labor market, around age 25, which for the 1982–1983 cohorts was right at the start of Spain's Great Recession (2008), as shown in Panel B of Figure 7. Before the crisis, rising wages and high employment levels in manufacturing, construction, and other non-college sectors, where many low-income workers find their first jobs (Bernardi and Gil-Hernández, 2021), directly boosted upward mobility, since improvements in those industries lifted children from low-income backgrounds. By contrast, cohorts that entered the labor market during the recession faced record high youth unemployment, which disrupted their early-career earnings and likely reduced their prospects of upward mobility[9]. This is because early-career labor-market conditions matter as they shape both the skills young workers develop and the employer matches they secure, two channels that have lasting effects on earnings and thus on intergenerational income mobility (Nybom and Stuhler, 2021). Using, Arellano-Bover (2022) shows that cohorts facing higher youth unemployment enroll in fewer training programs and experience skill *scarring*, with declines in both numeracy and literacy that persist into mid-career. Complementing this, Arellano-Bover (2024) uses Spanish administrative data to document that the size of the firm where a worker lands their first job has a causal impact on long-run earnings: entry at large, productive firms delivers superior on-the-job learning and wage growth compared to entry at smaller employers. During downturns these mechanisms combine to depress skill accumulation and trap workers in lower-paying career paths. In Spain, where the Great Recession hit youth unemployment above 50% and stunted firm-size hiring, these entry-timing effects may explain much of the observed decrease in intergenerational mobility among cohorts born after 1983. Yet, disentangling them from other structural factors remains challenging and therefore this descriptive analysis of trends in intergenerational mobility should be taken with caution (Nybom and Stuhler, 2024).

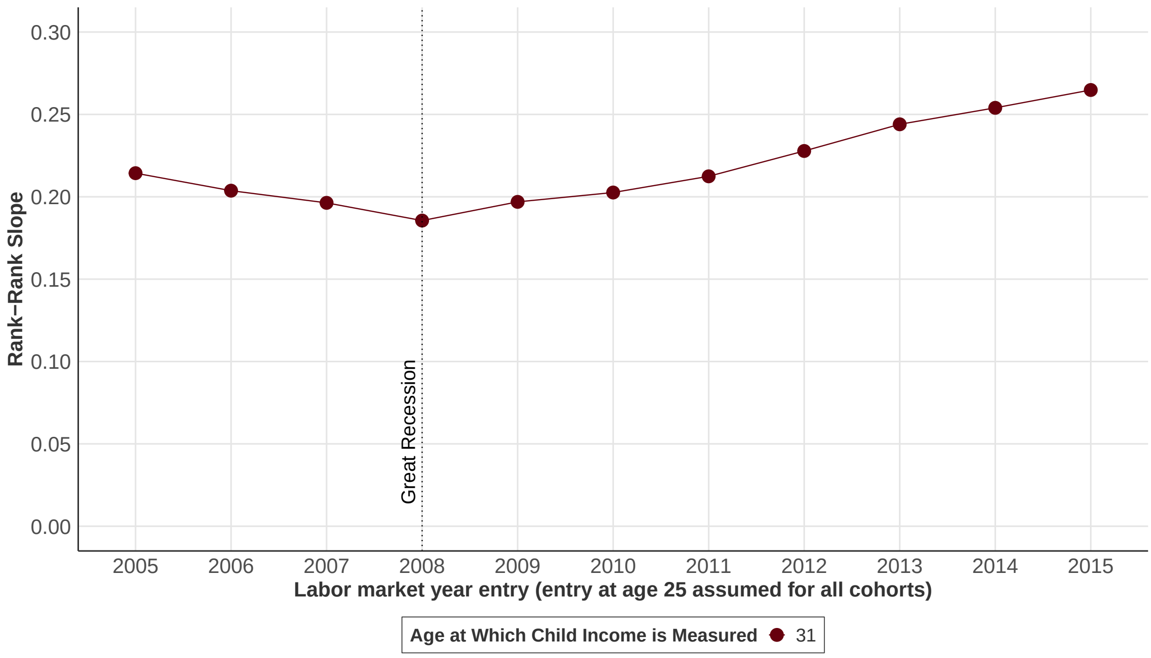
[9]See Appendix Figure A15 for a detailed evolution of the unemployment rate in Spain

Figure 7: Evolution of Intergenerational Mobility in Spain (1980-1990)

(a) Changes in the Rank–Rank Slope Across Birth Cohorts (1980–1990)



(b) Changes in the Rank–Rank Slope Across Birth Cohorts by Labor Market Entry Timing (1980–1990)



Notes: Figure 7 Panel A displays the rank–rank slope for birth cohorts 1980–1990, with child income measured at age 31. Panel B plots the rank–rank slope for individuals entering the labor market each year between 2006 and 2015 (child income measured some years later, at age 31), with the vertical dashed line marking the Great Recession onset in 2008. Both panels use the same OLS specification as our baseline: parental income is averaged over 1998–2000; child income is averaged over a two-year window around the measurement age.

4.4 Other Outcomes

We now turn to how parental income conditions children's outcomes other than income that can be measured in our tax records. Figure 8 documents how parental income rank predicts variation in: (a) social assistance program enrollment (specifically, Minimum Basic Income or IMV)[10], (b) scholarships [11], (c) disability benefits[12], and (d) maternity and paternity leave reception.

Panel (a) displays the distribution of recipients of the Minimal Basic Income (IMV) across parental income ventiles, revealing patterns relevant to intergenerational mobility. The IMV is a non-contributory social benefit in Spain designed to prevent poverty and social exclusion by guaranteeing a minimum level of income for vulnerable individuals and households. As depicted in the panel, approximately 4% of children in the lowest parental income ventile are IMV recipients, a figure that declines to less than 0.5% for children in the highest income ventile. This steep negative gradient underscores the program's role as a well-targeted means-tested transfer but also provides compelling empirical evidence of intergenerational social reproduction within our sample, highlighting that children originating from the most disadvantaged parental backgrounds are more likely to experience the persistent low-income situations targeted by the IMV in adulthood. This also serves as a validation that the classification and matching of parents and children in our data captures inter-generational dynamics, thereby increasing confidence in the robustness of our baseline sample. Lastly, a consistent pattern emerges within our sample, showing that women are more likely than men to be IMV recipients across all observed parental income levels.

Panel (b) illustrates the relationship between parental household income and the probability of a child receiving a scholarship, revealing significant gender differences. While there is an overall tendency for children from lower-income households to receive scholarships, consistent with the design of means-tested aid (though with a less steep gradient than for transfers like IMV), this pattern is strongly differentiated by gender. Specifically, scholarship receipt among women exhibits a clear and substantial negative correlation with parental income. In contrast, the probability of a man receiving an educational scholarship appears largely

[10] The *Ingreso Mínimo Vital* (IMV), introduced in Spain in June 2020, is a state non-contributory social benefit that covered around 284,000 recipients in 2022 (Autoridad Independiente de Responsabilidad Fiscal (AIReF), 2023). Its primary objective is to combat poverty and social exclusion by providing a safety net for individuals and households lacking sufficient economic resources. Eligibility and the specific benefit amount are determined based on a rigorous means test that considers household income, assets, and composition relative to established thresholds. The program is designed to ensure a minimum living standard and includes incentives to encourage labor market integration. The IMV is administered by the National Social Security Institute (INSS).

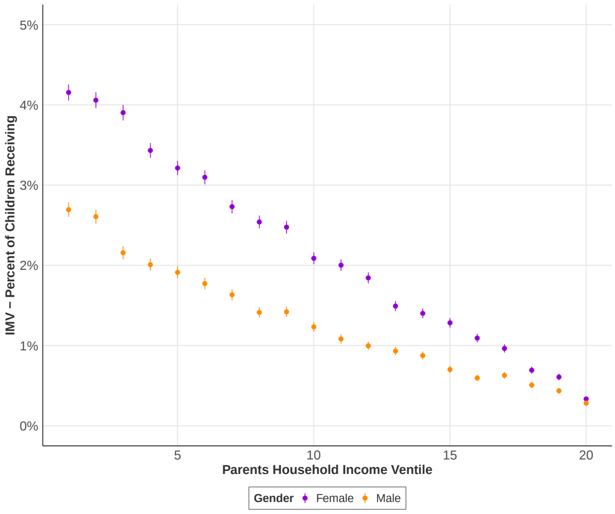
[11] This category covers all scholarships for both regulated studies and research activities, awarded by public bodies, certain non-profit entities, and banking foundations. Specifically, they include public scholarships and those granted by qualifying non-profit entities (Law 49/2002) and banking foundations (Law 26/2013) for regulated studies at all educational levels, domestically or internationally. Also included are public scholarships and those from said non-profit entities and banking foundations for research under RD 63/2006, as well as research scholarships awarded by these entities to public administration personnel and university teaching/research staff. Of these, the most popular is the scholarship awarded by the Ministry of Education (MEC). These refer to the system of means-tested scholarships and study grants provided by the Spanish Ministry of Education (*Ministerio de Educación, Formación Profesional y Deportes*) to support students in post-compulsory education (including university and vocational training) based on economic and academic criteria.

[12] This includes disability benefits recognized by the Social Security system (or its substitutes) for permanent absolute disability or great disability (*gran invalidez*). Similar benefits from mutual provident societies for professionals not covered by the standard self-employed Social Security scheme are also included. This is covered under Spanish income tax law (Ley 35/2006, Art. 7f).

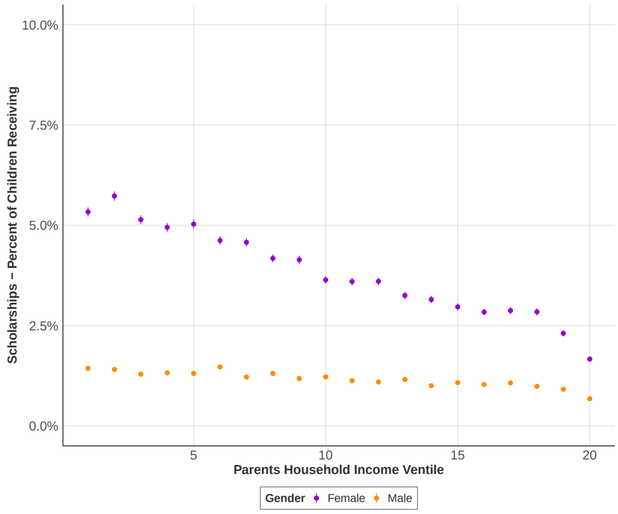
invariant to his parents' income level, presenting a notably flatter gradient across income ventiles. Potential explanations include differences in the academic criteria met by male and female students across the income distribution, as academic eligibility is a key component of many scholarships. Furthermore, compositional differences in the types of scholarships pursued and received are likely influential; if men are relatively more successful in securing merit-based scholarships, which are less sensitive to financial need than means-tested programs, this would inherently produce a flatter income-scholarship profile for males. Differential sorting into educational tracks or fields of study with varying scholarship structures could also contribute to this observed gender gap in income sensitivity.

A negative income gradient is also evident for disability benefits, as shown in Panel (c). Adult children from households in the bottom ventile of parental income are approximately twice as likely to receive disability benefits compared to their counterparts from the top ventile. Disparities in disability are multicausal and may be partly attributable to factors such as intergenerational differences in educational attainment and subsequent exposure to occupational hazards (Pérez-Hernández et al., 2019). Specifically, individuals from lower-income backgrounds may have a higher propensity to enter employment sectors characterized by greater physical risks, thereby increasing their likelihood of incurring permanent or severe disabilities. Finally, Panel (d) reveals a deviation from other benefit patterns: a positive income gradient for the reception of maternity and paternity leave benefits. This indicates that individuals from higher-income parental backgrounds are more likely to receive these benefits compared to those from the lowest parental income ventiles. One hypothesis for this finding relates to the influence of employment and financial stability on fertility decisions. It is plausible that households facing greater economic insecurity—a condition exacerbated by factors such as fixed-term contracts and unemployment—may defer childbearing or opt for smaller family sizes. This pattern of fertility being sensitive to financial instability is well-documented in Southern European contexts like Spain and has reportedly intensified over time, potentially explaining why the observed reception of parental leave is more concentrated among more economically secure, higher-income groups who are more likely to proceed with or expand their families (Barbieri et al., 2015; Alderotti et al., 2021).

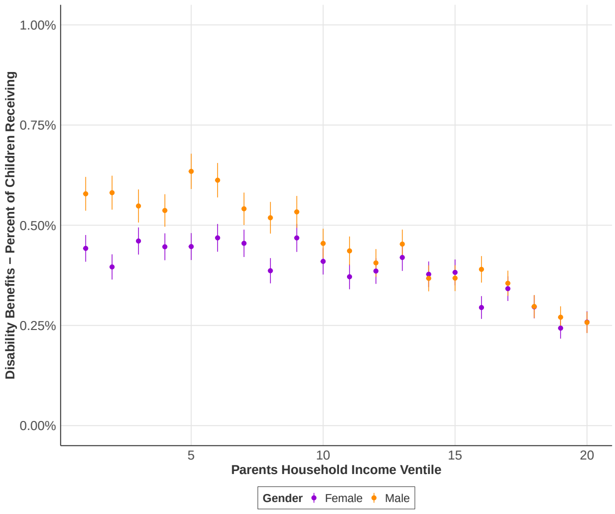
Figure 8: Long-Term Outcomes for Children by Parent Income Ventile



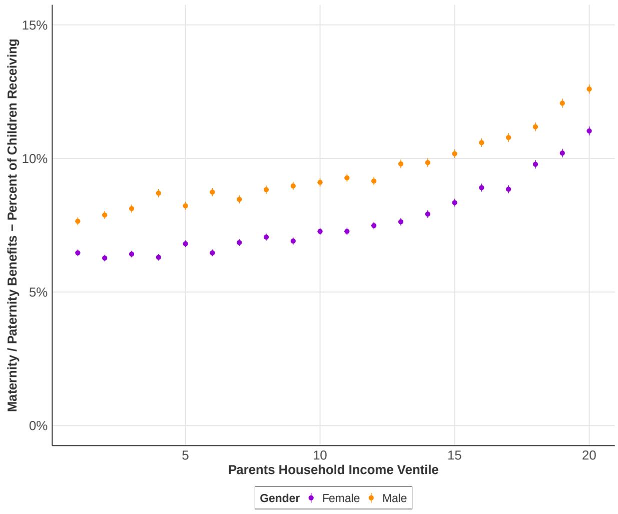
(a) Minimal Basic Income (IMV) Recipients by Gender (2022)



(b) Scholarship Recipients by Gender (2022)



(c) Disability Benefits by Gender (2022)



(d) Parental Leave by Gender (2022)

4.5 Robustness of National Results

Life-cycle bias A key concern in the estimation of intergenerational income mobility is life-cycle bias, which arises when child income is measured too early in adulthood. This bias stems from the fact that individuals with high lifetime incomes—particularly those pursuing higher education—tend to experience steeper earnings profiles in early adulthood. As a result, mobility estimates based on early-career income may understate the true influence of parental background (Haider and Solon, 2006; Solon, 2002; Böhlmark et al., 2006; Chetty et al., 2014a). In other words, child income ranks tend to stabilize only later in the life cycle, once individuals have completed their school-to-work transitions and income growth slows down.

This issue is particularly salient in countries like Spain, where long transitions from education to stable employment are common due to extended periods of study, internships, and delayed labor market entry (Salvà-Mut et al., 2016). As shown in Appendix Figure A17, the estimated rank–rank slope varies substantially in our data when child income is observed at younger ages. However, from age 36 onward, the slopes for all cohorts converge closely toward the baseline results value of 0.274 (dashed line), indicating that children's income have stabilized and parental rank dependence is consistently estimated. This is why, in order to minimize life-cycle bias, we focus on cohorts born 1980–1986, whose child income is measured between ages 36 and 42. Furthermore, Appendix Figure A18 shows that regardless of whether we measure child income over one, two, three, or four years and whether we include cohorts up to 1990 or restrict to 1980–1986 the estimated rank–rank slope remains centered around our baseline value of 0.274. Such consistency reinforces the validity of our baseline sample (cohorts 1980–1986, ages 36–42) and gives us confidence that our main results are not driven by life-cycle or cohort-selection biases.

Attenuation bias A second common concern in the measurement of intergenerational mobility is attenuation bias, which occurs when parental or child income is measured with error. As shown by Nybom et al. (2018); Böhlmark et al. (2006), relying on income from a single year introduces classical measurement error that can significantly attenuate the estimated relationship between parent and child income, particularly when estimating the rank-rank slope. This is because income in a single year may not be a reliable proxy for an individual's permanent or lifetime income. To measure how the length of the parental-income averaging window affects our estimate of persistence, we show the rank-rank slope estimate by the number of years used to compute mean parent income in Appendix Figure A19. When we use only one year of parental income, the rank–rank slope is 0.261. However, extending the window to three years raises the slope to 0.274 (a 5% increase), our baseline result, and further to six years increases it to 0.280 (an additional 2.2%). The modest additional rise from three to six years indicates that our three-year average captures nearly all of the permanent income signal without suffering from substantial attenuation bias, validating our baseline choice.

5 The Geography of Intergenerational Mobility in Spain

We now turn to examine the geographic landscape of intergenerational income mobility in Spain. To do so, we replicate the estimation of our key national-level intergenerational mobility measures – the Rank-Rank Slope (RRS) and Absolute Upward Mobility (μ_{25}) – for distinct geographic regions and municipalities. Following standard practice in the literature (Chetty et al., 2014b, 2020; G.C. Britto et al., 2022; Acciari et al., 2022; Kenedi and Sirugue, 2022), we link children to their geographic unit of origin using the ZIP code where they were first claimed by their parents in the 1998 tax returns. This measure captures the earliest observed location of residence during childhood based on administrative records, and serves as a proxy for the environment in which children spent their formative years. We then measure their outcomes between ages 36 and 42, following the baseline sample definition, regardless of where they reside as adults [13].

In practice, for each geographic unit g, we estimate the following linear model relating child rank (y_i) to parental rank (p_i):

$$y_i = \alpha_g + \beta_g p_i + \varepsilon_i$$

The resulting slope, β_g, provides a measure of relative mobility specific to area g. Absolute Upward Mobility in area g for those starting at the 25th percentile of the parental income distribution, $\mu_{25,g}$, is subsequently computed as:

$$\mu_{25,g} = \alpha_g + 25 \times \beta_g$$

The subsequent discussion outlines the methodological challenges inherent in estimating these parameters reliably at fine geographic scales and introduces our approach to overcome them.

5.1 Bayesian Hierarchical Estimation of Intergenerational Mobility at the Local Level

Estimating intergenerational income mobility rates at fine geographic units, such as municipalities or ZIP codes, presents a significant methodological challenge due to the typically sparse number of observations available for each local unit. The population in Spain, like many countries, is very unequally distributed, meaning there are numerous geographical units at the ZIP code and municipality levels with a small number of observations. Applying traditional estimation methods to these units often yields unreliable estimates,

[13] In robustness checks, we restrict the sample to children who did not change geographic areas between 1998 and 2005, ensuring they effectively spent their adolescence in the same place, and find that the geographic pattern of intergenerational mobility remains virtually unchanged.

including results that are statistically impossible (e.g., an Absolute Upward Mobility (AUM) rate higher than 100% or lower than 1%) or statistically implausible (e.g., a negative or completely flat Rank-Rank Slope (RRS) where a positive gradient is expected). A common approach to address this is to remove units with insufficient data; however, in the context of Spain, restricting analysis to cells with over 100 observations would mean losing 74% of our ZIP codes and 71% of municipalities.

More fundamentally, estimating parameters independently for each geographic unit discards valuable information by treating each area in isolation. Information about the general distribution or typical values of mobility measures (such as the rank-rank slope or absolute upward mobility), derived from data-rich areas, provides valuable context that could substantially improve estimates in data-sparse areas. By estimating parameters for each unit independently, traditional models fail to "borrow strength" across units. This inability to pool information constitutes a substantial loss for generating robust local-level estimates. As McElreath (2020) vividly describes, it leads to models that effectively suffer from amnesia, forgetting what they could learn from other units when estimating parameters for a new one.

To overcome this challenge, we introduce a novel methodology based on Bayesian hierarchical models (Gelman et al., 2020; Gelman and Hill, 2007; McElreath, 2020). Hierarchical models offer a powerful compromise between estimating parameters for each unit independently ("no pooling") and treating all units as a single homogenous group ("full pooling"). By assuming that the parameters for each local unit originate from a common distribution, these models induce a partial pooling of information across all units included in the model. In practice, this results in the "shrinking" of estimates for geographic units with limited data towards the overall mean or relationships observed across the larger group, while estimates for geographic units with sufficient data remain largely unchanged. Crucially, this approach provides a complete correction for otherwise implausible and impossible estimates encountered under sparse data conditions, allowing us to generate more reliable estimates even for units with limited data.

AUM and RRS: Using this hierarchical modeling approach, we estimate two key measures of intergenerational mobility at the local level (ZIP code and municipality): Absolute Upward Mobility (AUM) and the Rank-Rank Slope (RRS). Our first model, primarily used for municipality-level estimates, includes two different levels of hierarchy: provinces and municipalities. This allows the intercept (α) and slope (β) parameters to vary across both levels, enabling us to separate the variance driven by each hierarchy, captured by the standard deviation parameters τ_p, τ_m, τ_{b_p}, and τ_{b_m}. The basic structure of this model, where y_i represents the child's rank for individual i and y_p is the parental rank, is defined as follows:

$$y_i \sim Normal(\mu_i, \sigma) \tag{4}$$

$$\mu_i = \alpha + \alpha_p + \alpha_m + (\beta + \beta_p + \beta_m) \cdot y_p \tag{5}$$

$$\alpha_p \sim Normal(0, \tau_p), \tag{6}$$

$$\alpha_m \sim Normal(0, \tau_m) \tag{7}$$

$$\beta_p \sim Normal(0, \tau_{b_p}), \tag{8}$$

$$\beta_m \sim Normal(0, \tau_{b_m}) \tag{9}$$

Here, α and β represent the overall intercept and slope across all units, while $\alpha_p, \alpha_m, \beta_p, \beta_m$ are the deviations for province and municipality respectively, and σ is the residual standard deviation. An analogous second model for ZIP code level estimates, including province and ZIP code hierarchies, is presented in Appendix A.3. While incorporating additional hierarchical levels (e.g., autonomous communities) is theoretically possible, we opt not to do so in this study primarily because several autonomous communities in Spain perfectly overlap with existing provinces, preventing proper identification of effects at these separate levels.

Rags to Riches: We apply similar hierarchical modeling principles to estimate the "rags-to-riches" probability, specifically focusing on the likelihood of upward mobility from the bottom parental income quintile to the top child income quintile at the local level. In past work, quintile-to-quintile transition matrices were often calculated empirically. However, the presence of sparse data cells significantly limited these estimates to only large regions or highly aggregated geographical units. To estimate local rags-to-riches probabilities, we implement a hierarchical ordered logistic model. This model includes province-varying cutpoints ($c_{p_i,k}$) and incorporates monotonic effects of parental income quintile (x_i), allowing us to model the full quintile-to-quintile transition matrix. The discrimination parameter is also allowed to vary by province and parental quintile. For an observation i belonging to province p_i with parental income quintile x_i and ordinal outcome y_i (child quintile $1, \ldots, K$), the basic cumulative probability defined by the ordered logistic model is given by:

$$P(y_i \leq k | x_i, p_i) = \text{logit}^{-1}(c_{p_i,k} - \eta_i)$$

where η_i is the latent linear predictor for observation i. Again, the full specification of this hierarchical ordered logistic model is laid out in Appendix A.3.

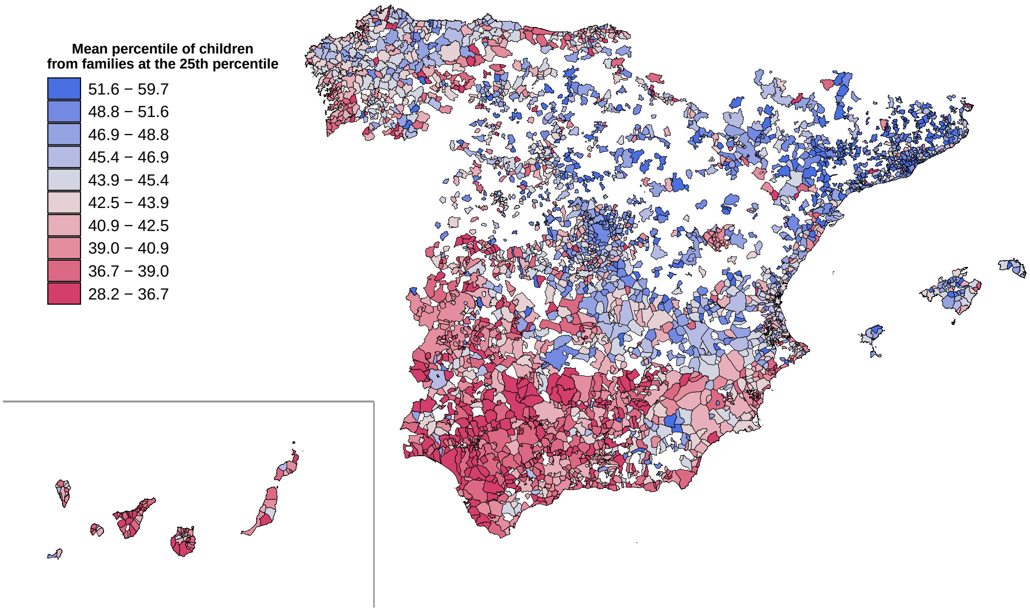
Improving Causal Design Estimation: Finally, we also leverage these same techniques to improve the estimation of causal effects using a movers' design, which presents similar challenges related to sparse data. Specifically, non-parametric estimation of expected outcomes for permanent residents by geography and cohort often suffers from insufficient sample sizes. In the context of Spain, applying purely non-parametric approaches leads to extremely noisy estimates and a dramatic reduction in the usable sample, as a purely non-parametric design would discard municipalities or cohorts lacking sufficient permanent resident observations in a given year. Instead, we model the expected outcomes for permanent residents at the municipality level using a hierarchical approach. This model is similar in structure to the hierarchical model used for estimating mobility rates across all children (discussed above). A key difference is that, following the canonical (Chetty and Hendren, 2018b) design, we introduce varying intercepts and slopes for children's cohorts and observation years. This allows the model to capture systematic differences and temporal shocks that may affect outcomes independently of geography, thereby enhancing the robustness of our causal effect estimates. A detailed explanation of the model and process is laid out in Appendix A.3.

5.2 Geographic Variation in Mobility Rates

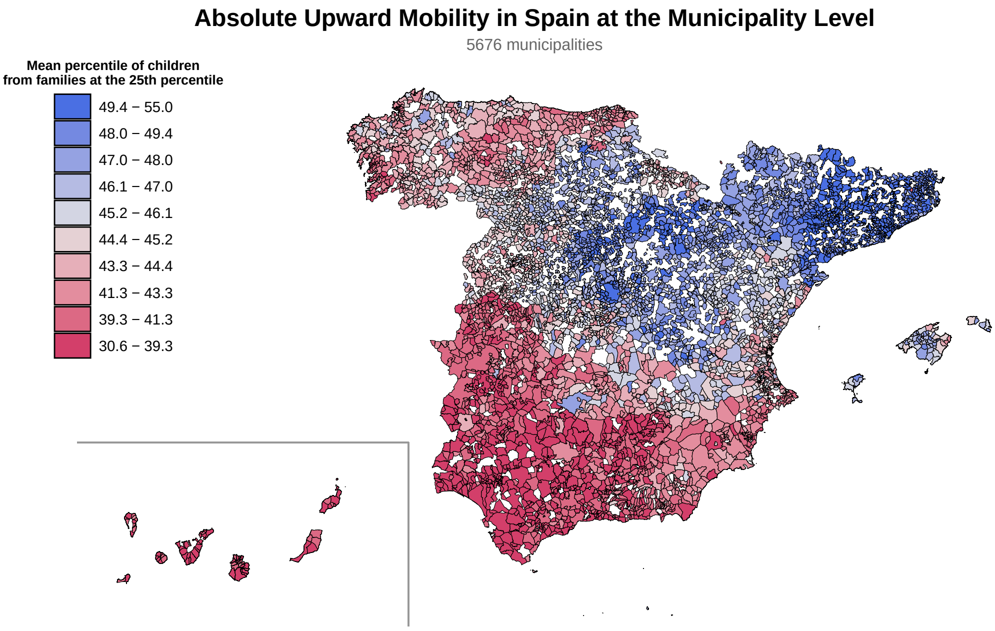
Figure 9 shows the expected income rank of children growing up in families at the 25th percentile of the national parental income distribution, mapped by their municipality of origin as defined in the previous subsection. Panel A presents direct estimates, while Panel B displays the estimates derived from our Bayesian hierarchical model.

Figure 9: Geographic Variation in Mean Child Income Rank at the 25th Percentile of Parent Income Rank

(a) Mean Child Income Rank at the 25th Percentile of Parent Income Rank (Direct Estimates)



(b) Mean Child Income Rank at the 25th Percentile of Parent Income Rank (Bayesian Hierarchical Model)



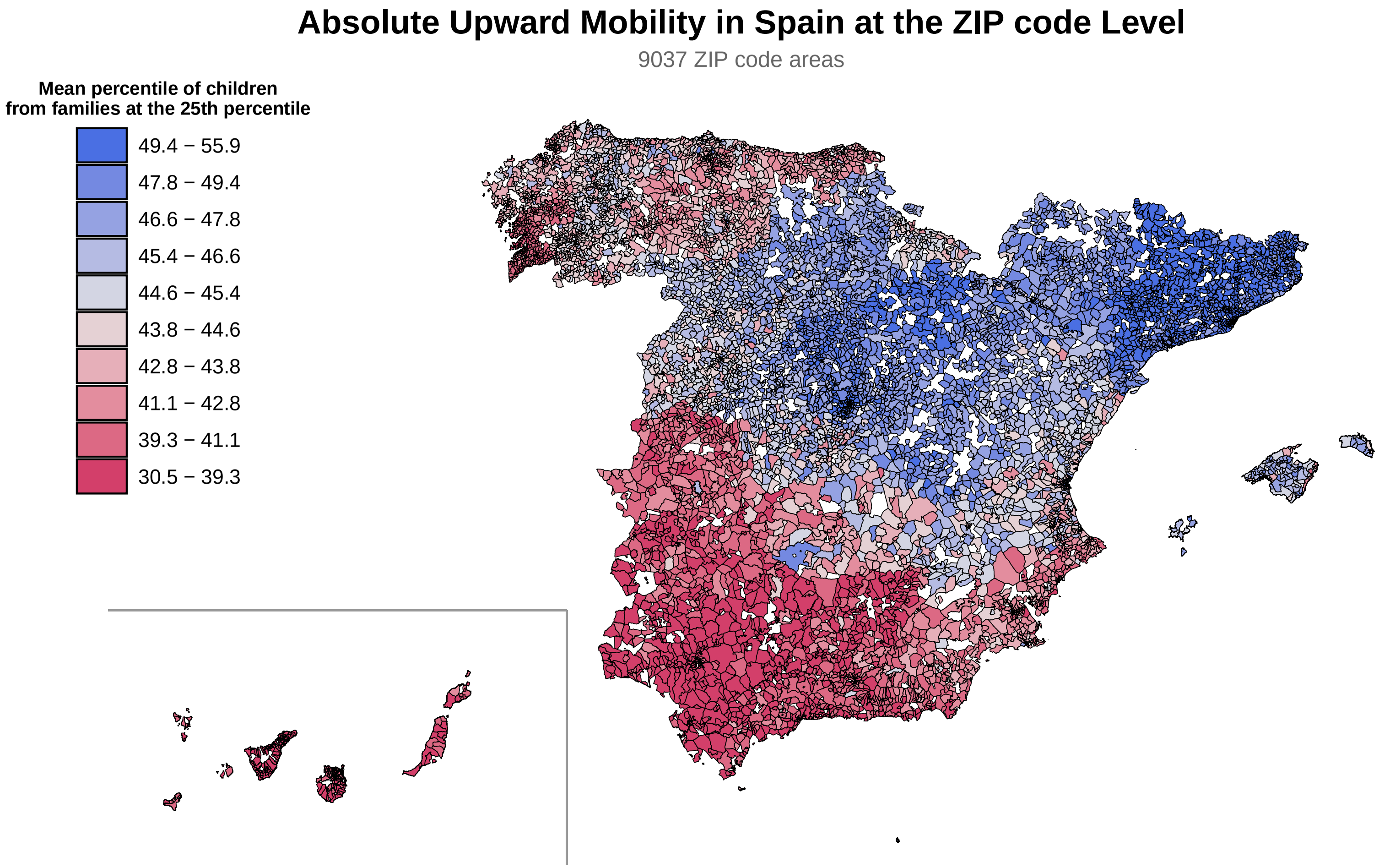
Notes: This figure illustrates the geographic variation in intergenerational income mobility across municipalities in Spain. Both panels show the estimated mean child income rank for children from families at the 25th percentile of the parental income rank distribution. Panel (a) presents estimates derived using a direct local estimation approach, which results in significant noise and patchiness, particularly visible in areas with sparse data. Panel (b) presents estimates derived from our Bayesian hierarchical model. By partially pooling information across geographic units, the hierarchical model produces smoother and more reliable estimates, providing a clearer representation of underlying regional mobility patterns at the municipal level. The color scales in both panels represent the mean child income percentile.

Comparing Panel (a) and Panel (b) of Figure 9 highlights the changes introduced by our Bayesian hierarchical modeling approach. Panel (a), based on traditional estimation methods, displays a highly fragmented and noisy spatial pattern, particularly noticeable in areas with lower population density. This pattern, characterized by abrupt color shifts and scattered extreme values, is a direct consequence of sparse data leading to unreliable estimates for many individual municipalities, as discussed in our methodology. In contrast, Panel (b) demonstrates a much smoother and spatially more coherent representation of mobility rates. The Bayesian hierarchical model achieves this by effectively borrowing strength across different geographic units, partially pooling information from municipalities and provinces to produce more stable estimates, especially for areas with limited data. This process mitigates the influence of random noise and corrects otherwise implausible estimates, providing a more robust and interpretable map of mobility across all municipalities. To further illustrate this, Figure 10 zooms in to show the Bayesian estimates at the most granular geographic level available, ZIP codes, and reveals that the same spatial patterns of upward mobility persist at this finer scale[14].

The advantages of this hierarchical modeling extend beyond mapping average mobility levels like μ_{25}. Figure 11 further illustrates the enhanced precision when estimating other important mobility measures, such as the 'rags-to-riches' probability—the likelihood of a child from the bottom parental income quintile reaching the top child income quintile (P(Q5|Q1)). The figure shows estimates from our Bayesian hierarchical ordered logistic model (blue markers) against non-parametric estimates (black markers) for various Spanish localities. For many areas, particularly those with smaller effective sample sizes for such quintile-to-quintile transitions, the non-parametric estimates exhibit wide confidence intervals, reflecting considerable uncertainty. Our Bayesian hierarchical and semi-parametric approach, by systematically incorporating information across units and smoothing estimates based on the overall data structure, yields more precise estimates, as indicated by the generally narrower confidence intervals around the blue markers.

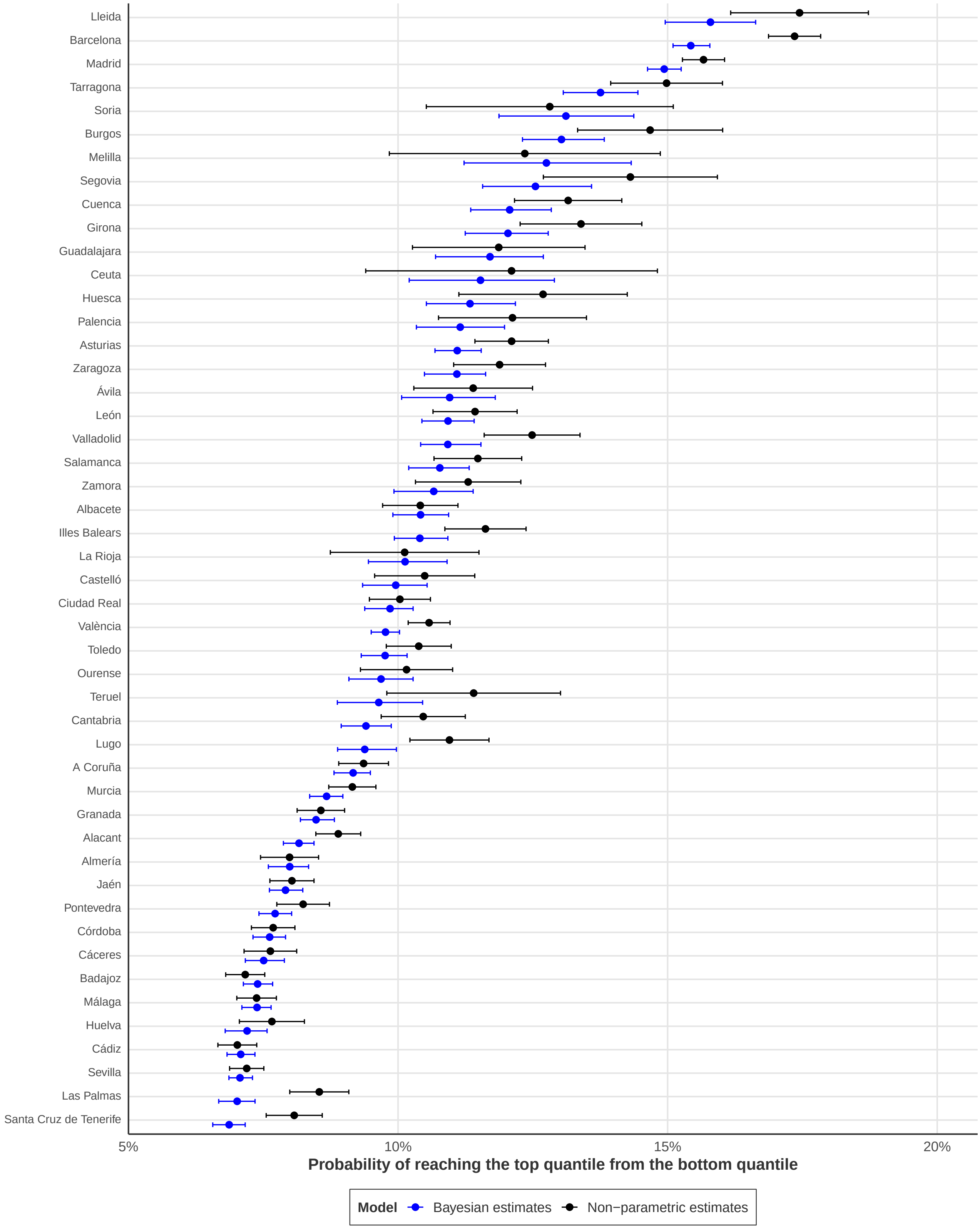
[14] Outside of urban areas, the vast majority of municipalities in Spain correspond to a single ZIP code, meaning that ZIP-level and municipality-level estimates are often identical in rural areas.

Figure 10: Geographic Variation in Expected Child Rank at the ZIP Code Level



Notes: This map illustrates the geographic variation in expected child income across ZIP codes in Spain. The color gradient represents the estimated mean expected income for children residing in each ZIP code. These estimates provide insight into the spatial distribution of economic outcomes for children at a fine geographic resolution.

Figure 11: Comparison of Bayesian Hierarchical and Non-Parametric Estimates of Rags-to-Riches Mobility ($P(Q_5|Q_1)$) Across Provinces



Notes: This figure compares two estimation methods for rags-to-riches mobility—the probability of a child reaching the top income quintile given their parents were in the bottom income quintile ($P(Q_5|Q_1)$)—across Spanish provinces (listed on the y-axis). Blue points represent estimates from our Bayesian hierarchical ordered logistic model, while black points show traditional non-parametric estimates. Horizontal lines indicate 95% confidence intervals. The Bayesian hierarchical model provides more stable and precise estimates, particularly for areas with smaller sample sizes, by borrowing strength across units and mitigating the noise inherent in purely non-parametric approaches.

5.2.1 Main Patterns

As shown in previous figures, this granular analysis reveals substantial geographic variation in absolute upward mobility (AUM, μ_{25}) across Spain, with a primary pattern being a stark North-East to South-West divide. Areas exhibiting the highest levels of AUM are concentrated in the North-East—including Catalonia, parts of Aragon, the Madrid metropolitan area, and surrounding provinces like Segovia, Soria, and Guadalajara. Conversely, the lowest AUM levels are predominantly found in the South-West, particularly in Andalucía, Extremadura, and the Canary Islands. The estimated difference in expected AUM between the highest and lowest-ranked municipalities exceeds 25 percentile points. This geographic cleavage in opportunity persists when examining mobility patterns at the urban area levels (Appendix Figure A11), the province (Appendix Figure A12) and autonomous community (Appendix Figure A13)[15].

The origins of these regional inequalities date back centuries and still cast a long shadow on these observed disparities in economic opportunity. Oto-Peralías and Romero-Ávila (2016) points to the long-term consequences of the Reconquest—a medieval process of territorial expansion by Christian kingdoms into Muslim-held lands—as one of the major determinants of Spain's current regional disparities in different socioeconomic outcomes. In particular, the speed and institutional organization of this frontier expansion contributed to enduring patterns of inequality. In regions where the Reconquest progressed rapidly, economic and political power was concentrated in the hands of a narrow elite, excluding large segments of the population from access to land and economic opportunity. These regions later entered the industrial era with weaker social capital and lower levels of human development. Moreover, the military insecurity of frontier zones during the colonization of central Spain conditioned the way territories were settled, leading to sparse population densities and uneven spatial distribution that persist to this day (Oto-Peralías, 2020). Over time, such structural legacies have contributed to an economic geography marked by dualism, with spatial polarization reinforcing historical divides between a wealthier, more urbanized north-east and a poorer, more rural south-west (Tirado et al., 2016; Santiago-Caballero, 2011).

Beyond this dominant regional split, our results also highlight the distinct role of urban centers as relative hotspots of mobility, which represents one of the main differences between the geographic analysis Spain and the United States wehre the largest cities are not typically pockets of opportunity (Chetty et al., 2014a; Chetty and Hendren, 2018b). Major metropolitan areas like Madrid and Barcelona clearly stand out on the maps as large clusters of higher upward mobility when compared to their surrounding rural and less populated areas. This suggests a potential urban advantage in providing opportunities for upward mobility for disadvantaged children.

[15]In this paper, 'urban areas' refer to the Functional Urban Areas (Áreas Urbanas Funcionales, AUF) as defined by the Spanish Ministry of Transport, Mobility and Urban Agenda (MITMA). The detailed methodology for the development of urban areas is available in Appendix A.5.

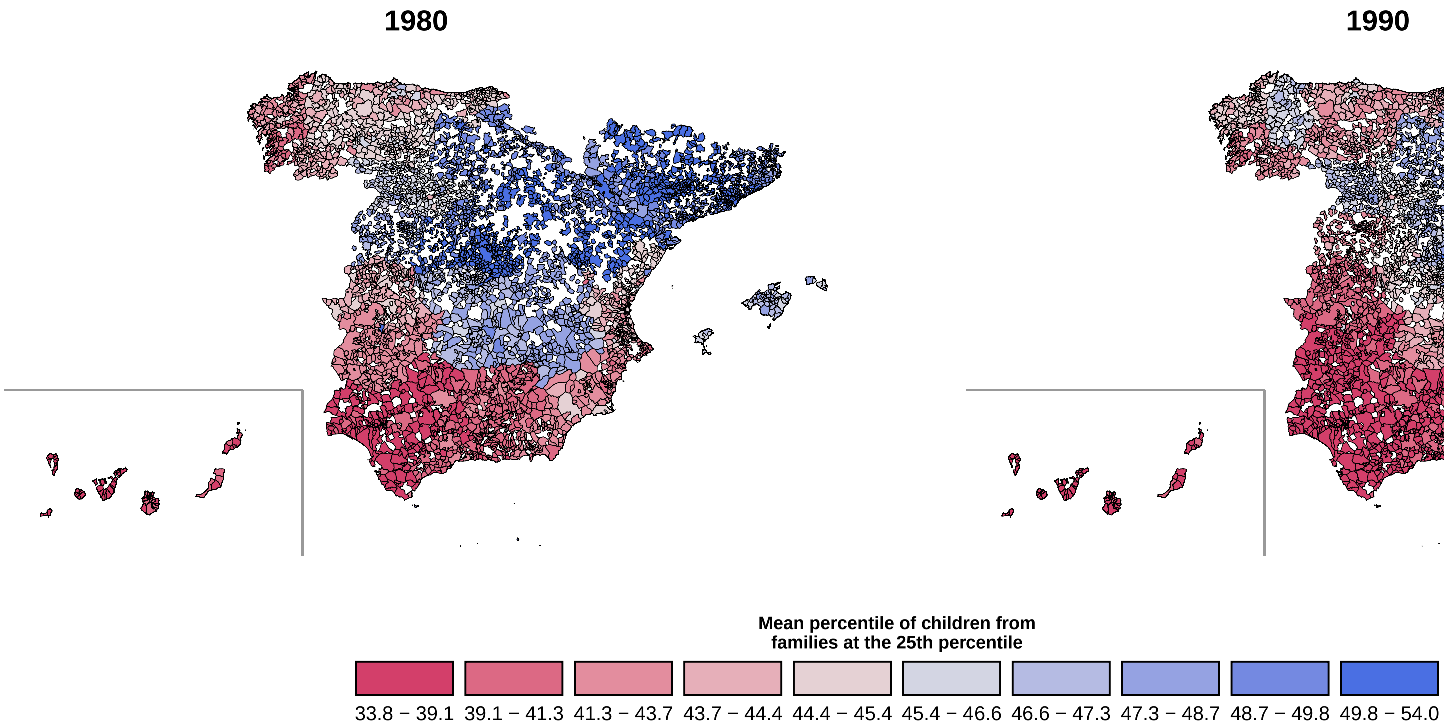
While AUM captures average outcomes for children from the 25th percentile, rags-to-riches probabilities focus on the chances of achieving a more substantial leap up the income ladder. The geographic patterns for P(Q5|Q1) shown on Figure 11 largely echo those observed for AUM. Areas such as Madrid and several Catalan provinces consistently rank among those offering higher probabilities of such long-distance upward mobility, whereas provinces in Andalucía and the Canary Islands tend to exhibit lower chances. Overall, children born in families in the poorest income quintile in Barcelona and Lleida are over three times more likely to reach the top income quintile than children born in similar households in Tenerife or Sevilla.

5.2.2 The evolution of upward mobility across municipalities

How have children's absolute mobility prospects evolved over time depending on where they grew up? Figure 12 explores this question by showing the evolution of absolute upward mobility (AUM) at the municipality level between the 1980 and 1990 birth cohorts. A visual comparison of Panel (a), representing the 1980 cohort, and Panel (b), representing the 1990 cohort, reveals a widespread deterioration in mobility prospects across many parts of Spain. The prevalence of areas with lower AUM (indicated by reddish hues) appears to intensify and expand in the map for the 1990 cohort. While some traditional high-mobility zones in the North-East and around major urban centers retain comparatively better outcomes, many of these also exhibit a visible reduction in the extent or intensity of high AUM levels (blue hues) compared to the earlier cohort.

The national downturn in AUM between the 1980 and 1990 cohorts, evident in Figure 12, is not completely uniform. Figure A14 presents the evolution of AUM for the 50 largest municipalities, revealing a general but heterogeneous decrease in AUM. For instance, many municipalities in Catalonia, including Terrassa, Barcelona, and L'Hospitalet de Llobregat, demonstrate relative resilience, maintaining comparatively high levels of upward mobility for the 1990 cohort. In contrast, the Community of Madrid and several of its major cities (e.g., Móstoles, or Getafe) exhibit a more substantial decline in AUM from the 1980 to the 1990 cohort, leading to a re-shuffling where some Catalan municipalities emerge as national leaders in AUM for the more recent cohort. Interestingly, pockets of stability or even improvement are observable in certain areas; some municipalities in Galicia and the Valencian Community, for example, managed to sustain or enhance their AUM levels against the broader national trend. Similarly, areas within Castilla y León did not experience declines as sharply as those seen in some other regions.

Figure 12: Evolution of Absolute Upward Mobility (μ_{25}) at the Municipality Level by Child Birth Cohort



Notes: This figure displays the geographic variation in Absolute Upward Mobility (μ_{25}) at the municipality level for child birth cohorts born in 1980 and 1990. μ_{25} represents the mean income percentile in adulthood for children whose parents were at the 25th percentile of the national parental income distribution. Panel (a) shows μ_{25} for children born in 1980, and Panel (b) shows μ_{25} for children born in 1990. Both maps use the same color scale, where darker shades of blue indicate higher upward mobility and darker shades of red indicate lower upward mobility. These estimates are derived using our Bayesian hierarchical model.

5.3 Correlates of Intergenerational Mobility

In this section, we examine which local characteristics are most strongly associated with upward mobility in Spain. To do so, we compile detailed information of the socioeconomic characteristics of municipalities from multiple Spanish administrative sources, with a particular focus on the 2001 Census from the *Instituto Nacional de Estadística* (INE) and the *Atlas Digital de las Áreas Urbanas* published by *Ministerio de Vivienda y Agenda Urbana*. These datasets provide rich and spatially granular indicators of demographics, educational attainment, labor market conditions, housing, family structure, and urban infrastructure which are used to characterize the environments in which children grow up (See detailed list in Appendix A.5)

5.3.1 Municipality level

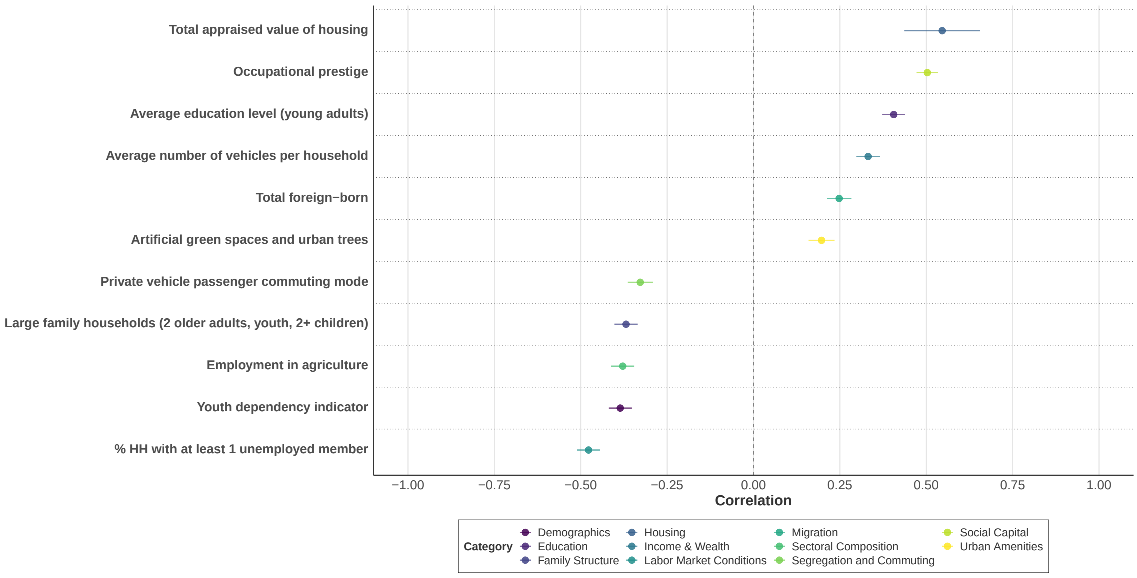
We start our analysis by estimating a series of univariate correlations between a comprehensive set of municipal-level covariates and our measure of absolute upward mobility (i.e., the mean child income percentile of children from families at the 25th percentile). We show the top correlates per category in Figure 13[16]. To facilitate interpretation and comparative analysis, all variables are standardized to have a mean of zero and a standard deviation of one prior to estimation. To ensure data quality and robustness, we restrict the sample to municipalities with at least 20 observed children and apply non-parametric filtering to exclude outliers. After this cleaning process, the final OLS sample comprises 3,075 municipalities (see Appendix A.7 for methodological and data cleaning details).

The univariate correlations presented in Figure 13 reveal a consistent profile for high-mobility municipalities in Spain. Areas offering children greater opportunities for upward mobility tend to be characterized by higher real estate values, a more educated and professionally prestigious adult population, and superior spatial accessibility, often proxied by indicators such as higher train usage and the availability of green spaces. These attributes are frequently hallmarks of thriving urban cores and suggest that such environments benefit from, and contribute to, better infrastructure, public services, and social milieus that reinforce educational achievement and economic aspiration.

This concentration of opportunity in urban centers appears to be a salient feature of the Spanish mobility landscape, distinguishing it from the experience in the United States, where the largest cities are not always the primary engines of upward mobility for disadvantaged children (Chetty et al., 2014a; Chetty and Hendren, 2018b). Our findings resonate with the work of De La Roca et al. (2023), who show that larger Spanish cities not only offer an immediate static earnings premium but also facilitate the accumulation of more valuable work experience that yields persistent benefits, even for individuals who later move to smaller localities. Such 'learning by working' dynamics, alongside access to diverse educational institutions and denser social

[16] See Appendix Figure A22 for the top three correlates per category analysis

Figure 13: Main Correlates by Category of Intergenerational Mobility at the Municipality Level in Spain



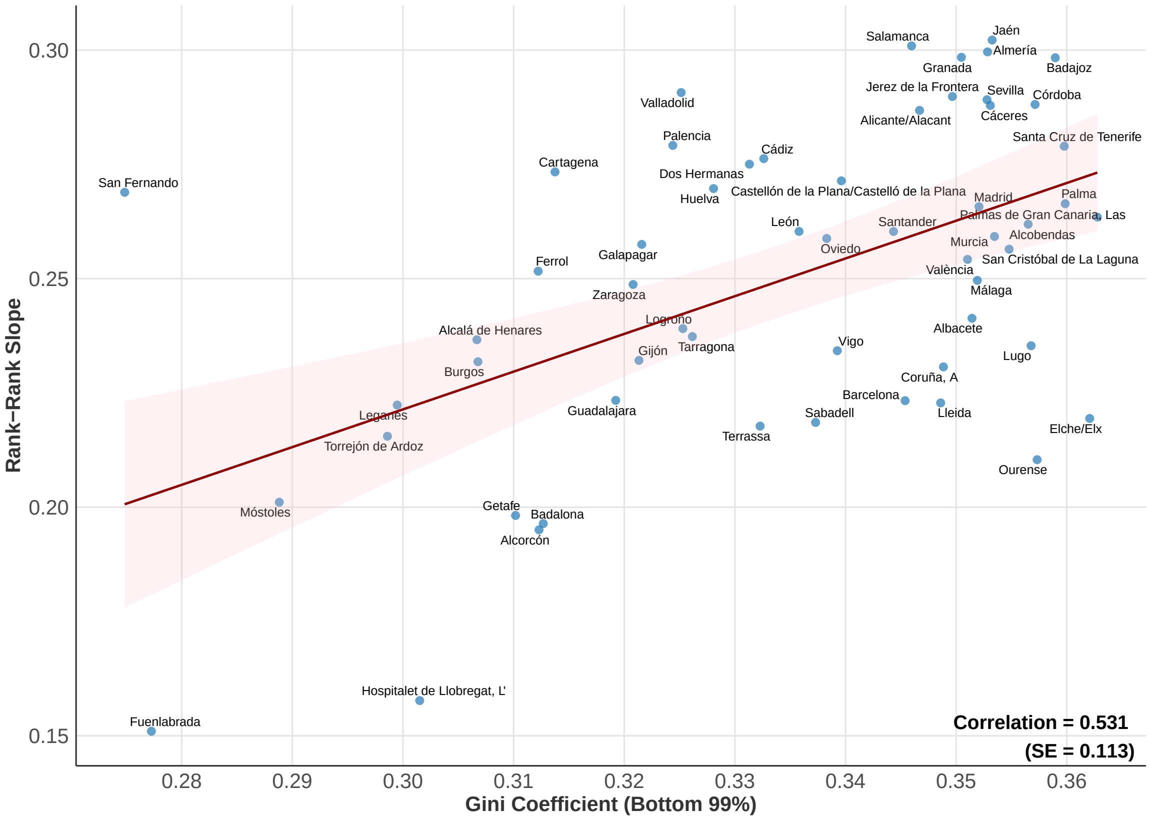
Notes: This figure presents the estimated associations between selected socioeconomic indicators and Absolute Upward Mobility (AUM) at the municipality level. Each dot represents the coefficient from a univariate linear regression where the dependent variable is AUM and the independent variable is one standardized correlate (mean zero, standard deviation one). Horizontal lines denote 95% confidence intervals. Variables are grouped into eight thematic categories, shown by color: Demographics, Education, Housing, Income & Wealth, Migration, Sectoral Composition, Social Capital, and Urban Amenities. The figure displays the most predictive correlate from each group, based on the strength of association with upward mobility.

networks typical of urban areas, may underpin the role of Spanish cities as relative hotspots for intergenerational advancement.

Conversely, Figure 13 also shows that upward mobility is significantly lower in municipalities marked by economic precarity and social strain. High local unemployment rates, a greater prevalence of resource-stretched households (e.g., those with many dependents), and lower average adult educational attainment are all strongly associated with diminished prospects for children. Furthermore, demographic pressures, such as a high youth dependency ratio, and car-reliant spatial layouts also correlate negatively with mobility, potentially reflecting challenges related to public investment, service provision, or social fragmentation in these areas.

Beyond this set of top correlates, we analyze in more detail the relationship between income inequality and intergenerational mobility, the so-called “Great Gatsby Curve”, across Spanish municipalities. This curve captures the empirical regularity, observed across countries, that societies with higher income inequality tend to exhibit lower intergenerational mobility (Corak, 2013). In Figure 14, we correlate municipality-level Gini index with the rank-rank slope across the largest cities in Spain. We do so because in the Spanish context the positive relationship between income inequality and intergenerational persistence emerges clearly only in the largest municipalities due to a combination of statistical and structural factors that are more marked in the Spanish context, as shown in Appendix Figure A20. First, inequality measures in small towns are often noisy and unreliable, making it difficult to detect consistent patterns. Second, large cities are more socioeconomically segregated, meaning that measured inequality more accurately reflects real differences in neighborhood environments, access to opportunity, and public services that can shape children's long-run outcomes. Finally, the correlation is strongest when using the Gini coefficient restricted to the bottom 99% of the income distribution, which better captures the economic conditions that most families experience and avoids distortions caused by the extreme top end of the income scale. Taking together together, we observe that the places that best promote the economic opportunities of low-income children combine strong labor markets, affordable housing, low levels of income inequality and socially and physically integrated environments. These general patterns hold when we use the expanded municipality-level Bayesian estimates of absolute upward mobility (see Appendix Figure A21).

Figure 14: The Great Gatsby Curve Across Major Cities in Spain



Notes: This figure plots the relationship between income inequality and intergenerational income persistence across Spain's 50 largest municipalities. Each point represents a city, with the horizontal axis measuring the Gini coefficient (restricted to the bottom 99% of the income distribution) and the vertical axis measuring the OLS-based rank-rank slope, a standard metric of intergenerational persistence. The fitted line represents the linear regression line, with a shaded area denoting the 95% confidence interval. The estimated correlation is 0.531 (standard error = 0.113), confirming the existence of a strong "Great Gatsby Curve" at the urban level in Spain: cities with greater inequality also exhibit significantly lower intergenerational mobility.

While the previous univariate regressions offer valuable insight into how individual characteristics correlate with upward mobility, a key limitation is that many of these variables are highly correlated with one another. To address this issue, we implement a dimensionality reduction strategy. Specifically, we apply Principal Component Analysis (PCA) *within* each thematic category of variables. This allows us to summarize the underlying variation in each group through a small number of orthogonal components, capturing the dominant patterns in the data while reducing noise and multicollinearity. The following Table 1 presents the results of this analysis. Our principal component analysis uncovers eight distinct dimensions of local socioeconomic structure that explain substantial variation in upward mobility across Spanish municipalities.

Among these, the component of Strong Labor Market stands out as the most robust and consistent predictor of higher mobility, capturing local unemployment levels and labor force participation. Its explanatory power persists even after accounting for province and regional fixed effects, highlighting the role of employment stability and labor demand in shaping upward mobility in Spain, a pattern consistent with the relevance of unemployment dynamics highlighted in Section 4. Occupational Prestige, which reflects the socioeconomic status of the resident population, also correlates positively with mobility, although much of its influence appears to operate across rather than within regions. Additional negative predictors include Manual Jobs Concentration and Low-Density Housing Structures, both of which are associated with weaker mobility outcomes, likely due to occupational stagnation and reduced infrastructure spillovers. Other components, including Early Educational Participation, Peripheral Mobility and Spatial Isolation, and Youth Dependency and Nativity, reveal more nuanced patterns. Early education is weakly predictive of mobility and loses significance once broader geographic controls are introduced, suggesting selection effects or policy uniformity across space. Spatial isolation, as captured by car reliance and commuting patterns, consistently correlates with lower mobility—pointing to the importance of physical accessibility to jobs and services. Interestingly, Income and Wealth, while intuitively important, has limited independent explanatory power, suggesting that absolute resource levels are less critical than how those resources translate into opportunities (Chetty et al., 2014a).

Overall, these findings suggest that upward mobility is shaped by the spatial organization of opportunity, with labor market strength, occupational structure, and geographic connectivity playing particularly important roles. Many of these attributes are concentrated in, and defining features of, dynamic urban centers, which our findings identify as relative 'hotspots' of mobility—a pattern that aligns with evidence on the enhanced human capital accumulation. The substantial increase in explanatory power when introducing province and regional fixed effects further underscores the salience of spatially rooted inequalities: much of the variation in intergenerational mobility across municipalities reflects broader structural differences between regions. This pattern highlights the deeply territorial nature of opportunity in Spain, where institutional, economic, and social factors clustered at the regional level strongly condition children's long-run prospects for upward mobility.

Table 1: Conditional Correlates of Absolute Upward Mobility at the Municipality Level

	Dependent variable:										
	Absolute Upward Mobility (AUM)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Strong Labor Market	0.473***	0.240***	0.241***	0.216***	0.217***	0.213***	0.221***	0.205***	0.205***	0.116***	0.073***
	(0.016)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)
Occupational Prestige		0.338***	0.334***	0.304***	0.300***	0.283***	0.237***	0.241***	0.241***	0.092***	0.081**
		(0.021)	(0.021)	(0.021)	(0.021)	(0.024)	(0.030)	(0.029)	(0.029)	(0.031)	(0.032)
Low-Density and Dispersed Housing Structure			−0.079***	−0.069***	−0.063***	−0.061***	−0.061***	−0.059***	−0.059***	−0.038***	−0.031**
			(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)
Manual Jobs Concentration				−0.126***	−0.119***	−0.120***	−0.124***	−0.091***	−0.091***	−0.037**	−0.050***
				(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)
Early Educational Participation					0.047***	0.048***	0.049***	0.039**	0.039**	−0.025*	−0.022
					(0.016)	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)
Youth Dependency and Nativity						−0.030	−0.023	−0.014	−0.014	0.028	0.027
						(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Income and Wealth							0.059***	0.034	0.034	−0.022	−0.027
							(0.023)	(0.023)	(0.023)	(0.023)	(0.024)
Peripheral Mobility and Spatial Isolation								−0.139***	−0.139***	−0.047***	−0.041**
								(0.017)	(0.017)	(0.016)	(0.017)
Constant	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.685***	0.253**
	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.044)	(0.107)
CCAA FE	No	No	No	No	No	No	No	No	No	No	Yes
Prov FE	No	No	No	No	No	No	No	No	No	Yes	No
Observations	3,067	3,067	3,067	3,067	3,067	3,067	3,067	3,067	3,067	3,067	3,067
R^2	0.223	0.283	0.290	0.303	0.305	0.306	0.307	0.323	0.323	0.431	0.473
Adjusted R^2	0.223	0.283	0.289	0.302	0.304	0.304	0.306	0.321	0.321	0.427	0.464
Residual Std. Error	0.881 (df = 3065)	0.847 (df = 3064)	0.843 (df = 3063)	0.835 (df = 3062)	0.834 (df = 3061)	0.834 (df = 3060)	0.833 (df = 3059)	0.824 (df = 3058)	0.824 (df = 3058)	0.757 (df = 3044)	0.732 (df = 3013)
F Statistic	881.522*** (df = 1; 3065)	606.117*** (df = 2; 3064)	416.305*** (df = 3; 3063)	332.697*** (df = 4; 3062)	268.671*** (df = 5; 3061)	224.391*** (df = 6; 3060)	193.703*** (df = 7; 3059)	182.118*** (df = 8; 3058)	182.118*** (df = 8; 3058)	105.005*** (df = 22; 3044)	51.045*** (df = 53; 3013)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: This table presents the results of sequential multivariate regressions of Absolute Upward Mobility (AUM) on eight principal components summarizing thematic groups of correlates. “Strong Labor Market” loads on variables such as low unemployment rates and high labor force participation. “Occupational Prestige” captures the average socioeconomic and educational status of the adult population. “Low-Density and Dispersed Housing Structure” reflects the prevalence of detached housing, individual home ownership, and lower building density. “Manual Jobs Concentration” includes high shares of blue-collar or industrial employment. “Early Educational Participation” aggregates indicators of preschool and early childhood enrollment. “Youth Dependency and Nativity” summarizes the share of young dependents and native-born population in a municipality. “Income and Wealth” includes measures of median income and property values. “Peripheral Mobility and Spatial Isolation” captures long commuting times, car reliance, and distance to major employment hubs. All regressions are estimated using standardized components; fixed effects are introduced sequentially. Standard errors in parentheses

6 The Causal Effects of Neighborhoods on Upward Mobility

We observe substantial differences in intergenerational mobility rates across Spanish local areas: in some places, children from low-income families reach much higher income ranks in adulthood than in others. These geographic disparities raise a fundamental question: do they reflect causal effects of growing up in different environments, or simply selection, that is, differences in the types of families who live in each place? This distinction matters greatly for both research and policy. If the differences are purely due to selection, then improving mobility would require targeting the characteristics of families or individuals themselves. But if place effects are causal, then policy interventions aimed at changing the environment, such as school quality, housing policy, or neighborhood investments, could meaningfully improve upward mobility (Chyn and Katz, 2021; Gaubert et al., 2025).

To illustrate this distinction, consider two municipalities with the same average parental income, but where children's adult incomes differ markedly. If these differences are driven by selection, it could be that more motivated or better-educated families systematically choose to live in the high-mobility area. If instead the differences are causal, then simply growing up in that municipality — regardless of family characteristics — increases a child's chances of climbing up the income ladder. Distinguishing between these explanations is empirically challenging, as families choose where to live based on a range of observed and unobserved factors. To address this challenge, we follow the empirical strategy of Chetty and Hendren (2018b), also implemented by G.C. Britto et al. (2022) and Laliberté (2021), and adapt a movers design to our context that allows us to separate causal place effects from selection. By comparing children from similar family backgrounds who move to the same destination municipality at different ages, we exploit variation in exposure to place that is plausibly exogenous to long-term outcomes. This design enables us to estimate how the timing of a move affects adult income and to quantify the causal impact of growing up in a better destination.

6.1 Identification strategy

The key source of exogenous variation in our movers design comes from differences in the *age* at which children from similar families move to the same destination municipality. Conditional on origin municipality, parental income decile, and birth cohort, families that move to a given destination may do so when their children are at different ages. If the exact timing of the move is uncorrelated with the child's unobserved potential outcomes, then differences in adult income across age-at-move bins can be interpreted as the causal effect of years of exposure to the destination environment. Put differently, the key identifying assumption is that the unobserved factors influencing whether families move to higher–or lower–opportunity areas are uncorrelated with the child's age at the time of the move.

This identifying variation is especially plausible for moves occurring during childhood and adolescence, as these are typically driven by family-level circumstances (e.g., parental employment changes, housing needs, etc.) rather than the child's own decisions. Importantly, the design does not require that the choice of destination municipality be random — families can and do select where to move — but it does assume that, *conditional on moving to a given destination*, the age at which the move occurs is not strategically timed based on the child's future outcomes. For example, consider two children, both born in municipality A, both with parents in the same income decile and the same birth cohort. Suppose their families move to the same destination municipality B. One child moves at age 5, and the other at age 15. The destination is the same. The family background is the same. The only difference is how many years of childhood each child spends in municipality B. If the timing of the move — the age at which it occurs — is unrelated to each child's unobserved potential outcomes, then any systematic difference in their adult income ranks can be attributed to the causal effect of longer exposure to the destination environment.

A key challenge in this framework is to characterize the "quality" of each location in terms of the economic opportunities it provides to children from similar backgrounds. To do so, we construct predicted outcomes for permanent residents, that is, children who never changed their municipality of residence during childhood and early adulthood (in our case, 13 to 24). We compute permanent residents' average income rank at age 24, grouped by birth cohort, parental income decile, and municipality of residence (See Appendix A.3 for methodological details). These predicted outcomes reflect the long-term economic outcomes of children growing up in each location. For each origin-destination pair (o, d), we then compute the expected gain in rank for a child of parental income group p and cohort c from moving to d rather than staying in o, defined as $m_{odpc} = \mathrm{E}[y_{dpoc}] - \mathrm{E}[y_{opoc}]$. This measure captures the relative quality of destinations in terms of upward mobility.

We therefore exploit within-destination variation in exposure to place, isolating the causal impact of growing up in a given environment. All models include fixed effects for origin municipality, parental income group, cohort, and age at move, ensuring that comparisons are made between children from similar backgrounds. By interacting the destination-origin mobility difference m_{odpc} with indicators for age at move a_i, we estimate how adult income outcomes converge to those of permanent residents in the destination as exposure increases. In particular, we define a child's outcome y_i as their income rank at age 24. This is regressed on the predicted mobility difference between destination and origin municipalities, denoted Δm_{odpc}, which captures the difference in average income rank at age 24 for permanent residents conditional on origin o, destination d, parental income decile p, and cohort c. The specification includes interaction terms between Δm_{odpc} and the age at which the child moved, a_i, allowing us to trace how income outcomes vary with years of exposure to the new location. The estimation model is:

$$y_i = \alpha_{qosm} + \sum_{a=13}^{34} b_a \cdot \mathbf{1}(a_i = a) \cdot \Delta m_{odpc} + \sum_{c=1986}^{1994} \kappa_c \cdot \mathbf{1}(c_i = c) \cdot \Delta m_{odpc} + \varepsilon_i \tag{10}$$

The coefficients b_a capture the share of the predicted income difference between the destination and origin municipalities that is realized by children who move at age a. Intuitively, b_a measures how much of the long-term income advantage (or disadvantage) associated with growing up in the destination municipality is gained by a child who moves there at a specific age. A value of $b_a = 1$ implies full convergence: children who move at age a attain the same adult income rank as permanent residents of the destination, suggesting a strong causal effect of place. Conversely, $b_a = 0$ implies no convergence, indicating either no causal impact of place or that the timing of the move occurred too late to affect outcomes. In practice, we expect b_a to decline with age if exposure during earlier developmental periods is more consequential for long-term outcomes. This interpretation is valid for moves that occur before the age threshold at which mobility decisions are likely to reflect individual choices rather than family circumstances.The fixed effects α_{qosm} absorb differences across origin municipalities, parental income groups, birth cohorts, and age-at-move bins. The terms κ_c adjust for the fact that our ability to measure outcomes and observe moves might vary by cohort.

We classify as movers those individuals who changed municipalities at or before age 24 ($a \leq 24$). Moves during this period are more likely to be driven by parental decisions that reshape the environment in which the child is raised, and thus plausibly generate variation in childhood exposure to opportunity. Under the identifying assumptions of the movers design, the estimated coefficients b_a for $a \leq 24$ can be interpreted as causal effects of exposure: they capture the extent to which children who moved at age a achieve income outcomes closer to those of permanent residents in the destination municipality. In contrast, moves occurring after age 24 ($a > 24$) take place after outcomes are measured, and therefore cannot influence those outcomes through exposure. By construction, a move that occurs after income has already been observed cannot affect that income via the environment in which the child was raised. Consequently, the b_a coefficients for $a > 24$ cannot be interpreted as causal. Instead, they reflect selection effects: systematic differences in unobserved traits, such as ambition or ability, among individuals who choose to relocate to higher-opportunity municipalities during early adulthood. These post-outcome moves serve as a benchmark for selection bias, allowing us to estimate the average selection effect δ under the assumption that selection into destinations does not vary with age.

Finally, following Chetty and Hendren (2018b), we define the annual exposure effect γ as the difference in estimated coefficients across adjacent ages at move: $\gamma = b_{a+1} - b_a$. Intuitively, γ captures how much more similar a child's income outcome becomes to that of permanent residents in the destination when the move occurs one year earlier. When γ is approximately constant and negative, it implies that each additional year of earlier exposure to a higher-opportunity municipality yields a roughly uniform marginal improvement in long-run income rank. Importantly, this estimate can be interpreted as causal under the identifying assumption that selection effects are invariant with respect to age at move. That is, we assume that the component of the coefficient b_a attributable to selection — denoted δ_a — is the same for all ages of move a. If $\delta_a = \delta$ for all a, then differences in b_a across ages purely reflect variation in exposure, not selection. Under this assumption, the exposure effect $\gamma = b_{a+1} - b_a$ isolates the causal impact of one additional year of childhood spent in the destination municipality, independent of selection bias. The average level of the b_a coefficients for moves after age 24 provides an empirical estimate of the selection effect δ.

6.2 Main results

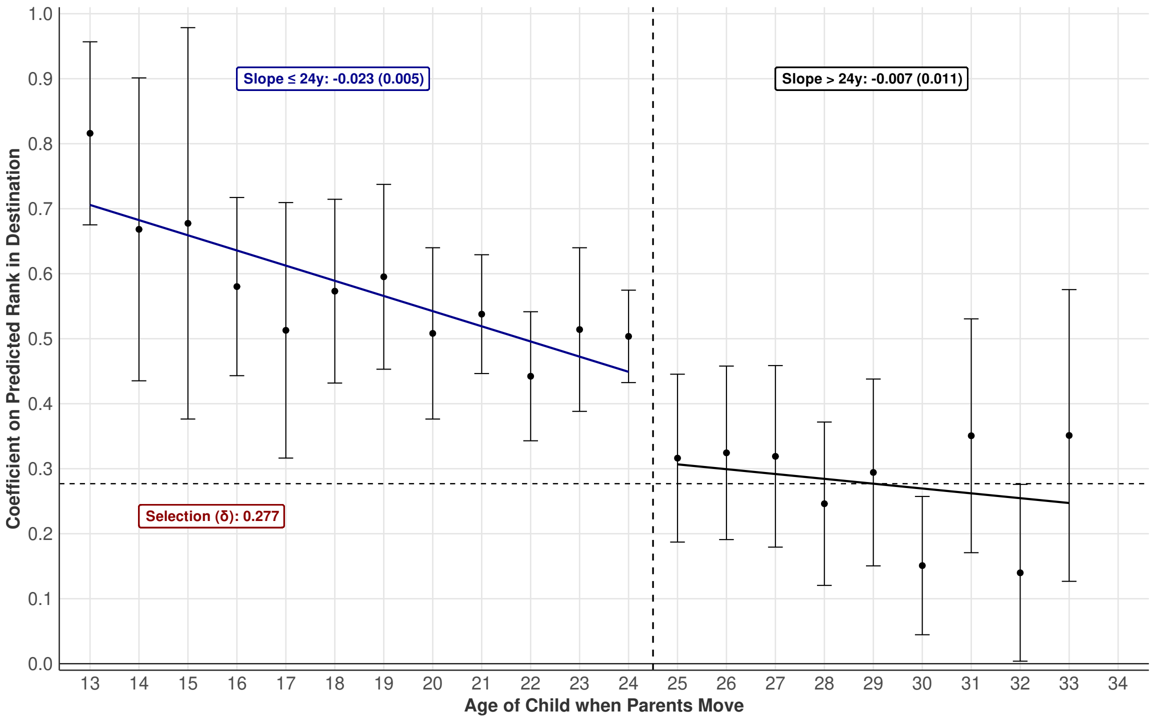
Figure 15 presents estimates of $\hat{b}_m$, the coefficient on predicted rank in the destination municipality, plotted against the child's age at move, m. Each point corresponds to a separate estimate of $\hat{b}_m$ for children who moved at that age. Following the approach of Chetty and Hendren (2018b), we fit separate linear trends on either side of age 24, which we interpret as the threshold between causal exposure effects and selection-driven differences in outcomes. The figure reveals two key empirical patterns. First, for moves occurring before age 24, the estimates of $\hat{b}_m$ decline approximately linearly with age at move. This downward slope suggests that earlier moves generate larger gains in income rank, consistent with the notion that growing up longer in a higher-opportunity municipality leads to better adult outcomes. The estimated slope of this decline is approximately −0.023, meaning that each additional year of earlier exposure is associated with a 2.3 percentile point increase in income rank. In other words, for children who move before age 24, outcomes progressively converge to those of permanent residents in the destination municipality the earlier the move takes place. However, for moves occurring at or after age 24, the slope of $\hat{b}_m$ is virtually flat. The estimated slope in this post-24 range is −0.007 (S.E 0.011), which is not statistically significant. This flat pattern suggests that moves in adulthood do not meaningfully affect long-term income outcomes, aligning with the view that neighborhood effects operate primarily through exposure during childhood rather than through adult location.

However, while the slope after age 24 is flat, the level of $\hat{b}_m$ remains significantly above zero. The average coefficient in this range is 0.277, which we interpret as a selection effect (δ). That is, individuals who move after age 24 to higher-opportunity places tend to have unobserved characteristics that predict higher income regardless of the move. This selection effect is larger than what has been observed in previous studies: Chetty and Hendren (2018a) estimate a value of around 0.126 in the United States, while G.C. Britto et al. (2022) report 0.138 for Brazil. The larger selection effect in Spain likely reflects institutional and cultural differences, such as more selective migration in early adulthood due to delayed residential independence, stronger family ties, and more segmented regional labor markets. Finally, in terms of magnitude, the exposure effect γ is approximated by the estimated convergence slope is approximately 0.023. This means that children who move at birth (i..e, spending 24 years is destination) to a municipality where permanent residents are expected to rank 10 percentiles higher will, on average, increase their own income rank by 5.52 percentile points purely due to causal exposure effects[17]. This implies that almost 60% the raw income rank gap across Spanish municipalities when comparing children growing up in lower- vs. higher-opportunity areas can be attributed to the causal

[17] Here we assume the same convergence slope during ages 0-13, that we cannot observe. Hence, 24 corresponds to a case in which a child moves to the destination place right after birth and spends the rest of her life in destination

effect of place, rather than selection or sorting, similar to the magnitude of estimates in Brazil (G.C. Britto et al., 2022) and the United States (Chetty and Hendren, 2018b).

Figure 15: Childhood Exposure Effects on Income Percentiles in Adulthood



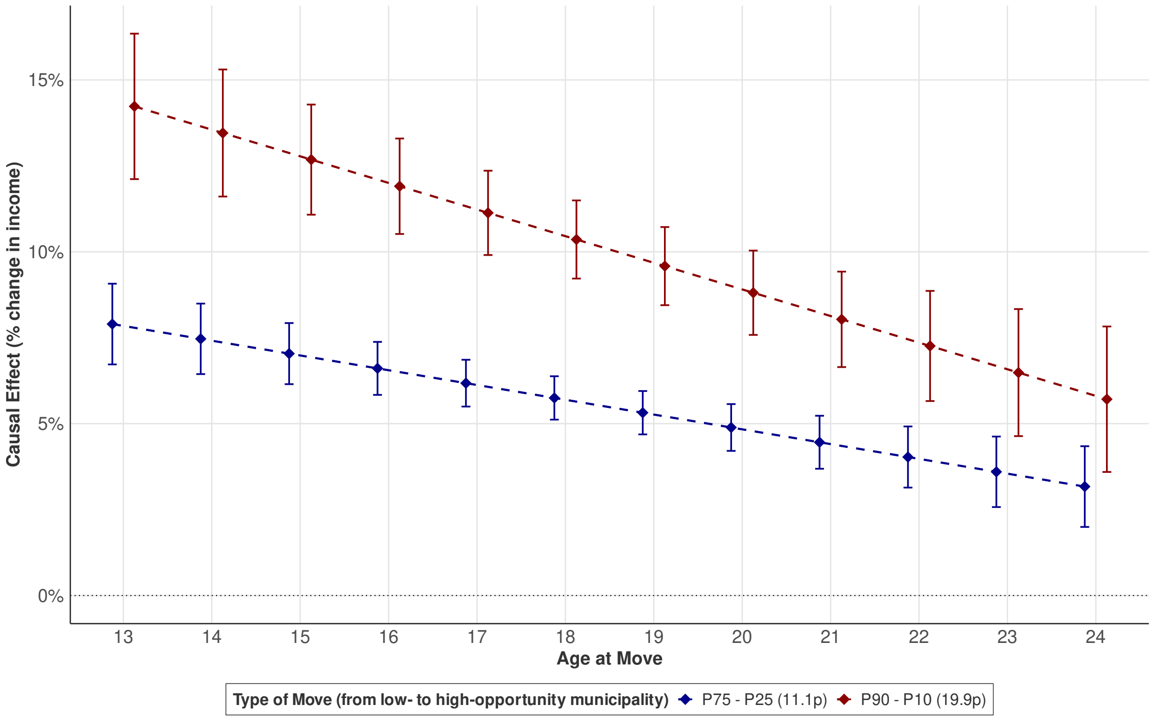
Notes: This figure plots estimates of the coefficients $\{\hat{b}_m\}$ against the child's age at the time of the parental move (m), based on the semiparametric specification described in Equation (5). Children's income ranks are measured at age 28. The analysis sample includes all children whose parents moved exactly once across Spanish municipalities between 2005 and 2022. Each coefficient $\hat{b}_m$ captures the extent to which children who moved at age m achieve outcomes closer to those of permanent residents in the destination relative to the origin. For moves occurring at or before age 24, the $\hat{b}_m$ coefficients primarily reflect causal effects of growing up in a higher-opportunity municipality. In contrast, coefficients estimated for moves after age 24 capture selection effects: since residential moves after early adulthood are unlikely to affect children's income ranks, differences in outcomes for late movers reflect differences in individual characteristics rather than causal exposure to place. The estimation includes fixed effects for origin municipality $\times$ parental income decile $\times$ birth cohort $\times$ age at move, ensuring that identification is based on within-group variation across destination municipalities.

6.3 Heterogeneity in causal effects by age and type of move

How much better off would a low-income child be if she moved, at different ages, to a municipality with significantly greater opportunities? Figure 16 presents estimates of the causal effect of childhood exposure to higher-opportunity municipalities on adult income, expressed as a percentage change relative to the average income of non-movers from low-income families. The figure is constructed using the linearized exposure estimates from the movers design, which isolate the component of income gains attributable to differences in place-based opportunity, net of selection (See Appendix A.4 for methodological details). The results are shown for two types of hypothetical moves: (i) from a municipality in the 25th percentile to one in the 75th percentile of expected mobility outcomes (a rank gap of 11.1 points), and (ii) from the 10th to the 90th percentile (a gap of 19.9 points). The estimated effects are strongly age-dependent. For children who move at age 13, the gains are substantial: a move from a low- to a high-opportunity municipality (P90–P10) leads to an average increase in adult income of approximately 14%, while a move between P25 and P75 yields a gain of about 8%. These effects decline steadily with age: by age 18, the gains fall to around 10.5% (P90–P10) and 6% (P75–P25), respectively. At age 24, the estimated effects fall to approximately 5.8% and 4.0%.

These patterns align with a cumulative exposure model: children benefit more when they move earlier in life, thus spending a larger share of their developmental years in higher-opportunity contexts. The distance between the two series (corresponding to moderate versus extreme improvements in expected outcomes) quantifies the marginal value of accessing the very top of the opportunity distribution. As expected, confidence intervals widen with age, reflecting both greater heterogeneity in late moves and declining precision in estimates due to smaller sample sizes and potentially more selective moves. Overall, these results highlight the sizable long-term benefits of early exposure to opportunity: for children from disadvantaged backgrounds, moving to a high-opportunity municipality in early adolescence can generate income gains of up to 15%, underlining the powerful role of place in shaping economic mobility.

Figure 16: Causal Effects of Childhood Exposure on Adult Income by Age at Move (Percentage Changes)



Notes: This figure plots the estimated causal effect of moving to a higher-opportunity municipality at different ages during childhood, expressed as a percentage change in adult income relative to the baseline income of children from low-income families (p25). The estimates are shown for two types of hypothetical moves: (i) from the 25th to the 75th percentile of expected mobility outcomes (a rank gap of 11.1 points), and (ii) from the 10th to the 90th percentile (a gap of 19.9 points). Effects are computed using the fitted linear model of causal exposure effects before age 24 and converted into monetary and percentage terms based on administrative income data. Confidence intervals are shown at the 95% level.

7 Conclusions

This paper provides a novel and comprehensive analysis of intergenerational income mobility in Spain, leveraging a large-scale administrative panel dataset that links millions of parents and children over a 25-year period. Our research offers new empirical estimates, introduces methodological innovations for geographic analysis, and presents, to our knowledge, the first estimates of the causal effects of neighborhood exposure on long-term economic outcomes using a movers' design in a European context.

Our primary empirical finding is that intergenerational income persistence in Spain is higher than previously understood using other data or methodologies and is located in the middle-to-lower tier of intergenerational mobility in international perspective. A 10 percentile point increase in parental income rank is associated with a 2.74 percentile increase in a child's adult income rank, higher than similar countries such as Italy or Germany, but lower than France and the United States. Furthermore, we introduce the Top-Tail Relative Persistence Ratio (TTRPR) and find that Spain exhibits exceptionally high persistence at the top of the income distribution: children from the top 1% of parental income backgrounds are over 51 times more likely to reach the top 1% themselves compared to children from the bottom 10%, a ratio higher than in other comparable developed nations. This highlights significant "glass floor" and "glass ceiling" effects at the extremes of the distribution. We also present evidence regarding recent trends in intergenerational mobility. Our analysis of different birth cohorts suggests that key mobility measures have worsened for more recent generations. These findings, while requiring further investigation, align with concerns about diminishing economic opportunities, potentially linked to major economic events such as the Great Recession, which significantly impacted the labor market trajectories of new entrants starting in 2008.

Methodologically, this study makes several contributions. We develop and apply Bayesian hierarchical models to estimate local-level mobility rates (including Absolute Upward Mobility, Rank-Rank Slopes, and rags-to-riches probabilities) with enhanced reliability, particularly in data-sparse municipalities and ZIP codes. This approach "borrows strength" across geographic units, correcting for implausible estimates and providing a more nuanced map of opportunity throughout Spain. These methods are broadly applicable to other contexts where granular data analysis is hampered by small sample sizes at local or subgroup levels.

Our analysis of the geography of opportunity reveals substantial regional disparities. While some areas, particularly in the North and North-East extending towards the Madrid metropolitan region, exhibit relatively high upward mobility, other regions, notably in the South and West, show considerably lower levels. Key local-level correlates associated with higher upward mobility include lower unemployment rates, higher occupational prestige, a stronger industrial employment base, and higher educational attainment within the community. Furthermore, by adapting a movers' design, we estimate the causal impact of childhood environment. We find that neighborhoods exert a significant causal influence on children's long-term economic prospects. For instance, a move from a low-opportunity (e.g., 10th percentile) to a high-opportunity (e.g., 90th percentile) municipality at age 13 is associated with an estimated 14% increase in adult income, with the benefits of exposure diminishing as children age increases.

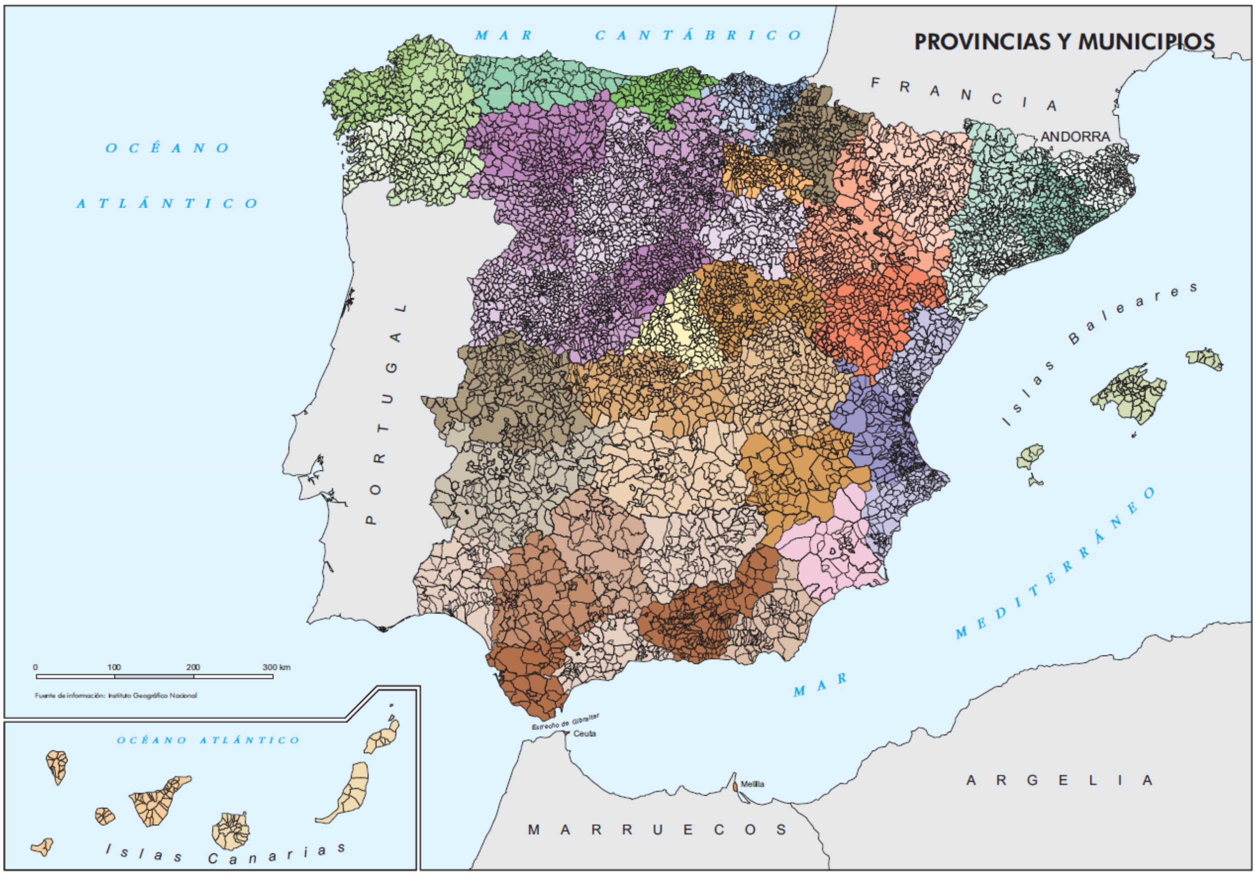
These findings have important policy implications. The high overall and top-tail income persistence, coupled with significant geographic disparities and the causal role of neighborhoods, suggests that interventions aimed at both individuals and places may be necessary to enhance equality of opportunity in Spain. Place-based policies that improve conditions in disadvantaged areas or policies that facilitate residential mobility to higher-opportunity areas for low-income families, could serve as effective levers. Future research could further explore the specific mechanisms driving neighborhood effects and better understand the factors behind the evolution of mobility trends in the wake of recent economic transformations.

Appendix

Figure A1: Map of Provinces in Spain, Coloured by Region

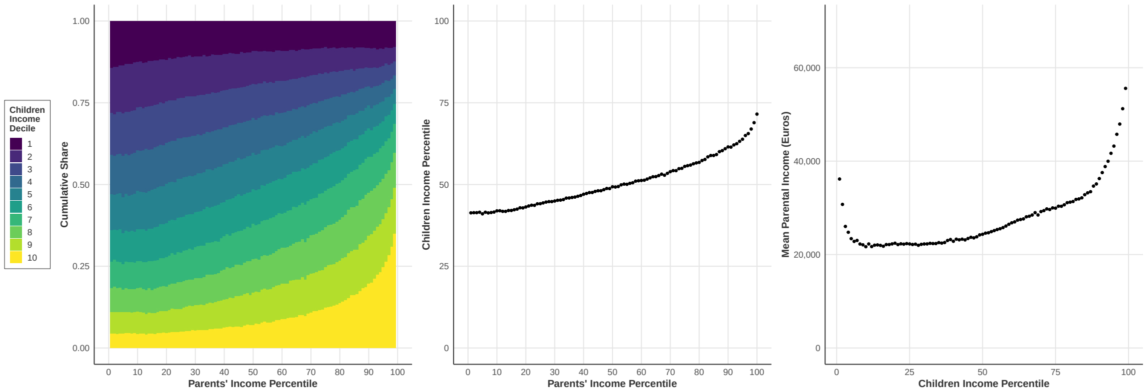
Notes: This figure presents a map of provinces in Spain colored by regions (Comunidad Autónoma). Regions in Spain haver their own parliaments and a high degree of independence in important areas of public policy as health, education or transports.

Figure A2: Map of Municipalities in Spain, Colored by Province

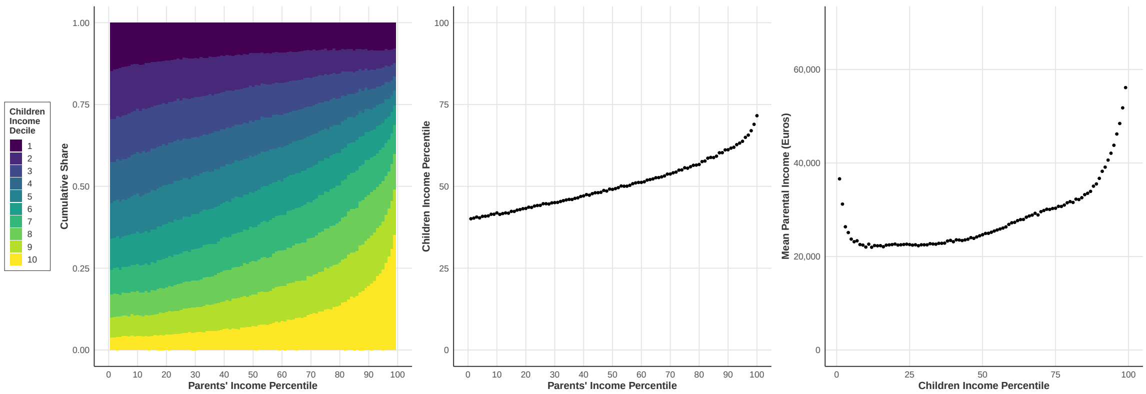


Notes: This figure presents a map of municipalities in Spain colored by provinces.

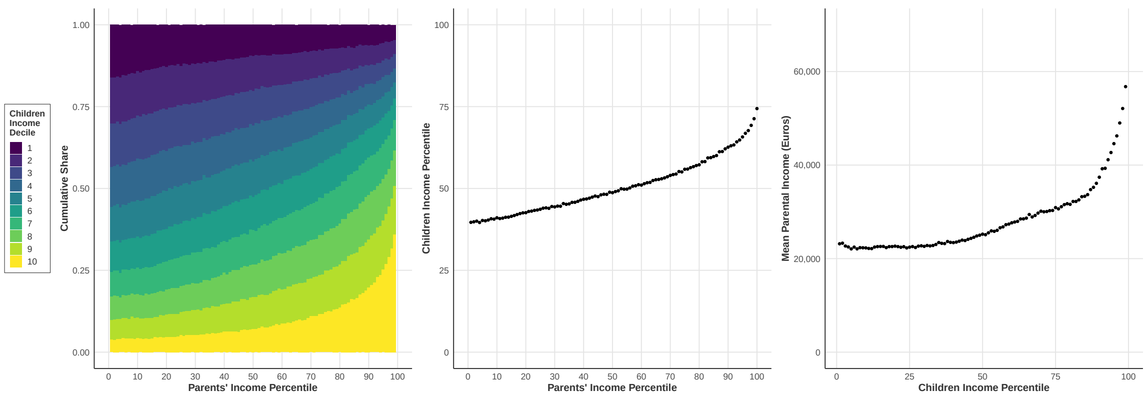
Figure A3: Effect of Sample Selection Criteria on the Relationship Between Parental and Child Income Ranks



(a) Sample after Negative Income Filtering



(b) Sample After Parental Real Estate Income Filtering



(c) Final Analysis Sample After All Filters

Notes: This figure illustrates the impact of sequential data filtering steps on the observed distribution of parental and child income percentiles. Each panel displays a heatmap of child income deciles by parental income percentile (left), the mean child income percentile by parental income percentile (center), and the mean parental income by child income percentile (right). Panel (a) shows the data after initial filtering of households with negative income. Panel (b) shows the sample after the filtering based on real estate income. Panel (c) presents the final analytical sample after the bottom 5% of children's income, as detailed in Section 3.3.

Table A1: Descriptive statistics (Baseline sample)

Variable	**Level**	**N**	**Mean**	**SD**	**Median**	**P25**	**P75**
Children income		1580994	29231.22	44750.68	23285.86	14986.05	36286.27
Children year of birth		1580994	1983.19	1.98	1983	1981	1985
Parents household income		1580994	29247.13	37212.21	21434.78	13633.36	35117.68
Parent 1 year of birth		1544194	1953.27	5.9	1954	1950	1957
Parent 2 year of birth		335525	1953.80	5.26	1954	1951	1957
Gender children	Female	792519	50.13				
Gender children	Male	788463	49.87				
Gender parent 1	Female	306186	19.83				
Gender parent 1	Male	1237757	80.17				
Gender parent 2	Female	172323	51.36				
Gender parent 2	Male	163191	48.64				
Civil status parent 1	0	4	0.00				
Civil status parent 1	1	17322	1.12				
Civil status parent 1	2	1429504	92.54				
Civil status parent 1	3	33169	2.15				
Civil status parent 1	4	64804	4.19				
Civil status parent 1	5	3	0.00				
Civil status parent 2	0	3	0.00				
Civil status parent 2	2	332533	99.10				
Civil status parent 2	3	207	0.06				
Civil status parent 2	4	1726	0.51				

Notes: This table summarizes key variables used in the baseline analysis. Children's income is measured at the individual level in 2022, while parental income refers to household-level earnings observed during the child's adolescence (1998–2000). Percentiles are computed within cohort-year and gender cells. Parent 1 corresponds to the primary tax filer linked to the child; Parent 2 is the cohabiting or married partner when available. Civil status codes follow administrative classifications: 0 = unknown, 1 = single, 2 = married or registered partner, 3 = separated, 4 = divorced, 5 = widowed.

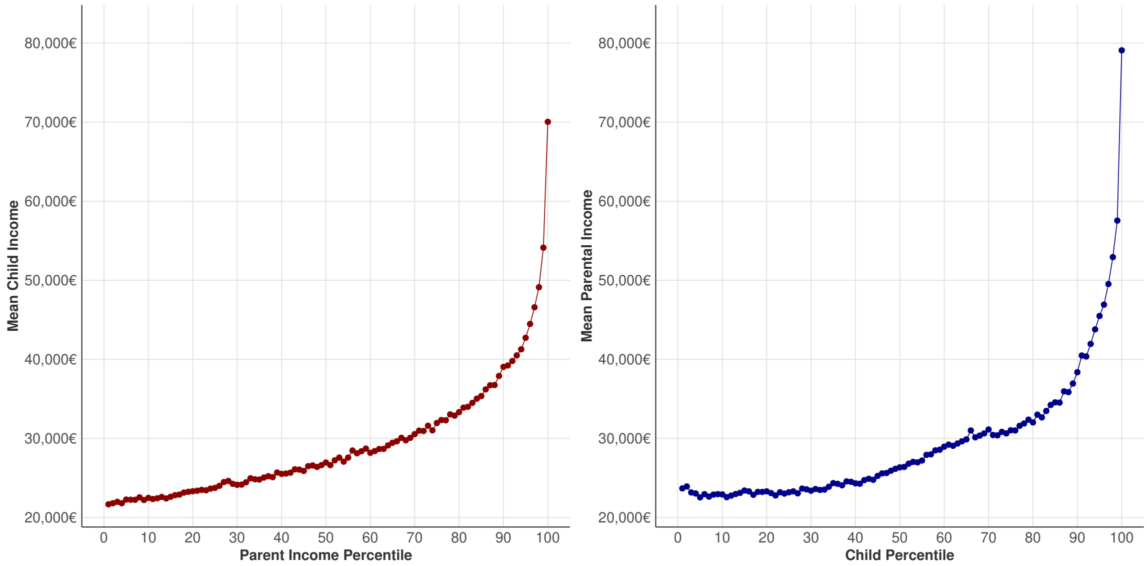
Table A2: Intergenerational Mobility at the National Level in Spain by Subgroups

	Dependent variable: Child Income Percentile											
	Baseline	Baseline (Fixed Parental Age)	Male	Female	2nd Gen Migrant	1st Gen Migrant	First Born	Not First Born	Married Parents	Unmarried Parents	Divorced Parents	Extended Sample (1980-1990)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Parental Income Rank	0.274***	0.273***	0.260***	0.285***	0.276***	0.251***	0.277***	0.279***	0.280***	0.242***	0.247***	0.277***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.008)	(0.004)	(0.004)	(0.001)	(0.008)	(0.006)	(0.001)
Constant	36.650***	33.492***	41.336***	32.152***	36.049***	36.743***	36.552***	35.549***	36.261***	37.433***	38.664***	36.527***
	(0.044)	(0.124)	(0.062)	(0.062)	(0.551)	(0.411)	(0.208)	(0.255)	(0.048)	(0.366)	(0.272)	(0.035)
AUM	43.505	40.327	47.83	39.289	42.959	43.017	43.471	42.524	43.258	43.472	44.828	43.443
PQ5Q1	10.394	10.394	8.22	12.71	9.755	12.356	10.178	10.078	9.627	12.18	12.208	10.204
Observations	1,580,994	1,544,194	788,463	792,519	14,085	13,219	68,801	45,620	1,429,504	17,322	33,169	2,495,136
R^2	0.075	0.076	0.070	0.082	0.072	0.064	0.078	0.081	0.078	0.052	0.050	0.077
Adjusted R^2	0.075	0.076	0.070	0.082	0.072	0.064	0.078	0.081	0.078	0.052	0.050	0.077

Note: *p<0.1; **p<0.05; ***p<0.01

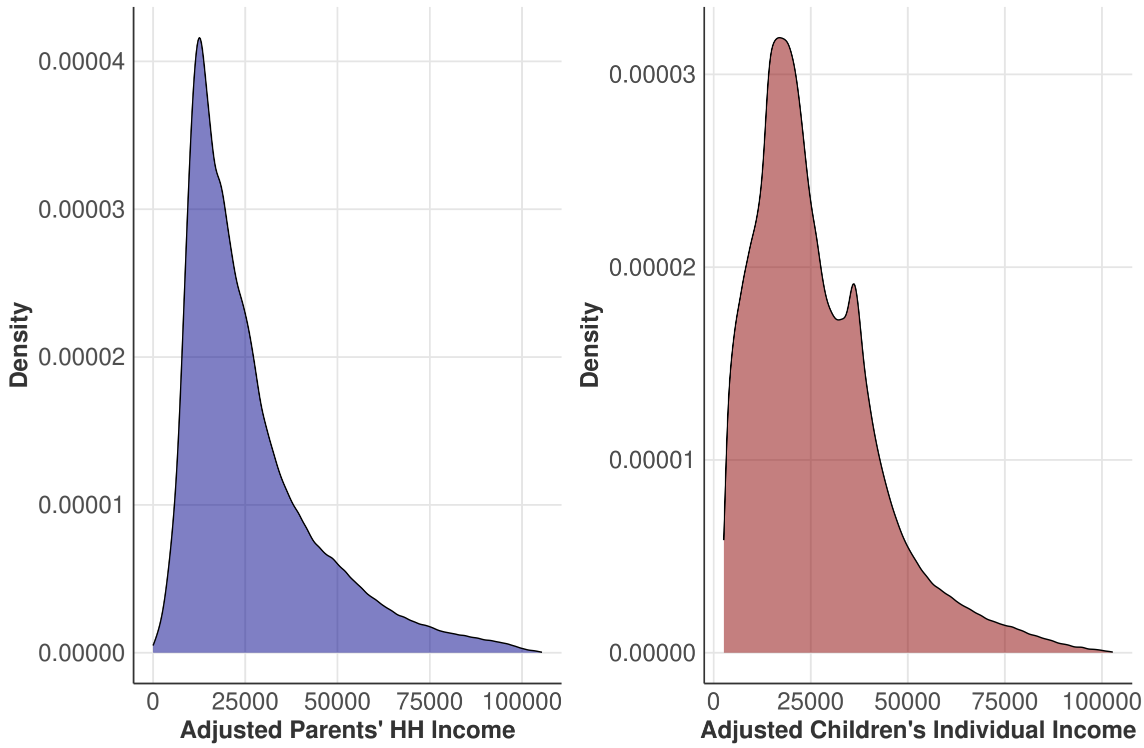
Each cell in this table reports the coefficient from a univariate OLS regression of child income percentile on parental income percentile, with standard errors in parentheses. Column (1) reports baseline results using the national sample of children born between 1980 and 1986, where parental income is averaged over 1998–2000 and child income is averaged over 2020–2022 at ages 36–42. Column (2) adds a control for parental age at the time of the child's birth. Columns (3) and (4) restrict the sample to male and female children, respectively. Columns (5) and (6) examine second-generation migrants (children born in Spain with foreign-born fathers) and first-generation migrants (children born abroad and raised in Spain). Columns (7) and (8) divide the sample by birth order, identifying first-born and not-first-born children. First-born children are identified as the eldest child within households where multiple children are present, and the age gap between siblings is small (indicating closely spaced births). In households with only one child or where the age gap between siblings is unusually large, the first-born status is not assigned to ensure accuracy. Columns (9), (10), and (11) separate children by parental marital status: married, unmarried, or divorced. Column (12) extends the baseline sample to include children born between 1980 and 1990. AUM (Absolute Upward Mobility) measures the expected rank in the income distribution of children whose parents are at the 25th percentile. PQ5Q1 is the probability of moving from the bottom income quintile (Q1) to the top income quintile (Q5).

Figure A4: Income Profiles Across the Parental and Child Distributions



Notes: This figure plots average income in euros at each percentile of the parent and child income distributions. Income is measured at the household level for parents (averaged over 1998–2000) and at the individual level for children in 2022. Percentiles are computed within cohort-year and gender cells. The steep upward slope at the top of the distribution in both panels illustrates strong income concentration and motivates the use of rank-based approaches to mitigate the influence of extreme values.

Figure A5: Child and Parent Income Distribution

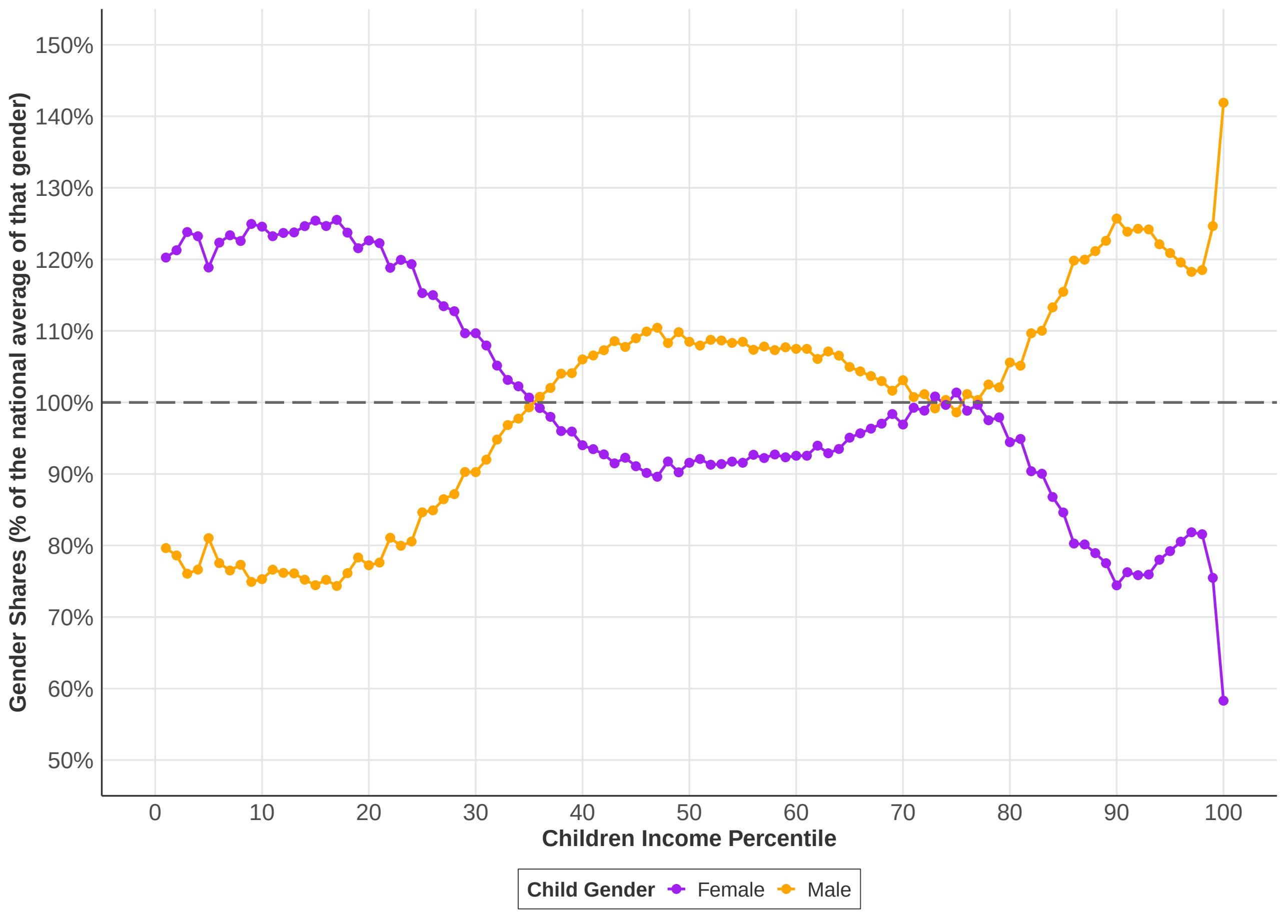


Notes: This figure shows kernel density plots of adjusted household income for parents (left panel) and adjusted individual income for children (right panel), both expressed in euros and trimmed at the 99th percentile. Excluding the top 1% reduces the influence of extreme values and allows for a clearer view of the mass of the income distribution.

Figure A6: National Decile Transition Matrix

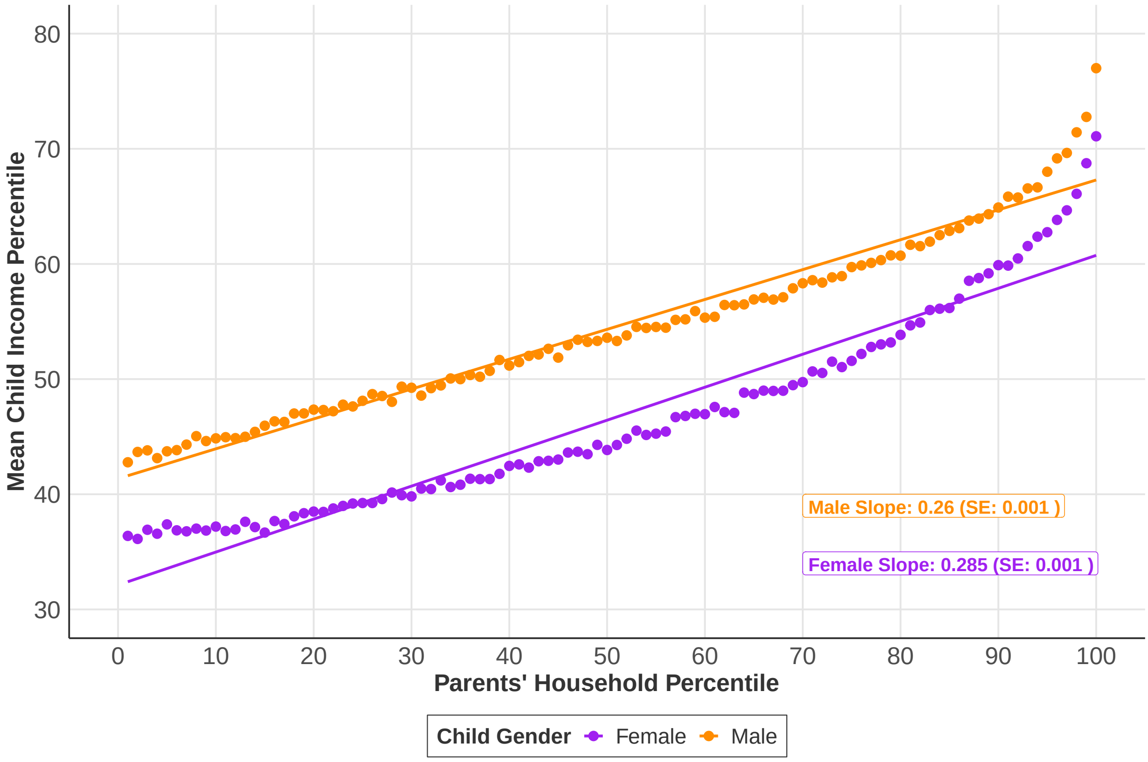
Notes: This figure presents the national-level decile transition matrix in the form of a heatmap, illustrating the probability of children transitioning across income quantiles based on their parents' household income decile. Each row represents the children's individual income decile in adulthood, while each column corresponds to the parental household income decile. The percentages inside each cell indicate the probability that a child born into a specific parental income decile reaches a given decile in adulthood. The color intensity reflects the probability magnitude: darker shades indicate higher probabilities, highlighting the persistence of income across generations. A strong diagonal pattern suggests low intergenerational mobility, meaning children are likely to remain in the same income quintile as their parents. In contrast, more even shading across rows suggests higher mobility, where children's income is less dependent on their parents' income. Income definitions follow those used in the baseline results sample.

Figure A7: Gender Composition Across Child Income Percentiles



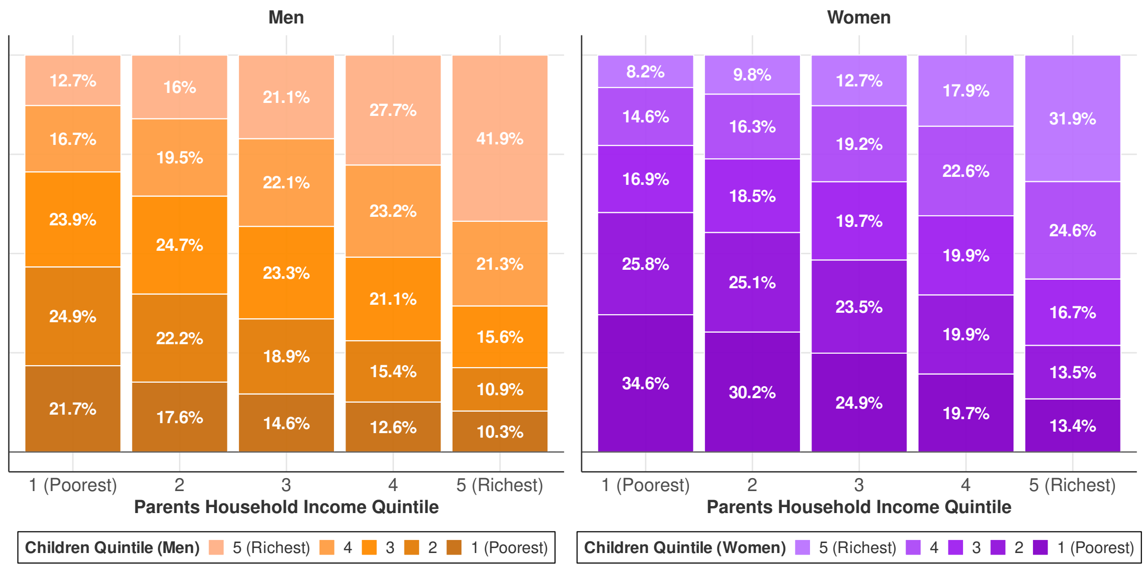
Notes: The figure plots, for each child income percentile, the share of that percentile comprised of male (orange) and female (purple) children, expressed as a percentage of the national average gender share (dashed line at 100%). Values above 100% indicate over-representation relative to the overall gender distribution; values below 100% indicate under-representation. For example, at the lowest income percentiles (0–20), females exceed their national average share by up to 25pp, whereas males are underrepresented in the bottom quintile. Above the 50th percentile, male representation gradually increases—peaking at over 140% in the top percentile—while female representation falls below 80%, illustrating a pronounced gender gap in access to top-income positions.

Figure A8: Mean Child Income Rank vs. Parental Income Rank at the National Level by Gender



Notes: This figure shows a nonparametric binned scatter plots depict the mean child income percentile by parental household income percentile separately for male (orange) and female (purple) children in the baseline sample. Lines show OLS fits: the estimated rank–rank slope is 0.260 (SE: 0.001) for males and 0.285 (SE: 0.001) for females.

Figure A9: National Results- Quintile Transition Matrix by Gender



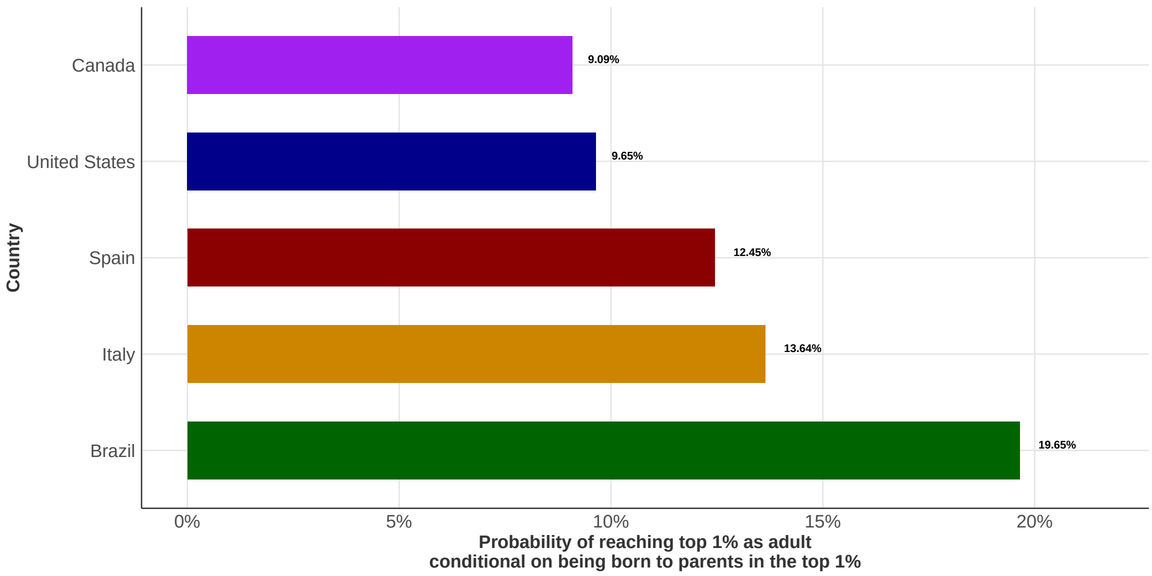
Notes: This figure shows the quintile transition matrix by gender, illustrating the probability of children transitioning across income quintiles based on their parents' household income quintiles. The left panel represents outcomes for men, while the right panel depicts outcomes for women. Each bar on the x-axis corresponds to a parental quintile, with the stacked segments representing the distribution of children's individual income across destination quintiles. The percentages shown within each segment indicate the likelihood of a child moving from the corresponding parental quintile to a specific destination quintile. Child individual income and parental household income are defined as in the baseline national-level figures. Child individual income refers to the income earned by the child independently, while parental household income is the total income of the child's household during childhood. Both metrics follow the methodology and definitions outlined in the baseline national-level analyses.

Table A3: Rank-Rank Slope in International Perspective

Country	RRS	# obs.	Data	Child Income Definition[1]	Child Cohort	Child Age or Year at Income Measurement	Parent Age or Year at Income Measurement	Source
Australia	0.215	1,025,800	Federal income tax returns	Average total pretax family income	1978-1982	2011-2015	1991-2001	Deutscher and Mazumder (2020, Table 2)
Brazil	0.546	1,304,586	Federal Revenue of Brazil	Pretax and informal income	1988-1990	2012-2014	2010-2016	Britto et al. (2020, Figure 3)
Canada	0.242	N/A	Canadian census data	Average total pretax individual income	1980-1982	2011-2012	1996-2000	Connolly and Corak (2020, Table 7)
China	0.443	22,313	China Family Panel Studies (CFPS)	Average total pretax individual income	1987-1988	2010-2016	2010-2016	Yi Fan et al (2019, Table 2)
Denmark	0.253	$\approx 410,000$	Danish register data	Average total pretax individual income	1973-1979	2010-2012	when child between 7-15	Landersø and Heckman (2017, Table A6)
Ecuador	0.272	3,819,846	Statistical Registry of Social Security (REESS)	Labor (formal and informal) income	1987-1998	2018-2023	2006-2011	Del Pozo and Moreno (2025, p.3)
France	0.303	64,571	Permanent Demographic Sample	Parents: (predicted) household wage; Children: average total pretax household income	1972-1981	2010-2016 (between 35-45)	1978-1980	Kenedi and Sirugue (2023, p.3)
Germany	0.245	1,128	German Socio-Economic Panel	Average total pretax individual income	1957-1976	between 8-29	1984-1986	Bratberg et al. (2017, Table 3)
Italy	0.22	1,719,483	Electronic Database of Personal Income Returns	Total pretax individual income	1979-1983	2016-2017	1998-2000	Acciari et al (2022, Figure 1)
New Zealand	0.228	1,719,483	Electronic Database of Personal Income Returns	Total pretax individual income	1979-1983	2016-2017	1998-2000	Jenkins (2024, Figure 1)
Spain	0.274	1,492,107	Atlas de Oportunidades 2.0	Total pretax individual income	1980-1986	2020-2022	1998-2000	Soria and Medina (2025, Figure 1)
Sweden	0.197	927,008	Swedish Social Insurance Agency	Sum of taxable income	1968-1976	32-34	16-40	Heidrich (2017, Table 2)
Sweden	0.215	252,745	Swedish registry administrative data	Average pretax household income	1957-1964	1920-1950	1978-1990	Bratberg et al. (2017, p.75)
Switzerland	0.14	923,262	Social Security Earnings Records	Average total pretax individual income	1967-1984	30-33	when child between 15-20	Chuard-Keller and Grassi (2021, Fig 1)
US	0.341	9,867,736	Federal income tax records	Average total pretax family income	1980-1982	2011-2012	1996-2000	Chetty et al (2014, Table 1)

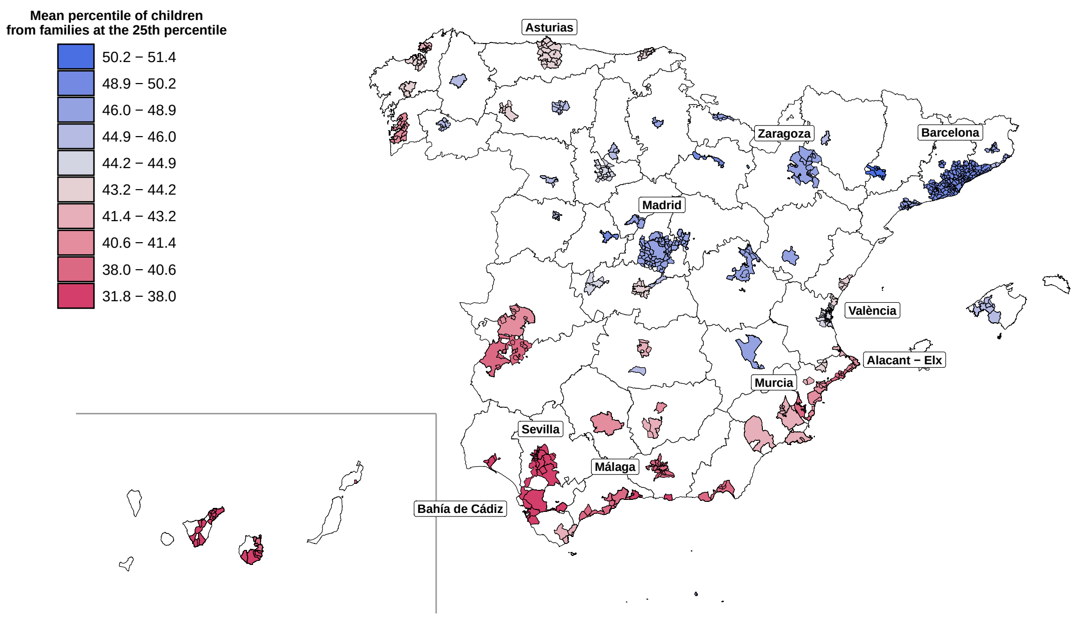
[1] The parent income definition is always at the family level.

Figure A10: Mean Child Income Rank vs. Parental Income Rank at the National Level by Gender



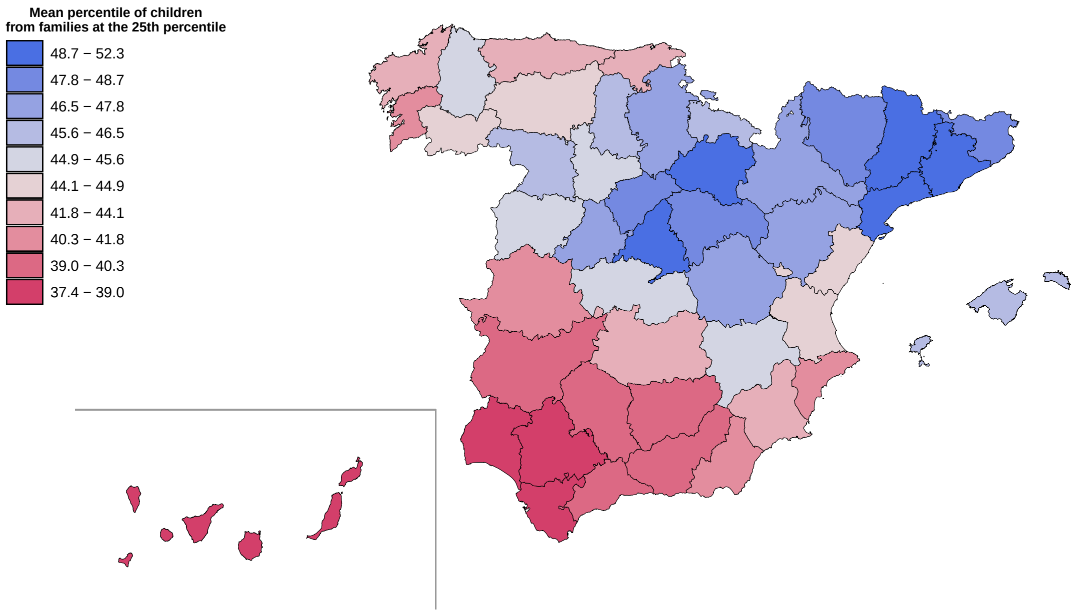
Notes: This figure shows the probability of reaching the top 1% in adulthood for children from top-percentile families

Figure A11: Geographic Variation in Absolute Upward Mobility (μ_{25}) by Urban Area



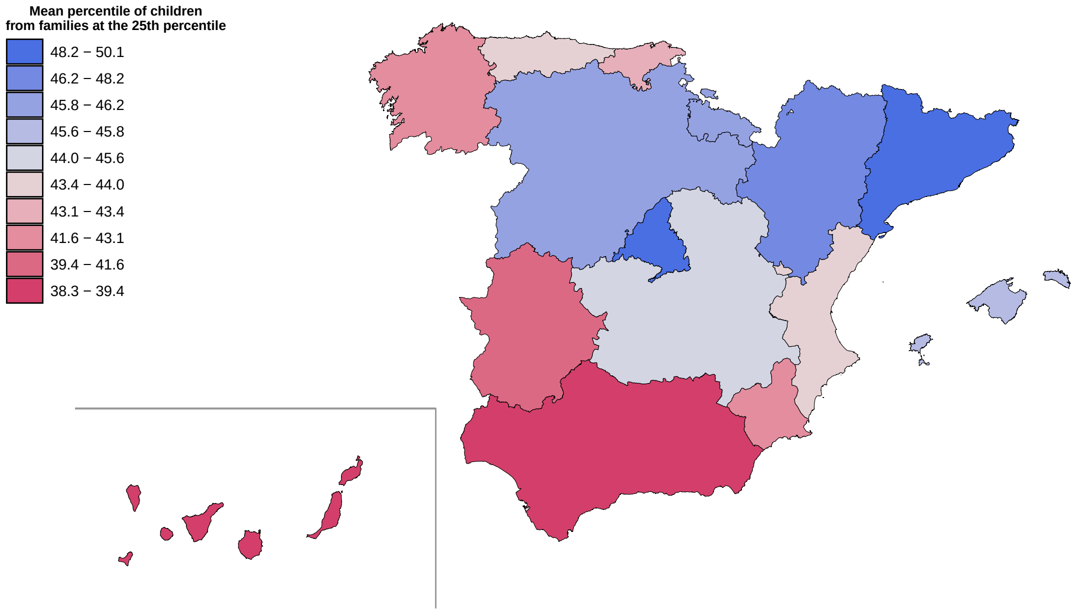
Notes: This figure displays estimates of absolute upward mobility, defined as the mean income percentile in adulthood for children whose parents were at the 25th percentile of the national parental income distribution. Estimates are shown for each Urban Area. Darker shades of blue indicate higher upward mobility (children reach higher income percentiles on average), while darker shades of red indicate lower upward mobility. Income definitions and sample construction follow the baseline methodology outlined in Section 3.

Figure A12: Geographic Variation in Absolute Upward Mobility (μ_{25}) by Province



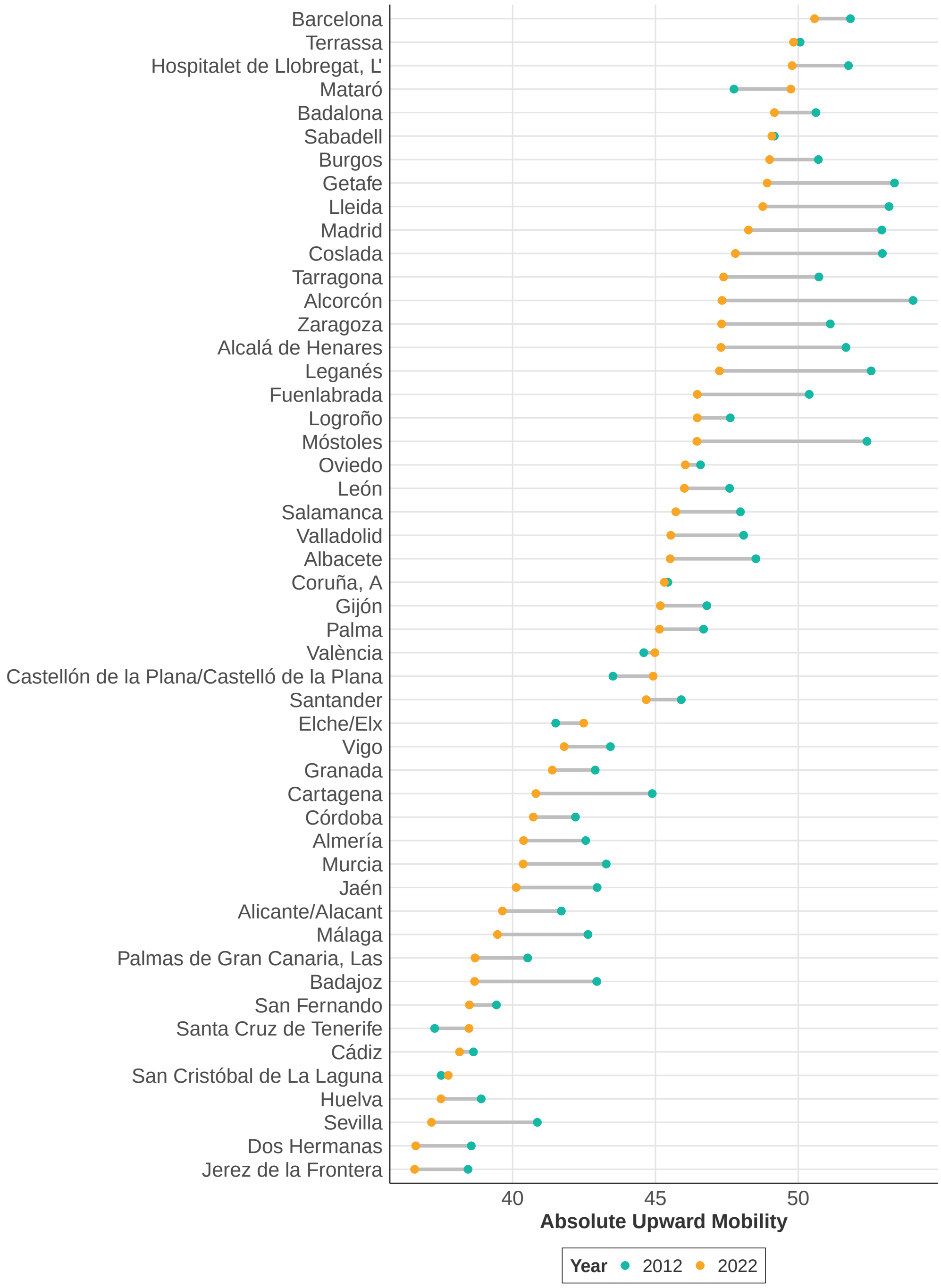
Notes: This figure displays estimates of absolute upward mobility, defined as the mean income percentile in adulthood for children whose parents were at the 25th percentile of the national parental income distribution. Estimates are shown for each province. Darker shades of blue indicate higher upward mobility (children reach higher income percentiles on average), while darker shades of red indicate lower upward mobility. Income definitions and sample construction follow the baseline methodology outlined in Section 3.

Figure A13: Geographic Variation in Absolute Upward Mobility (μ_{25}) by Autonomous Community



Notes: This figure displays estimates of absolute upward mobility, defined as the mean income percentile in adulthood for children whose parents were at the 25th percentile of the national parental income distribution. Estimates are shown for each Autonomous Community. Darker shades of blue indicate higher upward mobility (children reach higher income percentiles on average), while darker shades of red indicate lower upward mobility. Income definitions and sample construction follow the baseline methodology outlined in Section 3.

Figure A14: Evolution of Absolute Upward Mobility (μ_{25}) in Top 50 Spanish Municipalities by Population (1980 vs. 1990 Cohorts)



Notes: This figure illustrates the change in Absolute Upward Mobility (μ_{25}) between the 1980 cohort (orange markers) and 1990 cohort (teal markers) for the 50 Spanish municipalities with the highest population. Absolute Upward Mobility (μ_{25}) is defined as the mean income percentile in adulthood for children whose parents were at the 25th percentile of the national parental income distribution. Municipalities are listed on the y-axis, and their μ_{25} values for each year are plotted on the x-axis. Estimates are based on the baseline sample and income definitions detailed in Section 3.

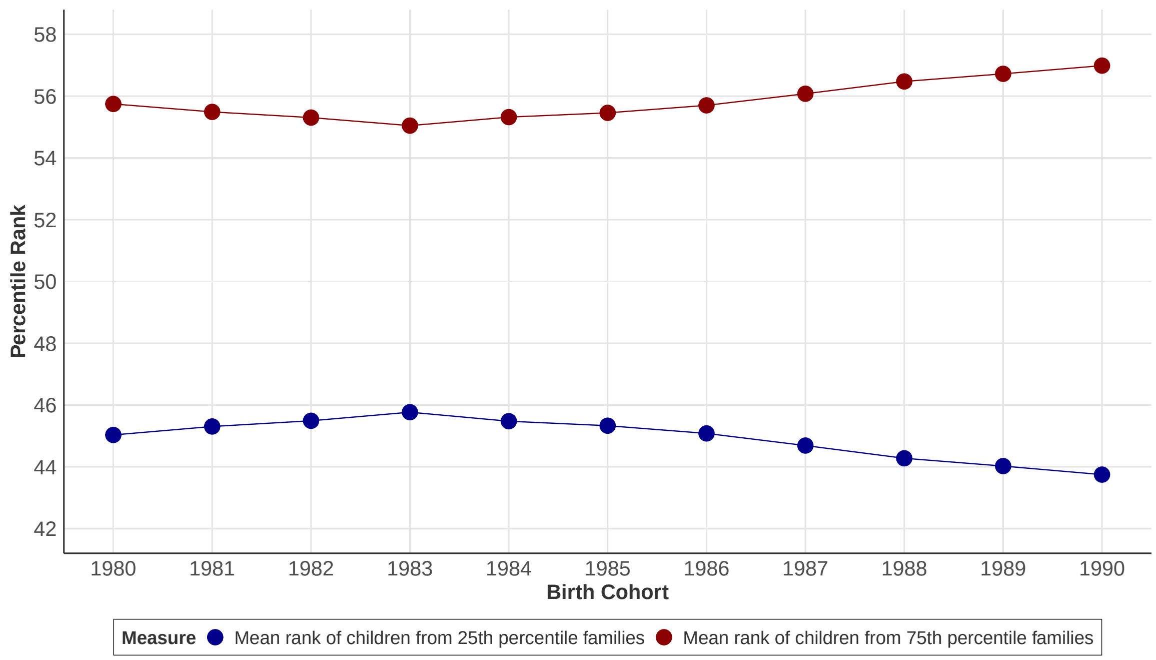
Table A4: Intergenerational Mobility in the Largest 50 Urban Areas of Spain

Urban Area Name	AUM	Population	P(Q3|Q1)	P(Q5|Q1)	RRS
Lleida	51.4	169620	0.22	0.19	0.20
Barcelona	50.21	5156625	0.22	0.18	0.22
Soria	49.89	39398	0.21	0.13	0.21
Ávila	49.28	57744	0.21	0.13	0.21
Manresa	48.96	104907	0.22	0.16	0.27
Madrid	48.85	6196700	0.26	0.17	0.23
Tarragona - Reus	48.68	386600	0.24	0.18	0.25
Guadalajara	48.50	161683	0.23	0.11	0.25
Girona	48.45	161582	0.26	0.13	0.26
Burgos	47.94	177935	0.23	0.15	0.21
Cuenca	47.29	54690	0.22	0.14	0.20
Zaragoza	47.28	754084	0.24	0.12	0.24
Segovia	47.19	69273	0.28	0.13	0.22
Teruel	47.15	35890	0.25	0.13	0.21
Sant Feliú de Guixols	46.49	61787	0.23	0.13	0.20
Albacete	46.31	173329	0.24	0.11	0.23
Logroño	46.25	176883	0.24	0.11	0.23
Melilla	46.23	86487	0.27	0.14	0.18
León	46.02	192082	0.26	0.13	0.21
Puertollano	45.84	47035	0.26	0.15	0.17
Aranjuez	45.74	59607	0.26	0.14	0.21
Zamora	45.47	66174	0.25	0.13	0.18
Palma de Mallorca	45.46	561538	0.26	0.12	0.24
Ourense	45.28	131000	0.21	0.11	0.18
Palencia	45.27	93853	0.28	0.11	0.24
Blanes - Lloret de Mar	45.17	83084	0.27	0.15	0.15
Salamanca	45.00	183965	0.30	0.13	0.18
Huesca	44.99	53132	0.27	0.10	0.20
Lugo	44.90	98276	0.23	0.12	0.19
València	44.86	1564253	0.25	0.11	0.22
Talavera de la Reina	44.80	94028	0.25	0.12	0.22
Valladolid	44.61	405071	0.29	0.14	0.21
Asturias	44.17	801390	0.23	0.13	0.22
Castellò de la Plana	44.10	306215	0.26	0.11	0.21
A Coruña	43.91	416345	0.23	0.11	0.22
Toledo	43.90	123509	0.25	0.10	0.22
Alcoi	43.87	79829	0.24	0.10	0.21
Sagunt	43.72	72837	0.24	0.11	0.21
Ponferrada	43.72	80485	0.18	0.09	0.21
Santiago de Compostela	43.53	147632	0.23	0.09	0.23
Ceuta	43.28	83179	0.26	0.13	0.14
Santander - Torrelavega	43.25	321695	0.26	0.11	0.22
Gandía	43.20	123545	0.27	0.10	0.14
Cartagena	42.83	215826	0.27	0.11	0.21
Lorca	42.71	94404	0.22	0.11	0.20
Ciudad Real	42.02	90114	0.28	0.08	0.23
Murcia	41.91	664058	0.25	0.10	0.22
Elda - Petrer	41.75	86894	0.21	0.10	0.19
Ferrol	41.58	128413	0.23	0.09	0.23

Figure A15: Evolution of the unemployment rate in Spain (1978-2023)

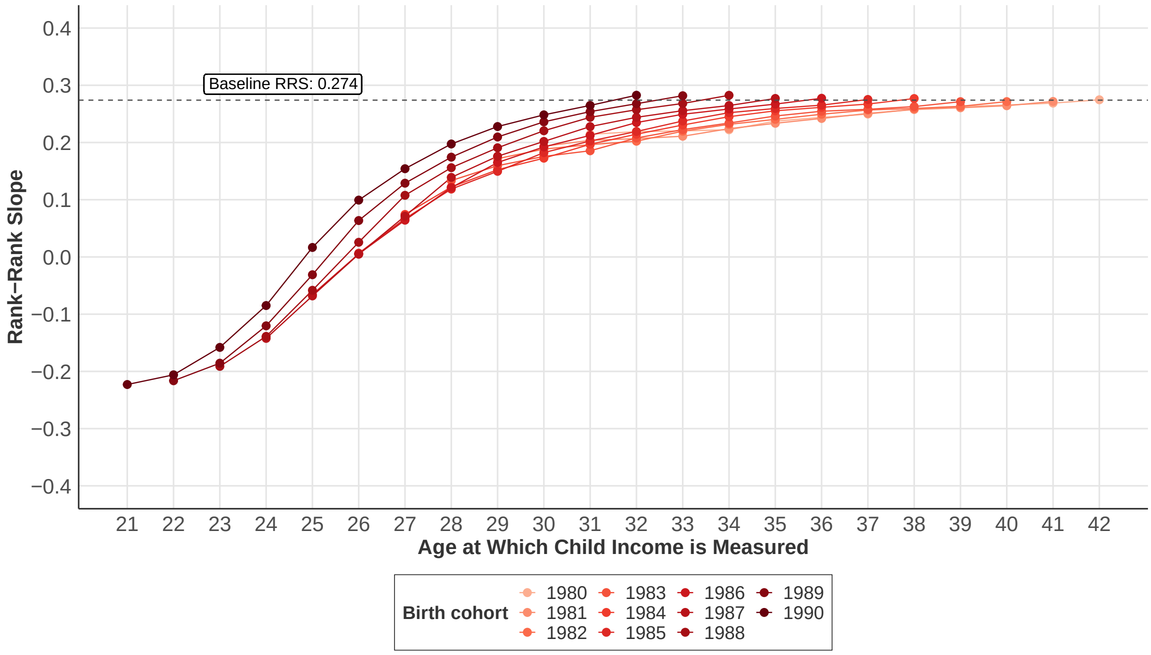
Notes: This figure shows the evolution of the unemployment rate from 1978 to 2023 (INE)

Figure A16: Evolution of the Mean Child Income Percentile of Children from p25 and p75 families Across Generations



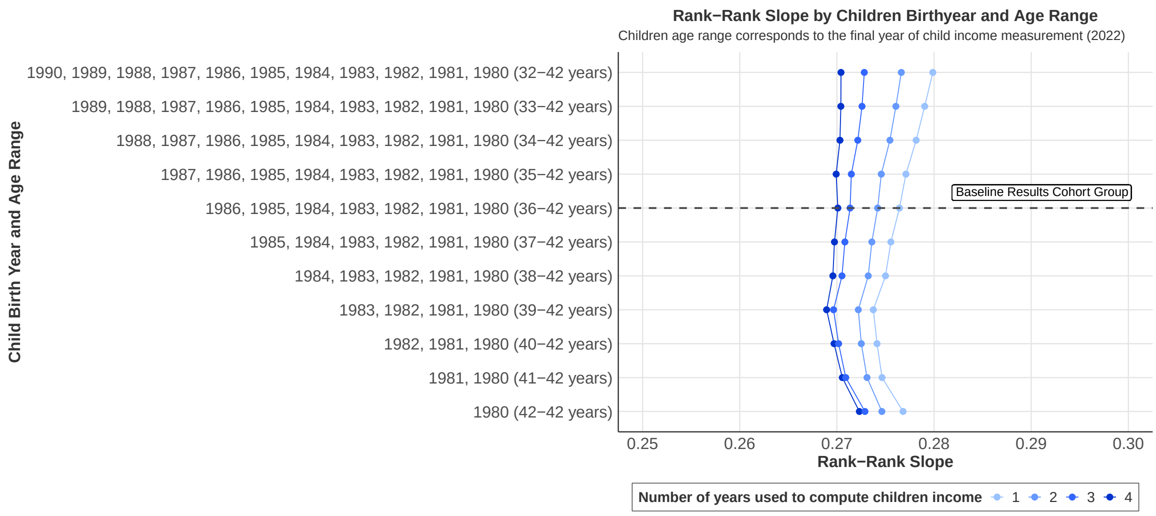
Notes: This figure shows the evolution of the unemployment rate from 1978 to 2023 (INE)

Figure A17: Lifecycle Bias: Intergenerational Income Correlation by Age at Which Child's Income is Measured



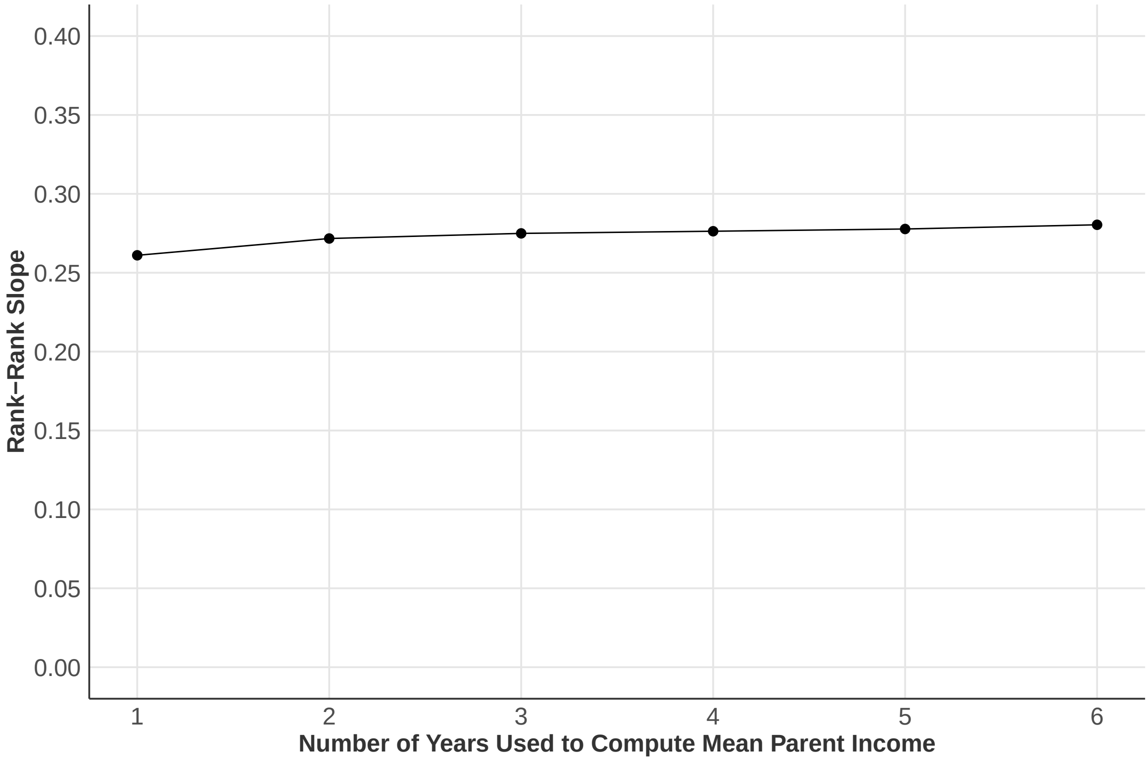
Notes: Each line plots the estimated parent–child rank–rank slope for a given birth cohort as the age at which the child's income is measured varies from 21 to 42. Child income is averaged over a two-year window centered on the age shown, while parental income is fixed as the three-year average from 1998–2000. The dashed horizontal line marks the baseline slope of 0.274 from our main sample (children aged 36–42 for cohorts 1980–1986). The convergence of all cohort-specific slopes toward the baseline line after age 36 demonstrates that measuring child income at these older ages minimizes life-cycle bias in mobility estimates.

Figure A18: Lifecycle Bias: Intergenerational Income Correlation by Number of Cohorts Included and Age Range



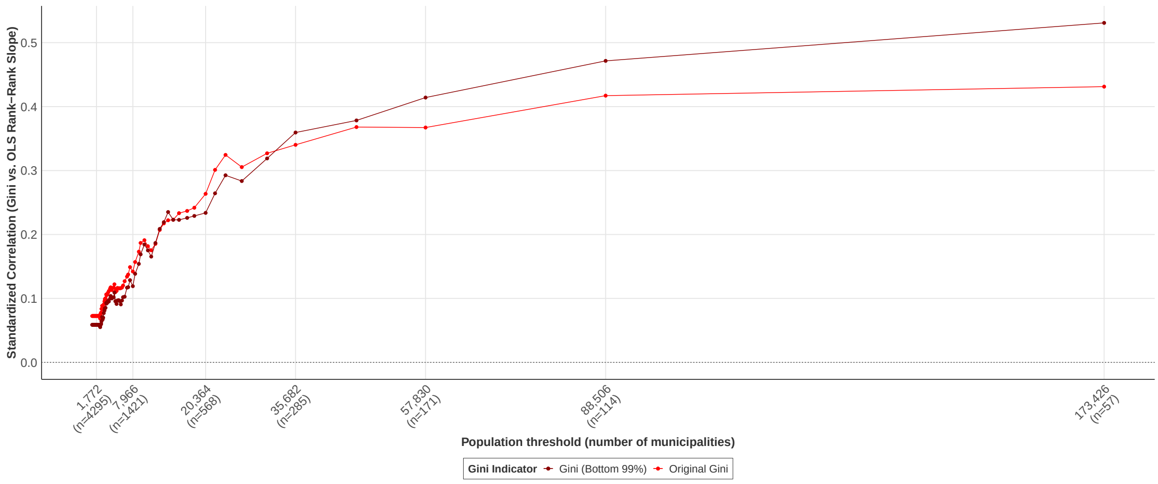
Notes: Each line shows the estimated parent–child rank–rank slope for successive birth-cohort groups (1980–1990), where child income is measured over varying age windows ending in 2022. Shades of blue correspond to the number of years of income used (1 to 4 years). The horizontal dashed line marks our baseline cohort sample (1980–1986 measured at ages 36–42) with slope 0.274. The tight clustering of slope estimates around the baseline—regardless of cohort range or income-measurement span—confirms the robustness of our core sample choice and suggests minimal bias from alternative age or cohort selections.

Figure A19: Attenuation Bias: Rank-Rank Slopes by Number of Years Used to Measure Parent Income



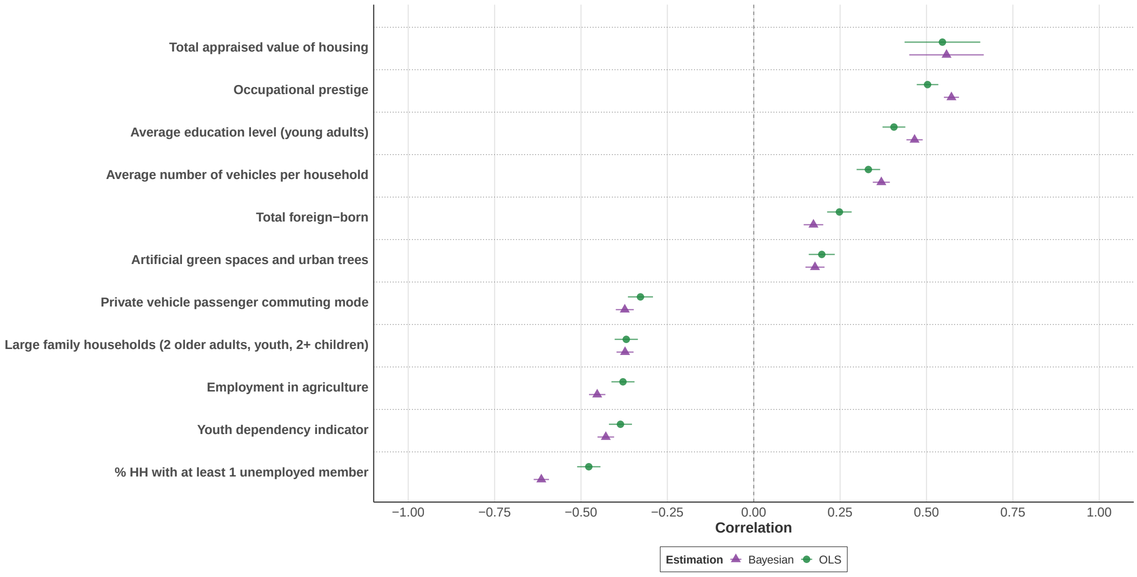
Notes: This figure plots the estimated parent–child rank–rank slope for our baseline cohort (1980–1986, children aged 36–42) as we vary the number of years of parental income used to compute the mean (from 1 to 6 years). Using only one year of parental income yields a slope of 0.261, whereas averaging over six years increases the slope to 0.280.

Figure A20: Correlation Between Inequality and Intergenerational Persistence by Municipality Size



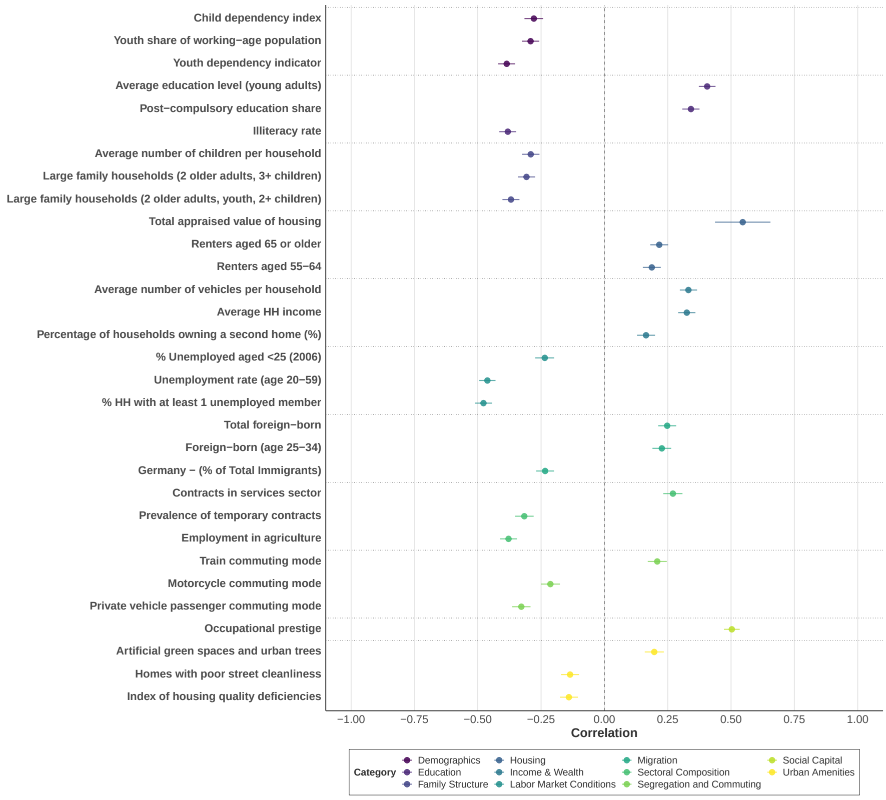
Notes: This figure plots the standardized correlation between the Gini index of income inequality and the OLS rank-rank slope (a measure of intergenerational persistence) across municipalities, conditional on different population thresholds. The x-axis shows increasing population cutoffs, and the y-axis reports the corresponding correlation. The analysis compares two Gini measures: the original Gini and a bottom 99% Gini that excludes extreme top incomes. While both measures yield similar patterns, the association between inequality and persistence only becomes salient in municipalities with populations exceeding 20,000, highlighting the urban specificity of the Great Gatsby Curve in Spain.

Figure A21: Main Correlates by Category of Intergenerational Mobility at the Municipality Level in Spain: Bayes vs. Direct OLS Estimates



Notes: This figure presents the estimated associations between selected socioeconomic indicators and Absolute Upward Mobility (AUM) at the municipality level. Each dot represents the coefficient from a univariate linear regression where the dependent variable is AUM and the independent variable is one standardized correlate (mean zero, standard deviation one). Horizontal lines denote 95% confidence intervals. Variables are grouped into eight thematic categories, shown by color: Demographics, Education, Housing, Income & Wealth, Migration, Sectoral Composition, Social Capital, and Urban Amenities. The figure displays the most predictive correlate from each group, based on the strength of association with upward mobility.

Figure A22: Top 3 Correlates by Category of Intergenerational Mobility at the Municipality Level in Spain



Notes: This figure presents the estimated associations between selected socioeconomic indicators and Absolute Upward Mobility (AUM) at the municipality level. Each dot represents the coefficient from a univariate linear regression where the dependent variable is AUM and the independent variable is one standardized correlate (mean zero, standard deviation one). Horizontal lines denote 95% confidence intervals. Variables are grouped into eight thematic categories, shown by color: Demographics, Education, Housing, Income & Wealth, Migration, Sectoral Composition, Social Capital, and Urban Amenities. The figure displays the most predictive correlate from each group, based on the strength of association with upward mobility.

Table A5: Conditional Correlates of Absolute Upward Mobility at the Urban Area Level

	Dependent variable:							
	Absolute Upward Mobility (AUM)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Occupational Prestige	0.713***	0.532***	0.299*	0.317**	0.280*	0.151	−0.027	−0.193
	(0.082)	(0.131)	(0.160)	(0.153)	(0.147)	(0.138)	(0.153)	(0.178)
Poverty and Material Deprivation		−0.229*	−0.327**	−0.187	−0.198	−0.152	−0.025	−0.119
		(0.131)	(0.133)	(0.138)	(0.132)	(0.121)	(0.129)	(0.114)
Multigenerational Large Households			−0.251**	−0.249**	−0.162	−0.274***	−0.241**	−0.197**
			(0.104)	(0.100)	(0.100)	(0.096)	(0.094)	(0.096)
College Education Attainment				0.237***	0.202**	0.185**	0.266***	0.194**
				(0.089)	(0.085)	(0.078)	(0.083)	(0.088)
Industrial Employment Index					0.237***	0.217***	0.342***	0.332***
					(0.083)	(0.076)	(0.090)	(0.086)
Ageing Index						0.291***	0.283***	0.081
						(0.076)	(0.074)	(0.075)
Unemployment Concentration							−0.303**	−0.323**
							(0.126)	(0.125)
Regional FE	No	No	No	No	No	No	No	Yes
Observations	76	76	76	76	76	76	76	76
R^2	0.508	0.528	0.563	0.603	0.644	0.707	0.729	0.897
Adjusted R^2	0.501	0.515	0.544	0.580	0.619	0.681	0.702	0.855
Residual Std. Error	0.706 (df = 74)	0.697 (df = 73)	0.675 (df = 72)	0.648 (df = 71)	0.617 (df = 70)	0.565 (df = 69)	0.546 (df = 68)	0.381 (df = 53)
F Statistic	76.403*** (df = 1; 74)	40.791*** (df = 2; 73)	30.884*** (df = 3; 72)	26.928*** (df = 4; 71)	25.363*** (df = 5; 70)	27.695*** (df = 6; 69)	26.195*** (df = 7; 68)	21.022*** (df = 22; 53)

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Note: All coefficients are standardized, meaning each component and the dependent variable have been scaled to have mean zero and standard deviation one. As a result, estimates indicate the standard deviation change in absolute upward mobility (AUM) associated with a one standard deviation increase in the corresponding principal component. PCA components summarize thematic sets of local indicators as follows. **Occupational Prestige** is based solely on the average socioeconomic condition (CSE) as classified by the INE, capturing the occupational status structure of an area. **Poverty and Material Deprivation** reflects household income levels, vehicle ownership, and second home availability, indicating local economic resources. **Multigenerational Large Households** captures household size and composition, particularly presence of multiple generations and elderly members. **College Education Attainment** reflects the share of residents with tertiary education. **Industrial Employment Index** includes employment and unemployment levels in industry and construction sectors, as well as blue-collar occupational shares. **Ageing Index** combines demographic dependency ratios and population change since the 1970s. **Unemployment Concentration** reflects overall unemployment levels and their distribution across age and gender groups.

A.1 Calculation of the Top-Tail Relative Persistence Ratio (TTRPR)

We compute the TTRPR in three steps:

1. **Compute conditional probabilities for each parental percentile.** Let p_i denote the event that parents lie in the ith income percentile, and let $y \in \text{Top1}$ denote the event that the child reaches the top 1% of the adult income distribution. For each $i = 1, \ldots, 100$ we calculate

$$q_i \;=\; P\big(y \in \text{Top1} \mid p_i\big) \;=\; \frac{\#\{\text{children with } p_i \text{ and } y \in \text{Top1}\}}{\#\{\text{children with } p_i\}} \times 100\%.$$

   Numerically, for $i = 100$ (the top 1% of parents), we obtain

$$q_{100} = P\big(y \in \text{Top1} \mid p_{100}\big) \approx 12.47\%.$$

2. **Aggregate probability for the bottom decile.** To measure the probability of reaching the top 1% from the bottom 10% of parents, we average the ten conditional probabilities $q_1, \ldots, q_{10}$:

$$\bar{q}_{1:10} \;=\; \frac{1}{10}\sum_{i=1}^{10} q_i \;\approx\; 0.24\%.$$

3. **Form the TTRPR as a ratio of conditional probabilities.** The Top-Tail Relative Persistence Ratio is defined as

$$\text{TTRPR} = \frac{P\big(y \in \text{Top1} \mid p_{100}\big)}{P\big(y \in \text{Top1} \mid p \in \text{Bottom10}\big)} = \frac{q_{100}}{\bar{q}_{1:10}} \;\approx\; \frac{12.47\%}{0.24\%} \;\approx\; 51.4.$$

   This indicates that a child born into the top 1% is about 51 times more likely to attain the top 1% than a child born into the bottom 10%.

A.2 Defining Local Context for Permanent Residents and Movers

To properly classify a child as a permanent resident, the municipality should reflect the location where the child lived continuously from birth through adulthood. Due to data limitations, however, we only observe residential location from 2005 onward. To address this, we use the earliest available observed municipality of residence for the parent as a proxy for the child's location of upbringing. This approach relies on the assumption that children classified as permanent residents did not change municipalities between birth and 2005. Empirically, we find strong support for this assumption: in approximately 95% of cases, the municipality observed in 1998 (first year of data) matches that of 2005. This provides reassurance that the chosen location measure is a valid proxy for long-term residence in the vast majority of cases between these two years. Although some degree of measurement error is possible due to unobserved mobility in early childhood, such errors are limited in scope and unlikely to systematically bias our estimates. Importantly, by restricting the sample to permanent residents, we ensure that predicted outcomes reflect the earnings rank a child would be expected to attain if raised entirely in that municipality. This aligns with the conceptual definition of place-based exposure effects and enables meaningful comparisons across origins and destinations in the movers design.

A.3 Bayesian methodological appendix

Bayesian Hierarchical Model for Local-Level AUM and RRS

To estimate key measures of intergenerational mobility—Absolute Upward Mobility (AUM, denoted μ_{25}) and the Rank-Rank Slope (RRS, denoted β_{local})—at granular geographic levels such as municipalities and ZIP codes, we employ a Bayesian hierarchical linear modeling approach. This strategy is essential for generating reliable local estimates, particularly in areas with smaller populations or fewer observed parent-child pairs. In such contexts, traditional Ordinary Least Squares (OLS) regressions applied independently to each locality would often yield noisy and statistically imprecise results due to limited sample sizes. The hierarchical structure of our model allows it to "borrow strength" across related geographic units, leading to more stable and plausible estimates of local mobility patterns.

The core of the model specifies the adult income rank of child i, denoted y_i, as a linear function of their parental income rank, y_p. Crucially, the parameters of this linear relationship (the intercept and the slope) are allowed to vary across different geographic units. For our primary municipality-level estimates, we incorporate a two-level hierarchy: municipalities (indexed by m) are nested within provinces (indexed by p). Note that the model for ZIP codes is essentially the same, replacing all municipalities m with ZIP codes z. The model is formally defined as follows:

1. **Likelihood of Child's Income Rank:** The income rank y_i for child i is assumed to be normally distributed around a predicted mean μ_i, with a common residual standard deviation σ across all observations:

$$y_i \sim \text{Normal}(\mu_i, \sigma) \tag{11}$$

2. **Linear Predictor for Mean Child Rank (μ_i):** The predicted mean child rank μ_i for an individual i (whose parents resided in municipality m within province p) is determined by the parental income rank y_p. Both the intercept and the slope of this relationship are allowed to vary hierarchically:

$$\mu_i = (\alpha_{overall} + \alpha_{p[i]} + \alpha_{m[i]}) + (\beta_{overall} + \beta_{p[i]} + \beta_{m[i]}) \cdot y_p \tag{12}$$

In this equation:

- $\alpha_{overall}$ represents the national average intercept. While the direct interpretation (expected child rank when parental rank is zero) is an extrapolation, this parameter helps anchor the regression line nationally.
- $\beta_{overall}$ is the national average Rank-Rank Slope (RRS), indicating the mean association between parental and child income ranks across all areas in Spain.
- $\alpha_{p[i]}$ and $\alpha_{m[i]}$ are the deviations from the national intercept $\alpha_{overall}$, specific to the province p and municipality m to which individual i belongs, respectively. These terms capture how the baseline level of child outcomes (more directly related to AUM when y_p is specified, e.g., at the 25th percentile) varies across provinces and, within provinces, across municipalities.
- $\beta_{p[i]}$ and $\beta_{m[i]}$ are the deviations from the national slope $\beta_{overall}$, specific to province p and municipality m. These terms allow the strength of the intergenerational income association (the local RRS) to differ across these geographic units.

3. **Hierarchical Priors for Random Effects:** The critical aspect of this hierarchical model is that the province-specific and municipality-specific deviations (the random effects $\alpha_p, \alpha_m, \beta_p, \beta_m$) are not estimated as entirely independent fixed parameters for each area. Instead, they are modeled as being drawn from common distributions centered at zero, with their respective variances (or standard deviations) estimated from the data. This hierarchical structure facilitates the pooling of information across units. Specifically:

$$\alpha_p \sim \text{Normal}(0, \tau_{\alpha_p}) \qquad \text{for each province } p \tag{13}$$

$$\alpha_m \sim \text{Normal}(0, \tau_{\alpha_m}) \qquad \text{for each municipality } m \text{ within its province} \tag{14}$$

$$\beta_p \sim \text{Normal}(0, \tau_{\beta_p}) \qquad \text{for each province } p \tag{15}$$

$$\beta_m \sim \text{Normal}(0, \tau_{\beta_m}) \qquad \text{for each municipality } m \text{ within its province} \tag{16}$$

The parameters τ_{α_p}, τ_{α_m}, τ_{β_p}, and τ_{β_m} are the standard deviations of these random effects, quantifying the extent of variation in intercepts and slopes at the provincial and municipal levels, respectively. These variance components are estimated from the data and are assigned weakly informative hyperpriors in a Bayesian framework (Exponential(1) in our case). The residual standard deviation σ from Equation (1) also receives a similar prior.

The model is estimated using Bayesian inference, typically through Markov Chain Monte Carlo (MCMC). For our modeling, we used Stan and the brms package, both of which use Hamiltonian Monte Carlo.

After the model converges and posterior distributions for all parameters are obtained, we can derive the local mobility measures:

- **Local Rank-Rank Slope (RRS):** For a specific municipality m located in province p, the estimated RRS is the sum of the national slope and the relevant deviations:

$$\text{RRS}_{pm} = \hat{\beta}_{overall} + \hat{\beta}_p + \hat{\beta}_m$$

  where the hatted terms denote posterior mean estimates.

- **Absolute Upward Mobility (AUM, μ_{25}):** For the same municipality m in province p, AUM is defined as the predicted child rank when the parental rank y_p is at the 25th percentile (i.e., $y_p = 25$). This is calculated using the estimated intercept and slope components for that locality:

$$\mu_{25,pm} = (\hat{\alpha}_{overall} + \hat{\alpha}_p + \hat{\alpha}_m) + (\hat{\beta}_{overall} + \hat{\beta}_p + \hat{\beta}_m) \cdot 25$$

An analogous hierarchical model structure is employed for generating estimates at the ZIP code level, with ZIP codes nested within provinces. As noted in the main text (Section 5), we chose not to include an additional hierarchical level for autonomous communities in this specific model. This decision was primarily driven by the fact that several autonomous communities in Spain are coextensive with a single province, which would lead to identification issues when attempting to separate variance components at these two levels simultaneously within this modeling framework.

Model for Estimating Quintile Transition Probabilities (including Rags-to-Riches)

To estimate the full matrix of intergenerational income quintile-to-quintile transition probabilities at the local level, including specific measures such as the 'rags-to-riches' probability ($P(Y = Q_5|X = Q_1)$, where Y is the child's income quintile and X is the parent's income quintile), we employ a Bayesian hierarchical ordered logistic model. This modeling choice is motivated by the ordinal nature of income quintiles and the need to generate stable and reliable estimates of transition probabilities, especially for geographic areas or specific parent-child quintile transitions where raw data may be sparse. Traditional non-parametric cell counts often suffer from high variance and can produce implausible estimates in such scenarios. Our hierarchical approach, by contrast, allows for systematic "borrowing of strength" across geographic units and income categories.

The fundamental assumption of the ordered logistic model is that an observed ordinal outcome for child i, $y_i \in \{1, \dots, K\}$ (where $K = 5$ for quintiles), is generated by an underlying continuous latent variable, y_i^*. The probability of observing child i in a specific income quintile k, conditional on their parental income quintile x_i and their geographic group g_i (e.g., municipality, province), is then given by:

$$P(y_i = k|x_i, g_i) = P(c_{g_i,k-1} < y_i^* \leq c_{g_i,k}) \tag{17}$$

where $c_{g_i,k}$ are group-specific ordered cutpoints (thresholds) on the latent scale, defining the boundaries between quintiles. By convention, $c_{g_i,0} = -\infty$ and $c_{g_i,K} = +\infty$.

The latent variable y_i^* is modeled as a function of a predictor, ϕ_i, which captures the influence of parental income and other factors, plus a logistic error term:

$$y_i^* = \phi_i \tag{18}$$

The predictor ϕ_i incorporates several key features designed to capture the structure inherent to the data:

1. **Group-Specific Monotonic Effect of Parental Income:** The core of the predictor ϕ_i models the effect of parental income quintile (x_i) on the child's latent income outcome. We impose a monotonicity constraint, ensuring that, all else equal, higher parental income does not lead to a lower expected child outcome. This relationship is allowed to have a group-specific shape (m_{g_i,x_i}) and an overall magnitude within that group (β_{g_i}). The shape component m_{g_i,x_i} is parameterized to be flexible yet monotonic across the J levels of parental income (e.g., $J = 5$ for quintiles):

    - $m_{g_i,1} = 0$ (baseline for the lowest parental income category).
    - $m_{g_i,j} = \sum_{l=1}^{j-1} q_{g_i,l}$ for $j = 2, \dots, J-1$.
    - $m_{g_i,J} = 1$ (normalized effect for the highest parental income category).
    - The positive increments $\mathbf{q}_{g_i} = (q_{g_i,1}, \dots, q_{g_i,J-1})$ are derived from underlying parameters $\boldsymbol{\alpha}_{q,g_i}$ via a softmax transformation, i.e., $\mathbf{q}_{g_i} \sim \text{Softmax}(\boldsymbol{\alpha}_{q,g_i})$.

    The full predictor term relating to the monotonic effect is $\beta_{g_i} \cdot m_{g_i,x_i}$.

2. **Predictor-Level Scaling (Heteroskedasticity):** To allow for the possibility that the variance of the

latent outcome y_i^* (or equivalently, the spacing of the cutpoints relative to the predictor effect) differs across levels of parental income x_i, we introduce a scaling factor δ_{x_i}. This factor modifies both the linear predictor and the cutpoints:

- Scaled Linear Predictor: $\phi'_i = \delta_{x_i} \cdot (\beta_{g_i} \cdot m_{g_i,x_i})$
- Scaled Cutpoints: $s\_cutpoints_{i,k} = \delta_{x_i} \cdot c_{g_i,k}$

The scaling factor itself, $\delta_{x_i} = 1/\exp(\sigma_{mono,x_i})$, is modeled to vary monotonically across the levels of x_i using another set of monotonic parameters $\sigma_{mono,j}$, which are also derived via a softmax transformation of underlying parameters $\boldsymbol{\eta}_\sigma$ and a magnitude β_σ. This allows, for example, the model to capture situations where outcomes for children from high-income families are predicted with different precision than for children from low-income families.

3. **Hierarchical Structure for Group Effects:** All group-specific parameters—those governing the monotonic shape ($\boldsymbol{\alpha}_{q,g_i}$), the monotonic magnitude (β_{g_i}), and the unscaled cutpoints ($c_{g_i,k}$)—are assigned hierarchical priors. This means that parameters for each geographic group g_i (e.g., municipality) are assumed to be drawn from a common national distribution, whose parameters (mean and standard deviation) are also estimated. For instance:

   - Shape parameters: $\boldsymbol{\alpha}_{q,g_i} = \boldsymbol{\mu}_q + \text{diag}(\boldsymbol{\tau}_q)\boldsymbol{\eta}_{q,g_i}$, where $\boldsymbol{\mu}_q$ is the mean shape vector and $\boldsymbol{\tau}_q$ are standard deviations.
   - Magnitude parameters: $\beta_{g_i} = \beta_{overall} + \tau_\beta \eta_{\beta,g_i}$, where $\beta_{overall}$ is the national average magnitude.
   - Cutpoints: Parameterized via a first cutpoint and log-gaps, e.g., $c_{g_i,1} = \mu_{c1} + \tau_{c1} z_{c1,g_i}$, with hierarchical priors on μ_{c1}, τ_{c1}, and similarly for the log-gaps.

The model is estimated using Bayesian inference, typically via Markov Chain Monte Carlo (MCMC) methods. In our case, we implemented the model in Stan. Once the posterior distributions of all parameters are obtained, we can calculate the predicted probability for any child i falling into a specific quintile k, given their parental income x_i and group g_i. For instance, the 'rags-to-riches' probability for group g (i.e., $P(y_i = Q_5 | x_i = Q_1, \text{group} = g)$) is derived using the estimated scaled cutpoints and the scaled linear predictor:

$$P(y_i = Q_5 | x_i = Q_1, g) = \Psi(s\_cutpoints_{g,Q_5} - \phi'(x_i = Q_1, g)) - \Psi(s\_cutpoints_{g,Q_4} - \phi'(x_i = Q_1, g)) \tag{19}$$

where Ψ is the standard logistic cumulative distribution function. Point estimates are typically taken as the posterior mean of these probabilities, and uncertainty is quantified using posterior credible intervals. This framework allows for the estimation of the complete $K \times J$ transition matrix for each geographic area.

Bayesian permanent residents outcomes calculation

The analysis of causal neighborhood effects using a movers' design (as detailed in Section 6) requires robust estimates of the expected adult income rank (y_i) for children who grow up as permanent residents in different localities. These "permanent resident outcomes" serve as the counterfactual benchmarks to assess the impact of moving to a different environment. We define permanent residents as children observed in our administrative data to reside in the same municipality throughout a significant portion of their formative years (e.g., between ages 13 and 24, or other consistent age range based on data availability for tracking residential locations).

To generate these baseline estimates, particularly in the presence of municipalities or specific cohort-municipality cells with sparse data, we employ a Bayesian hierarchical linear model. This approach allows us to "borrow strength" across units, leading to more stable and reliable predictions of permanent resident outcomes compared to simple cell-mean calculations or independent regressions for each locality.

The model for child i's adult income percentile (y_i), conditional on their parents' household income percentile (x_i) and their characteristics (municipality of residence mun$[i]$, province prov$[i]$, and observation year/cohort year$[i]$), is specified as:

$$y_i \sim \text{Normal}(\mu_i, \sigma)$$

The mean, μ_i, is modeled as a linear function of parental income rank, with both the intercept and slope allowed to vary hierarchically across different geographic levels and years/cohorts:

$$\mu_i = (\alpha+\alpha_{\text{mun}[i]}+\alpha_{\text{prov}[i]}+\alpha_{\text{year}[i]}+\alpha_{\text{year:prov}[i]}+\alpha_{\text{year:mun}[i]})+(\beta+\beta_{\text{mun}[i]}+\beta_{\text{prov}[i]}+\beta_{\text{year}[i]}+\beta_{\text{year:prov}[i]}+\beta_{\text{year:mun}[i]})x_i$$

In this specification:

- α and β represent the fixed national-level intercept and the national average rank-rank slope, respectively.
- $\alpha_{\text{mun}[i]}$ and $\beta_{\text{mun}[i]}$ are the random deviations from the national intercept and slope specific to the municipality (mun$[i]$) where the child (and their parents) resided.
- $\alpha_{\text{prov}[i]}$ and $\beta_{\text{prov}[i]}$ are the random deviations specific to the province (prov$[i]$).
- $\alpha_{\text{year}[i]}$ and $\beta_{\text{year}[i]}$ capture year-specific (or cohort-specific, if 'year' acts as a proxy for birth cohort)

deviations in the intercept and slope.

- The interaction terms (e.g., $\alpha_{\text{year:prov}[i]}$, $\beta_{\text{year:mun}[i]}$) allow these deviations to vary further by combinations of year/cohort and geographic unit, capturing more nuanced local trends over time.

All random effect terms are modeled as draws from zero-mean Normal distributions, with their respective variances (e.g., $\sigma^2_{\alpha,\text{mun}}$, $\sigma^2_{\beta,\text{mun}}$) estimated from the data:

$$\begin{aligned}
\alpha_{\text{mun}[m]} &\sim \text{Normal}(0, \sigma_{\alpha,\text{mun}}) \\
\beta_{\text{mun}[m]} &\sim \text{Normal}(0, \sigma_{\beta,\text{mun}}) \\
\vdots \quad &\quad \vdots \\
\alpha_{\text{year:mun}[ym]} &\sim \text{Normal}(0, \sigma_{\alpha,\text{year:mun}}) \\
\beta_{\text{year:mun}[ym]} &\sim \text{Normal}(0, \sigma_{\beta,\text{year:mun}})
\end{aligned}$$

The overall residual standard deviation of child ranks around their predicted mean is given by σ.

This model is estimated using only the subsample of children identified as permanent residents. After fitting the model (e.g., via Markov Chain Monte Carlo methods), we obtain posterior distributions for all parameters. The predicted permanent resident outcome for a child with specific characteristics (i.e., from a given parental income percentile p, in municipality m, province j, and cohort c) is then calculated as the posterior mean of μ_i:

$$\hat{y}_{mjpc} = E[\mu_i | x_i = p, \text{mun}[i] = m, \text{prov}[i] = j, \text{year}[i] = c, \text{data}]$$

This $\hat{y}_{mjpc}$ represents the expected adult income rank for a child who grew up in municipality m (within province j) from cohort c with parents at income percentile p, and did not move during the defined period (e.g., ages 13-24).

These predicted outcomes for permanent residents form the basis for calculating Δm_{odpc} (the difference in expected outcomes between destination d and origin o municipalities for a given parental income p and cohort c), which is the key exposure variable in our movers' design regression specified in Equation (10) of Section 6.1. The hierarchical estimation ensures that Δm_{odpc} is based on smoothed, reliable estimates of place quality, robust to variations in sample sizes across localities.

A.4: Translating Rank-Based Causal Effects into Income Terms

This appendix subsection details the methodology we use to convert rank-based causal exposure effects from our movers design into monetary values (euros) and interpretable relative income gains (percent change), with a specific focus on children from low-income families. The output of this process is shown in Figure 16

Step 1: Estimating causal exposure effects by age. We estimate Equation (10) in two ways: (i) a non-parametric model allowing a separate coefficient $\hat{b}_m$ for each age at move m, and (ii) a linear model restricted to ages below a cutoff ($m \leq 24$), following the methodology introduced in Chetty and Hendren (2018b). In both cases, each $\hat{b}_m$ reflects the reduced-form relationship between predicted outcomes in the destination and child income ranks for those who move at age m.

Our baseline model is the non-parametric specification of Figure 15. However, for the purposes of computing smoothed and interpretable monetary effects, we also consider a linear approximation. As in Chetty and Hendren (2018), we observe that the relationship between $\hat{b}_m$ and age at move is nearly linear for children moving at ages $m \leq 24$. This implies that the exposure effect $\gamma_m = \hat{b}_{m+1} - \hat{b}_m$ is approximately constant with respect to m in that range. We therefore fit a linear regression:

$$\hat{b}_m = \alpha + \beta \cdot m \quad \text{for } m \leq 24$$

and obtain predicted values $\hat{b}_m^{\text{linear}}$ for each relevant age. We then define the *causal effect of exposure* at age m as:

$$\text{causal\_exposure}_m = \hat{b}_m^{\text{linear}} - \delta$$

where δ is the average of $\hat{b}_m$ for ages with no expected exposure ($m > 24$), capturing residual selection effects.

Uncertainty is computed using the standard error of prediction from the linear model:

$$\text{se}_m^{\text{linear}} = \text{SE}(\hat{b}_m^{\text{linear}})$$

This smoothed estimator is used for downstream monetary and percentage conversions, but our benchmark exposure pattern remains the non-parametric estimate.

Step 2: Translating rank-based exposure into outcome gains. We multiply each causal_exposure$_m$ by an empirically observed rank gap g, representing the difference in expected adult rank between low- and high-opportunity municipalities. These gaps are estimated from the distribution of predicted outcomes of permanent residents:

$$g_{\text{P90–P10}} = 19.9 \quad \text{and} \quad g_{\text{P75–P25}} = 11.1$$

The total causal effect in rank points is:

$$\text{causal\_effect}_m = \text{causal\_exposure}_m \times g$$

Step 3: Converting percentile gains into euros. We translate rank-based gains into euros using administrative income data. Let $I(p)$ denote the average income at percentile p of the child outcome distribution. We approximate the income gradient at the outcome level typical of children from p25 families who do not move, which is $p = 40.3$. Using a centered difference approximation:

$$\gamma = \left.\frac{dI}{dp}\right|_{40.3} \approx \frac{I(40.8) - I(39.8)}{1} \approx 330\,\text{euros}$$

The causal effect in euros is then:

$$\text{causal\_effect\_eur}_m = \text{causal\_effect}_m \times \gamma$$

Step 4: Propagating uncertainty. We compute the standard error for each causal effect in euros using the delta method:

$$\text{se}_{\text{eur},m} = \text{se}_m^{\text{linear}} \times g \times \gamma$$

and derive 95% confidence intervals as:

$$[\text{causal\_effect\_eur}_m \pm 1.96 \cdot \text{se}_{\text{eur},m}]$$

Step 5: Expressing effects in relative terms. Finally, we express the effect in euros as a percentage increase relative to the average income at $p = 40.3$, estimated at €19,840.65:

$$\text{PctChange}_m = 100 \times \frac{\text{causal\_effect\_eur}_m}{I(40.3)}$$

Illustrative Example: Child moving at age 13. To illustrate this procedure, consider a child from a p25 family who moves at age 13. Based on the linear model fitted on ages ≤ 24, the estimated exposure component is:

$$\hat{b}_{13}^{\text{linear}} = 0.706, \quad \delta = 0.276 \Rightarrow \text{causal\_exposure}_{13} = 0.429$$

- **Step 2: Multiply by empirical rank gap.**
  - **P90–P10 (19.9p):** $0.429 \times 19.9 = 8.55$ percentile points
  - **P75–P25 (11.1p):** $0.429 \times 11.1 = 4.75$ percentile points

- **Step 3: Convert to euros using** $\gamma = 330$:
  - **P90–P10:** €2,823
  - **P75–P25:** €1,567
- **Step 4: Uncertainty and confidence intervals.**

$$\text{se}_{13}^{\text{linear}} = 0.0325$$

  - **P90–P10:** se = €214, CI = [€2,404, €3,243]
  - **P75–P25:** se = €119, CI = [€1,334, €1,800]
- **Step 5: Relative to baseline income €19,840.65**
  - **P90–P10:** 14.2% gain [12.1%, 16.3%]
  - **P75–P25:** 7.90% gain [6.72%, 9.07%]

A.5: Definition of Urban Areas

Definition and Coverage of Urban Areas

Our analysis at the "urban area" level utilizes the definition of Functional Urban Areas (Áreas Urbanas Funcionales, AUF) established by the Spanish Ministry of Transport, Mobility and Urban Agenda (MITMA) in its 2022 methodology (Ministerio de Transportes, Movilidad y Agenda Urbana, 2022). This approach, harmonized with Eurostat guidelines, defines an AUF as a densely populated core city (or cities) along with its surrounding commuting zone, reflecting functional economic integration.

Delineation Criteria for Functional Urban Areas

The MITMA (Ministerio de Transportes, Movilidad y Agenda Urbana, 2022) methodology employs a multi-layered set of criteria combining demographic, economic, and spatial information:

- Large Urban Areas (Grandes Áreas Urbanas): These generally require a principal municipality with at least 50,000 inhabitants. Exceptions are made for provincial capitals like Soria and Teruel, which are included despite smaller populations due to their central role in their respective provinces.
- Constituent Municipalities in Plurimunicipal Urban Areas: Each municipality within such an AUF must typically have a minimum of 1,000 inhabitants, though exceptions are made based on regional or functional significance.

- Data Sources for Delimitation: The classification primarily draws on recent municipal-level data, including the 2011 Population and Housing Census, the 2021 Active Population Survey (EPA), and the 2021 Population Nomenclator (*Padrón Continuo*).
- Smaller Urban Areas: For urban areas not classified as Large Urban Areas and centered around municipalities with populations between 5,000 and 20,000, a four-step filtering process is applied:
  1. Assessment of the "nuclear" population (core population minus dispersed inhabitants).
  2. Exclusion of municipalities with negative demographic evolution between 1960 and 2021.
  3. Application of an economic filter based on the share of employment in the service sector, an indicator of urbanization.
  4. Use of a "potential accommodation" indicator, which combines secondary and vacant dwellings (adjusted by a national occupancy index) with the core population.

This approach aims to ensure that the delineated urban areas reflect both physical density and functional economic integration. According to Ministerio de Transportes, Movilidad y Agenda Urbana (2022), this methodology classifies 1,084 municipalities as urban, representing 13.3% of all Spanish municipalities. These urban municipalities are home to 82.5% of the national population but occupy only 20.7% of Spain's territory.

Population Coverage of Urban Areas in Our Analysis

Due to data limitations in our primary dataset (as detailed in Section 3.2), we exclude the Basque Country and Navarre from our geographic mobility analyses. Consequently, for calculations involving urban area population coverage, we adjust both the numerator (population in urban areas) and the denominator (relevant national population).The official Ministerio de Transportes, Movilidad y Agenda Urbana (2022) definition includes four main urban areas located entirely within the Basque Country or Navarre: Bilbao, Donostia–San Sebastián, Vitoria-Gasteiz (all in the Basque Country), and Pamplona (Navarre). (The Irún–Hondarribia area, also in the Basque Country, is typically considered part of the San Sebastián AUF or as a minor urban area and is also excluded by extension). After excluding these four AUFs, our analysis considers the remaining 78 official urban areas. The total population of these included urban areas is approximately 37.1 million inhabitants (based on 2022 population data). The corresponding national population for Spain, excluding residents of the Basque Country and Navarre, is approximately 44.5 million (2022 data). Therefore, in the context of our study, approximately 83.3% of Spain's population (excluding the Basque Country and Navarre) resides within these 78 defined urban areas. This indicates that our urban area analysis captures the residential context of over four-fifths of the inhabitants in the regions covered by our intergenerational mobility estimates.

A.6: Classification of Municipality-Level Characteristics

This appendix presents the classification of the municipal-level correlates used in our geographical analysis of intergenerational mobility. The variables span a wide range of dimensions that capture the socioeconomic environment in which children grow up. They are grouped into eight broad thematic categories based on their conceptual relevance: Demographics, Education, Family Structure, Housing, Income & Wealth, Migration, Labor Market Conditions, Sectoral Composition, Social Capital, Segregation and Commuting, and Urban Amenities. These indicators are derived from a combination of sources, including the 2001 Population and Housing Census (Censo 2001), administrative registers from the National Institute of Statistics (INE), and data from the Ministry of Transport, Mobility and Urban Agenda (MITMA). The vast majority of variables used here are measured between 2000 and 2007, which is the closest we can get to the childhood environments of the generations in our dataset. Below, we describe the main thematic categories used in our analysis and the types of indicators included in each.

Demographics This category captures the age composition and dependency burden of each municipality. Variables include the child dependency index, youth share of the working-age population, and a general youth dependency indicator. These measures help characterize the demographic structure that children grow up in, indicating the potential demand on educational and social services as well as the density of peer networks and support systems in a given area.

Education Educational indicators reflect the prevailing level of human capital and access to learning opportunities within a municipality. The variables include the average education level among young adults, post-compulsory education attainment, and the illiteracy rate. These metrics describe the skill profile of local populations and shape the educational environment that children are exposed to during their formative years, including peer effects and aspiration channels.

Family Structure This group includes measures of household composition and the prevalence of multigenerational or large families. Indicators such as the average number of children per household and the share of large family households (with two older adults and two or more children) provide insight into caregiving structures, economic strain, and the intra-household distribution of resources and time that may influence children's development.

Housing Housing variables describe both the quality and accessibility of the residential environment. This includes the total appraised value of housing, renter shares by age group, the proportion of households owning a second home, and the incidence of housing quality deficiencies. These indicators proxy for material living conditions, housing market segmentation, and the degree of permanence or transience in residential patterns, which may affect neighborhood cohesion and child outcomes.

Income & Wealth This category summarizes the economic resources available to families and the broader local economy. Variables include average household income, the number of vehicles per household, and the share of households with at least one unemployed member. These indicators collectively capture material living standards, financial vulnerability, and consumption capacity, all of which shape the resources that families can invest in children.

Migration Migration indicators reflect the composition and diversity of the municipality's population. This includes the total foreign-born population, foreign-born youth (e.g., age 25–34), and origin-specific shares (e.g., from Germany). These measures speak to patterns of geographic mobility, cultural integration, and the social environments children may encounter—particularly in terms of linguistic, ethnic, and socio-economic diversity.

Labor Market Conditions These variables describe the strength, segmentation, and inclusivity of local labor markets. Indicators include the unemployment rate (general and youth-specific), the share of temporary contracts, and employment shares across sectors such as agriculture and services. These metrics influence the economic opportunities available in the community, exposure to job insecurity, and the likelihood that families face persistent or cyclical income shocks.

Sectoral Composition Sectoral variables provide information on the occupational and industrial landscape of a municipality. Indicators such as average occupational prestige summarize the types of jobs held by residents and reflect the status and wage potential of local employment. These factors influence local labor market signaling, aspirations, and access to professional networks that may matter for children's long-term prospects.

Segregation and Commuting This category captures how residents interact spatially with their environment, especially in relation to employment and services. Variables include commuting modes such as reliance on private vehicles, motorcycles, or trains. These indicators can be interpreted as proxies for geographic accessibility, urban infrastructure, and social isolation, all of which shape exposure to opportunity and the cost of access to resources.

Urban Amenities Urban amenity variables describe environmental and public space characteristics within municipalities. These include the availability of artificial green spaces, urban tree coverage, and indicators of urban cleanliness. These measures reflect municipal investment in the built environment, which may affect both children's physical well-being and their perception of social inclusion and quality of life.

A.7: Methodological Details of the Correlational Analysis

This appendix discusses the methodological details of the correlational analysis. We compute two types of correlation coefficients—**unweighted** and **population-weighted**—for each combination of geographic correlate and mobility outcome. We consider two main outcomes: (i) the *direct estimate* of absolute upward mobility (AUM) based on an OLS rank-rank slope following (Chetty et al., 2014a), and (ii) its *Bayesian counterpart*, which shrinks noisy municipal estimates using hierarchical priors. For each of these outcomes, we compute correlations in both unweighted and weighted forms:

Unweighted correlations. These are calculated using univariate OLS regressions of the standardized mobility outcome on the standardized correlate, excluding the intercept. This method is algebraically equivalent to computing the Pearson correlation coefficient. Standard errors are obtained using conventional OLS inference. These estimates capture the raw association across municipalities without accounting for population size.

Weighted correlations. To account for the varying population sizes across municipalities, we also compute population-weighted Pearson correlations, using as weights the municipality's population in 2001. Because closed-form formulas for the standard error of weighted correlations are not available, we estimate uncertainty via a nonparametric bootstrap. Specifically, we draw 500 bootstrap samples of municipalities (with replacement), compute the weighted correlation in each, and take the standard deviation of the resulting distribution as the bootstrap standard error.

Implementation. Correlations are computed between standardized variables at the municipal level. For OLS-based AUM, we restrict the sample to municipalities with at least 20 observed children and apply interquartile-range (IQR) filtering to remove extreme outliers. Specifically, we first exclude all municipalities where the rank-to-rank slope lies outside the theoretical range of [0,1], which removes 304 out of 3,557 municipalities (8.55%). We then apply the IQR method to the rank-to-rank slope to identify and exclude an additional 139 outliers (4.27% of the remaining cases). Next, we apply IQR filtering to AUM, our main absolute mobility measure defined as the mean child income percentile for children from families at the 25th percentile, removing a further 30 municipalities (0.96%). Finally, we drop 2 municipalities (0.06%) where the estimated probability of reaching the top quintile from the bottom quintile equals 1, an implausible upper bound for a probability. After this multi-step filtering process, the OLS-based sample comprises 3,075 municipalities (86.45% of the original set). For Bayesian mobility estimates, we include all municipalities with at least one observed child without filtering (5,876 municipalities).

A.8: PCA-based Correlational Analysis at the Urban Area level

We perform a similar PCA-based analysis to reduce dimensionality and correlate the components with upward mobility at the immediate higher geographical level: urban area. Appendix Table A5 reveals several key structural characteristics that are strongly associated with intergenerational mobility at the urban level. Among the seven extracted components[18], the most robust predictor is the concentration of industrial and construction employment, which consistently correlates with higher absolute upward mobility even after accounting for regional differences. This suggests that access to stable, accessible jobs in these sectors can significantly boost the long-run economic outcomes of children from low-income families. Likewise, the presence of a highly educated adult population—captured through the college education attainment component—emerges as another strong predictor of mobility, particularly in baseline models. This likely reflects the benefits of human capital spillovers, better school environments, and greater educational aspirations among youth. Other components display important, though more context-dependent, effects. High local unemployment rates strongly predict lower mobility outcomes, underlining the adverse impact of joblessness on children's opportunities. Demographic indicators, such as an older age structure, initially appear positively associated with mobility but lose significance when regional patterns are controlled for, suggesting that this is more a regional than a local effect. Multigenerational and larger households show a stable negative association, likely due to resource dilution and lower educational investment per child. By contrast, material poverty and occupational prestige lose significance in multivariate models, indicating that their effects may be channeled through other, more proximate institutional or economic factors. Together, these results highlight the centrality of local labor markets and household structure, while also pointing to the strong regional patterning of opportunity across Spain, in line with national- and municipality-level analysis.

However, a key distinction between the urban area and municipality-level analyses is the much higher explanatory power of the PCA models at the urban level: around 90% of the variation in upward mobility is explained at the urban scale (Appendix Table A5), compared to just 50% at the municipal level (Table 1). This difference arises for several reasons. First, aggregating municipalities into urban areas may help to smooth

[18]We include more principal components in the municipality-level analysis than in the urban area analysis for several reasons. First, we have many more observations at the municipal level, which allows us to estimate more complex models without risking overfitting. Second, the components explain more of the variation in upward mobility in urban areas than in municipalities, so we need to include more components at the municipal level to reach a similar level of explanatory power. Third, municipalities show more variation in local conditions than urban areas, especially in Spain where public services and economic structures can differ a lot even within the same region. Including more components helps capture this local complexity. Finally, the larger sample of municipalities gives us enough statistical power to include additional components without losing precision.

over local noise and idiosyncrasies, making the patterns of upward mobility clearer. Second, urban areas tend to be more internally consistent, with coordinated systems of education, infrastructure, and labor markets that shape opportunity across municipalities. Third, many drivers of mobility, such as access to jobs or schools, operate at a broader spatial scale than the municipality, meaning they are better captured at the urban level. Finally, regional fixed effects explain more of the variation at the urban level, where cross-regional differences in policy and economic structure are more sharply reflected than in the more granular municipality structure.

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