Regional intergenerational mobility in Ecuador: Many lands in one country

Abstract

We analyse the regional differences in eight measures of intergenerational mobility across cantons in Ecuador. Within-country estimates show heterogeneity with lands of opportunity, such as the Galápagos, and areas where poverty traps prevail, namely the Central Andes. This study also finds that better opportunities for children are associated with locations that have higher levels of migration, schooling, agriculture, family self-employment and oil activity, while inequality and the share of indigenous people provide worse opportunities for mobility. These relationships are reinforced by spillovers across space, which, in Ecuador, are more likely to results in poverty cycles than privilege ones.

JEL: D63, I24, R12, O15, J62

Keywords: regional intergenerational mobility, social persistence, education, geography, inequality, Ecuador

1. Introduction

Interest in intergenerational mobility studies has increased in the past decade because of the widespread notion that higher cross-sectional inequality is associated with lower mobility across generations, hence linking inequality of opportunity with inequality of outcomes. In Latin America, the second most unequal region in the world, the United Nations Development Programme (UNDP, 2021) has linked low social mobility to the stark inequalities and 'development trap' that the region experiences. Furthermore, the region has been labelled the least socially mobile in the world by a great margin (Torche, 2021).

Studies have been carried out estimating mobility at the subnational level (e.g. Chetty et al., 2014), unveiling stark within-country differences (Acciari et al., 2022; Chetty et al., 2014; Corak, 2020) with marked patterns of spatial correlation. This not only leaves room for future studies to delve into the importance and effects of the correlations when trying to explain mobility, but it is also consistent with the theoretical models of intergenerational mobility developed by Benabou (1993) and Durlauf (1996a, 1996b) and, more recently, by Becker et al. (2018), who posit that spillovers in mobility across places can generate positive or negative cycles. A potential step towards explaining mobility would be to study the effects of spatial dependence and the possibility for spillovers.

We take this regional evidence into consideration and incorporate spatial statistical tools to estimate and explain the intergenerational transmission of socioeconomic status, using education as a proxy. We use Ecuador as a case study as it is the third least mobile country in Latin America (Daude & Robano, 2015), where 86 per cent of the population think that inequality is the result of an unfair society and only 21 per cent believe that upward mobility may be possible for their children (Latinobarómetro, 2018). Between 2006 and 2017, Ecuador experienced a substantial reduction in poverty and the rise of the middle class in line with the regional pattern. Mobility from lower to higher social classes, however, has proved to be a rather weak process driven by the boom in commodities and the redistributive policies it allowed (Azevedo et al., 2015) and not by better social mobility indicators (Torche, 2021). Therefore, this analysis can contribute to the broader audience of countries where, like in Ecuador, there is a significant presence of primary sector activities while the space for structural changes in terms of social mobility is still limited.

Furthermore, empirical evidence on this topic is rather scarce for Ecuador: research has been conducted mainly at the country level as part of international surveys and using only one concept, that of origin dependence (Andersen, 2001; Daude & Robano, 2015; Hertz et al., 2007; Neidhöfer et al., 2018). In contrast, we estimate eight measures of intergenerational mobility for 114 cantons and identify marked geographical differences for such a small country. The results reflect the unequal/unfair nature of the country in which higher inequality is associated with larger parent-child status correlations, coexisting with reduced rates of upward mobility and a high chance of poverty traps. Furthermore, we formally document evidence of a significant spatial correlation of mobility estimates, which allows it to be treated as a spatial phenomenon and its potential spillovers to be explored.

The structure of this paper is as follows. Section 2 presents a brief literature review of the drivers of intergenerational mobility. Section 3 describes the eight measures of mobility that we calculate and the spatial techniques applied to study its drivers. Section 4 describes the data sources and their handling, as well as the territorial unit of analysis. Section 5 presents the results: it is divided into (i) a description of intergenerational mobility through the set of measures and (ii) a spatial analysis of mobility. Section 6 offers some concluding remarks.

2. The drivers of intergenerational mobility

The regional literature on intergenerational mobility has experienced a surge since the study by Chetty et al. (2014) and it has contributed by consistently finding large variations yet clear spatial correlations across subnational territories (Acciari et al., 2022). Furthermore, the geography of intergenerational mobility seems to be more important in some countries than in others (Delajara et al., 2021) and has emphasised that the local—both micro- and meso-level—contexts that individuals face are key for mobility (Connor & Storper, 2020; Granström & Engzell, 2023).

This literature has also identified multiple drivers to explain the observed heterogeneity. These differ depending on the dimension and the measure of intergenerational mobility under analysis. Following Granström and Engzell (2023), they can be divided into categories representing the human capital, labour, demographics, and socio-spatial structure of a country. Since our second aim is to explain what drives mobility, we describe in what follows the set of variables that we select for this.

Based on the literature, we know that one of the most common and robust drivers of subnational mobility is migration, which is usually found to increase the probability of moving up the social ladder (Acciari et al., 2022; Corak, 2020; Song et al., 2000). This is explained by the fact that migrants move for better jobs and overall better economic opportunities. Hence, locations with higher immigration rates might highly reflect this 'moving to opportunity' behaviour (Berger et al., 2023). A second important demographic driver is the proportion of disadvantaged ethnic groups. For instance, mobility is inversely correlated to the share of indigenous groups in Chile and Australia (Cortés Orihuela et al., 2022; Deutscher & Mazumder, 2020), and to black populations in the US (Chetty et al., 2014). The mechanisms behind this pattern have not been studied in detail, but it is argued that differences in the institutions and industries developed in the areas with a larger presence of these ethnicities might be one mechanism, while racial segregation might be another (Chetty et al., 2014).

Human capital is another category that is widely studied and measured in a variety of ways. Overall, regions with better performance in human capital dimensions such as average schooling, tertiary attendance, share of professionals and school completion predict better social mobility opportunities (Connolly et al., 2019; Granström & Engzell, 2022). Connor and Storper (2020) argue that the mechanism underlying this relationship is that in modern societies, where schooling is strongly rewarded, its expansion may result in reductions in interpersonal inequality and favour better economic and social opportunities for all households in a region, improving social mobility. Among the variables relating to human capital, measures of education inequality are also important and can provide an insight into the existence of a Great Gatsby curve in education. This suggests that greater inequality in one generation is associated with decreased social mobility. According to Durlauf and Seshadri (2018), at the subnational level, the underlying mechanism of this relationship is territorial segregation: inequality increases segregation and segregation is related to parental status; hence, inequality increases the transmission of parental status—i.e. it decreases mobility.

The variables of the labour market structure are diverse and include shares of unemployment as well as teenage and youth labour and the population outside of the labour force, the unionisation rate, job automation and the sectoral composition of employment (Berger & Engzell, 2022; Connolly et al., 2019; Corak, 2020; Delajara et al., 2021). Within the sectoral composition of employment, the concentration of industrial employment has been associated with both positive and negative effects on mobility, while agricultural employment has been mostly linked to lower mobility (Granström & Engzell, 2023), especially upward mobility in industrialised economies (Alesina et al., 2021; Berger et al., 2023; Corak, 2020). Another relevant variable for Ecuador, as in other developing countries, is self-employment, which in fact accounts for six out of ten workers. Going into this type of employment is mainly explained by necessity and family tradition. Self-employment has been found to be highly correlated among parents and children in European countries (Giménez-Nadal et al., 2022). Furthermore, Acciari et al. (2022) note that intergenerational mobility is higher for the sons of self-employed parents. We take this into consideration by including a variable capturing the percentage of workers who are self-employed due to family tradition. The mechanisms through which this could affect mobility can be found in recent theoretical models where family and social explanations are at the core, with parental role models as a key factor defining belief formation and aspirations (Cholli & Durlauf, 2022).

3. Methodology

3.1. Concepts and dimensions of mobility

The measurement of intergenerational mobility can encompass different dimensions and concepts: this has resulted in at least 20 different proposed indices (Jäntti & Jenkins, 2015). The dimension[1] refers to the variable selected for calculating mobility: education. This choice has been extensively evaluated and is particularly informative in our case because education is the main predictor of earnings in Latin America (Psacharopoulos & Patrinos, 2018). Therefore, it is associated with multiple non-pecuniary outcomes such as health and parenting, crime and political engagement (UNDP, 2021). Furthermore, it can be strongly related to mobility in other domains such as the economic and occupational (Torche, 2021), although this has been challenged depending on the context (Fletcher & Jajtner, 2023).

Studying educational mobility has several advantages with respect to income mobility (Neidhöfer, 2019). Firstly, educational attainment is usually fixed and time-invariant once a certain age is reached, representing a suitable proxy for lifetime socioeconomic status. This contributes to avoiding attenuation and lifecycle bias (Black & Devereux, 2011). Secondly, while revealing one's income can be sensitive and is avoided by some people, this is rarely the case with education. Therefore, it is more reliable and less affected by measurement errors. Given these advantages, mobility indicators in the area of education are broadly available for developed and developing countries, making it a convenient measurement for comparison purposes, too.

A number of concepts refer to how mobility is defined and hence interpreted. Two of the most used concepts of mobility are 'movement' and 'origin dependence' (Ferreira et al., 2012). Movement defines mobility as gross and net movements along the distribution from one generation to another (e.g. moving downward or upward in the distribution). The concept of origin dependence views mobility as the extent to which one generation's future is independent of the preceding generation.

Within these two concepts are indices of absolute and relative mobility. Absolute mobility measures capture the total change from one generation to another, which might result from economic expansion or growth, while relative mobility measures capture the change in relative positions along the distribution between generations. Since growth may make everybody better off while they all retain their relative positions, absolute and relative measures provide different views of mobility. Relative measures are believed to reflect the structure of opportunities in a society better and its degree of 'openness' (Erikson & Goldthorpe, 1992). We estimate eight measures covering the two concepts.

3.2. Measures of mobility

The single most used measure of intergenerational mobility is the slope of a cross-sectional linear regression of children's outcomes on parental outcomes (Cholli & Durlauf, 2022; Jäntti & Jenkins, 2015; Stuhler, 2018). In our case, we regress schooling years of children in region c (y_{1c}) on the schooling years of parents (y_0), as follows:

$$y_{1c} = \alpha_c + \beta_c y_0 + \varepsilon_{ic} \qquad (1)$$

β_c is a measure of relative intergenerational mobility that follows the concept of origin dependence since it reflects the strength of the association between children and parental outcomes. The higher the coefficient, the greater the origin dependence or persistence (i.e. the lower the intergenerational mobility).

Following the literature (Deutscher & Mazumder, 2020; Neidhöfer et al., 2018; Torche, 2021), as a complement of β_c, we also present the Pearson correlation coefficient between children and parental income. This is a measure of origin dependence as well, but it differs from β_c by netting out the cross-sectional inequality of education across generations, providing a standardised index:

$$\rho_c = \beta_c \frac{y_0}{y_{1c}} \qquad (2)$$

The next measure, the intergenerational rank association (IRA), constitutes an increasingly prevalent index in the empirical literature and was introduced by Dahl and DeLeire (2008), who adopted the method used in the literature on intergenerational occupational mobility. Here, it is necessary to construct rankings for everyone within their generation and then regress the education rank of children who live in region c on the education rank of parents:

$$R_{1c} = a_c + b_c R_0 + \varepsilon_{ic} \qquad (3)$$

b_c is the IRA or rank–rank slope coefficient, capturing the movement concept of mobility. It identifies persistence in rank position and can be viewed as abstracting changes in inequality. When the ranks are built from the population in question, b_c allows mobility to be studied on a 'fixed' national scale. This is simply the Spearman correlation (Deutscher & Mazumder, 2020); it has been emphasised since the work of Chetty et al. (2014) as a relative measure of mobility (Corak, 2020; Delajara et al., 2021; Deutscher & Mazumder, 2020; Neidhöfer et al., 2018).

The intercepts α_c and a_c from Equations (1) and (3) are also used in the literature as absolute measures reflecting the concept of movement. Following Corak (2020), α_c captures differences in schooling growth between regions. On the other hand, a_c measures the expected rank for children from families at the bottom of the income distribution (Chetty et al., 2014).

The remaining measures of mobility come from the matrix of transition probabilities across quintiles of the national education distribution. Since linearity is not assumed, mobility matrices have the advantage of allowing asymmetric patterns of mobility (Stuhler, 2018); therefore, they complement other indicators. Mobility matrices, also referred to as positional measures, represent relative measures of mobility and follow the movement concept. Following the literature (Acciari et al., 2022; Corak, 2020; Delajara et al., 2021; Neidhöfer et al., 2018), we will focus on three specific cells from the matrix:

$$Q1Q1 = Pr\{R_{1c} \leq 20 \mid R_0 \leq 20\} \qquad (4)$$

$$Q5Q5 = Pr\{R_{1c} \geq 80 \mid R_0 \geq 80\} \qquad (5)$$

$$Q1Q5 = Pr\{R_{1c} \geq 80 \mid R_0 \leq 20\} \qquad (6)$$

These capture the so-called intergenerational cycles of poverty (Q1Q1), or the probability of being born and remaining in the bottom quintile of the distribution, and intergenerational cycles of privilege (Q5Q5), or the probability of being born and staying in the top quintile of the distribution. The third index (Q1Q5) has been called a measure of the American Dream (Chetty et al., 2014) or rags to riches (Corak, 2020); it measures movement from the bottom to the top quintile of the distribution. This is one of the most discussed measures in the literature (Deutscher & Mazumder, 2020).

3.3. Spatial analysis of mobility

To analyse the drivers of mobility, we introduce space as a relevant dimension based on the regional literature on intergenerational mobility, which has found patterns of spatial correlations, and the theoretical models by Becker et al. (2018), Benabou (1993) and Durlauf (1996a, 1996b), who argue that intergenerational mobility is reinforced by neighbourhood effects.

Benabou (1993) states that when adults choose their neighbourhood, they do this for themselves and their offspring. In the same vein, Troost et al. (2023) argue that this choice is based on a wide array of factors including their tastes and resources, with the aim of preserving or improving their status. Neighbourhoods are formed by and generate internal and external social interactions, which in turn affect individuals' sets of information, preferences and even aspirations (Lekfuangfu & Odermatt, 2022; Topa & Zenou, 2015). This process leads to spillover effects across territories. As a result, positive or negative cycles of mobility may arise. Evidence of neighbourhood effects where negative cycles of mobility may arise includes the study by Connor, Berg, et al. (2023).

One potential mechanism through which interaction happens is migration, which was first pointed out by Benabou (1993) when trying to explain high- versus low-skilled neighbourhoods. Evidence by Borck and Wrede (2018) supports this for the US, finding that internal migration can help explain the variation in intergenerational mobility within a country by sorting different skills into geographic areas.

To explore these potential neighbourhood effects, we apply econometric techniques to account for the spatial correlation between adjacent territories in Ecuador and identify the spillover effects. To our knowledge, previous contributions applying these techniques have not delved deep into studying the spatial correlations and spillovers (Qin et al., 2020; Wei et al., 2023), while others have not found support for spatial lags (Weber et al., 2018).

With this aim, we first conduct an exploratory analysis of our hypothesis that there are spatial correlations by calculating the global and local Moran's I statistic. After this, we move on to the spatial econometric analysis, where we depart from the general spatial regression that follows:

$$y_i = \rho W y_i + X_i \beta + W X_i \theta + \mu_i \qquad (7)$$

$$\mu_i = \lambda W \mu_i + \varepsilon_i \qquad (8)$$

Here, i represents the regional level (i=1, …, n). In our case, y_i denotes intergenerational mobility, while W represents the spatial weighting matrix to capture the spatial relationship between regions. X_i signifies a set of independent variables that, according to the literature and the structural characteristics of Ecuador, may drive mobility, and μ_i is a random error term with zero mean and constant variance.

The literature on spatial econometrics has proposed a collection of spatial econometric specifications for which Equation (7) is a generalisation, known as the spatial Durbin model (SDM). Under this general specification, the right-hand side of the equation includes as control variables the spatial lags of the dependent and independent variables denoted by Wy_i and WX_i, respectively. Coefficient ρ is the spatial dependence coefficient, λ is the spatial error lag, and β and θ are vectors of coefficients corresponding to the explanatory variables, the latter representing the spatial lag or the influence of these variables averaged over the neighbouring regions.

The primary definition of the spatial weights' matrix is a binary contiguity matrix with first-order neighbours and row standardisation. As sensitivity analysis, we also vary the matrix specification to a contiguity matrix with second-order neighbours and distance-based matrices with the inverse of the distance, the inverse of the squared distance, and a k-nearest neighbours matrix using the information of the four nearest.

4. Data

In this study, we use the Encuesta de Condiciones de Vida (ECV). This survey was first carried out in 1994 with the aim of measuring the quality of life of citizens and, overall, to assess poverty and welfare. The design is based on stratified two-stage sampling and is representative at the national and subnational levels of regions, provinces, and some cities. We use all the datasets collected from 1998 onwards. Since then, the ECV has gathered information on the education of parents and adult children and whether or not they live together. If they do, a retrospective question on parental education applies. This allows the usual limitation on longitudinal data availability in developing countries to be overcome and avoids the cohabitation bias that can arise if estimated only with adults who live with their parents.

We impose three restriction criteria on our sample. Firstly, we restrict the sample to the availability of information on the individuals' own and their parents' education. Secondly, we limit our sample to adults aged 25 to 64 years in each wave. Next, we exclude individuals who have not finished their studies and who report that they are enrolled in any education degree. An inspection of this criterion shows that nearly 3 per cent of the adults are enrolled in education, mainly tertiary, and the remaining 97 per cent are not studying. Together, these criteria help ensure that we work with a variable that captures the final schooling level of the individuals in our sample to the greatest extent possible.

Next, we define four cohorts of children aged 25–34, 35–44, 45–54 and 55–64 years in each wave and limit our sample to those observed at least twice, which rules out the oldest cohort of the first wave and the youngest of the last wave. With this, our final sample consists of 66,038 parent–child pairs. Schooling years have been calculated following the methodological approach by the Sistema Nacional de Información (2016). To calculate mobility, we use a variable of joint parental education, applying the dominance principle developed in sociology (Erikson, 1984)—that is, we use the maximum years of schooling of either the father or mother. To compute the measures from the transition probability matrix (Q1Q1, Q1Q5, Q5Q5), we generate quintiles of the national distribution of education (Acciari et al., 2022; Chetty et al., 2014).

To define the territorial unit for our estimates, we use the canton where the children reside, as in other studies that have focused on regional differences (Berger & Engzell, 2022; Granström & Engzell, 2023). Ecuador is geographically divided into four regions—the Galápagos, the coast, the Andes and the Amazon (Figure A.1 in the Supplementary Material)—and administratively divided into 24 provinces, 221 cantons, and 1,024 parishes. The great majority of cantons (91 per cent) have populations below the lowest threshold defined in the Nomenclature of Territorial Units for Statistics 3 region. Cantons have for a long time been the basic unit of territorial organisation in Ecuador (Benabent & Vivanco, 2021). They are the most common unit at which economic and social phenomena are studied; hence, we know there is high heterogeneity between them but shared characteristics within them in terms of their economic, social and demographic indicators (Pontarollo et al., 2019). Cantons have some important functions that aim to create employment and income opportunities for the local population (Benabent & Vivanco, 2021). Their importance for local economic and social development is reflected in the fact that, amongst the administrative divisions, they receive the largest share of central government transfers, reaching 67 per cent in the latest regulation code (Código Orgánico de Organización Territorial, Autonomía y Descentralización, 2010).

Cantons are very diverse in terms of population size, however, which can range from 2,000 residents to 2.5 million (Instituto Nacional de Estadística y Censos (INEC), 2020). As this entails very small sample sizes for a lot of cantons, we also restrict our sample to those with at least 100 parent–child pairs, which allows us to study intergenerational mobility in 124 cantons. These represent 57 per cent of the existing cantons which are home to 91 per cent of the population in Ecuador. All estimates are obtained by weighting each observation by the inverse probability of selection of the household divided by the household size for each survey wave.

Lastly, when addressing our aim of explaining regional differences in intergenerational mobility, we include the following variables: the share of migrants and the indigenous population to represent the demographic structure; average schooling and education inequality to reflect human capital; and the proportion of agricultural employment and the amount of family self-employment to signify the economic structure. All these variables are obtained at the canton level from the ECV. Descriptive information for the considered variables can be found in Table A.1 and Figure A.2 of the Supplementary Material.

5. Results

5.1. Describing intergenerational mobility

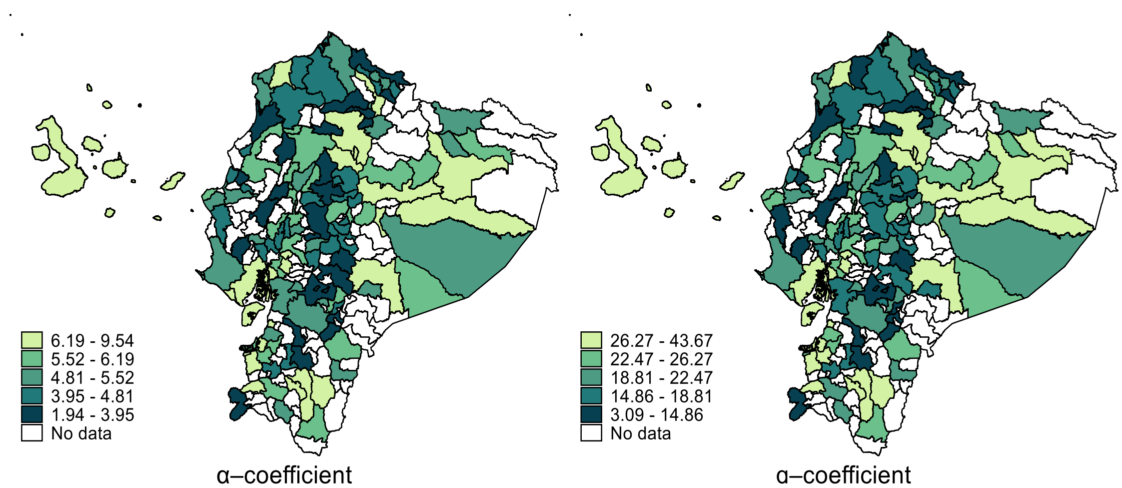
At the national level, the slope of the schooling regression (β coefficient) shows that, on average, a one-year increase in parental education will increase offspring's education by 0.66 years. The most comparable estimates are those of Daude and Robano (2015), who also find a β coefficient of 0.66 for Ecuador and a Latin American average of 0.65, placing the country as the third least mobile in the region. Other studies also rank the country as a low-mobility place for teenagers (Andersen, 2001) when considering different waves of the ECV (Hertz et al., 2007) and when using varying measures of mobility (Neidhöfer, 2019).

The cantonal indexes are mapped in Figures 1 and 2 and can be found in detail in Table A.2 of the Supplementary Material. For ease of interpretation, we plotted all the measures such that the darker areas correspond to more persistent (i.e. less mobile) cantons. According to the interpretation of each measure, this entails higher persistence—i.e. darker tones for higher values of β, ρ, b, $\mathrm{Q1Q1}$ and $\mathrm{Q5Q5}$ and for lower values of α, α and $\mathrm{Q1Q5}$.

The maps show large territorial heterogeneity underlying the aggregate behaviour, with places resembling both the least and the most mobile societies worldwide. Interestingly, Table A.2 shows that despite concentrating public services and economic activity, capital cantons do not follow any particular pattern. In fact, analysing the capitals only, the indicator varies greatly, ranging from 0.35 in the most mobile (San Cristobal, Galápagos) to 0.96 in the least (Guaranda, Central Andes).

Figure 1 maps the values of α_c and a_c. These indicators depict absolute mobility by capturing the schooling levels that children attain if their parents exhibit no schooling; hence, they represent cantonal schooling growth. Some patterns emerge: cantons in the Amazon and the Galápagos experience high rates of mobility in general, while those in the Central Andes display low mobility and those on the coast have both high and low mobility rates.

Figure 1. Absolute measures of schooling mobility: Canton level



Source: Own estimates based on ECV (INEC, 1998–2014). Note: The measures depict darker areas where schooling is lower and so is the potential for intergenerational mobility. Therefore, darker areas represent lower mobility.

Figure 2 compares the three measures of mobility that depict origin dependence. In general, we find that the Andes region is the least socially mobile. Within this region, the lowest levels of mobility are concentrated in the cantons in the central territory. This is followed by the central cantons on the coast, where mobility is at the middle level. The north and south cantons of these regions, alongside the cantons in the Amazon, are more heterogeneous.

Positional measures in Figure 3 also show great heterogeneity and, overall, great persistence between generations. We see, for instance, an average 56 per cent probability that a child raised by parents in the bottom quintile of education stays in the same position (Q1Q1), but this measure rises above 90 per cent for some cantons in the Central Andes and the north coast. The probability of persisting at the top (Q5Q5) is, on average, 52 per cent, rising to 80 per cent in some places.

These results show that in Ecuador, persistence under this concept is strong at the extremes of the transition matrix, with poverty cycles being stronger. Although not entirely comparable given the population, measures and data involved, Cano (2015) examines estimates of top-income persistence in Ecuador and also finds great persistence.

Figure 2. Origin dependence measures of schooling mobility: Canton level

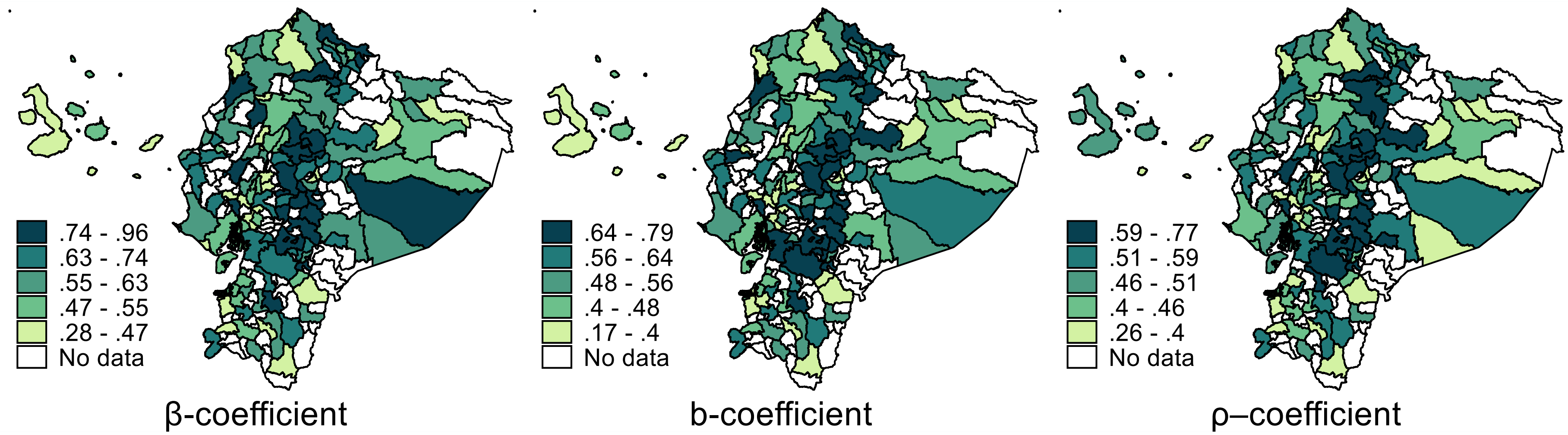
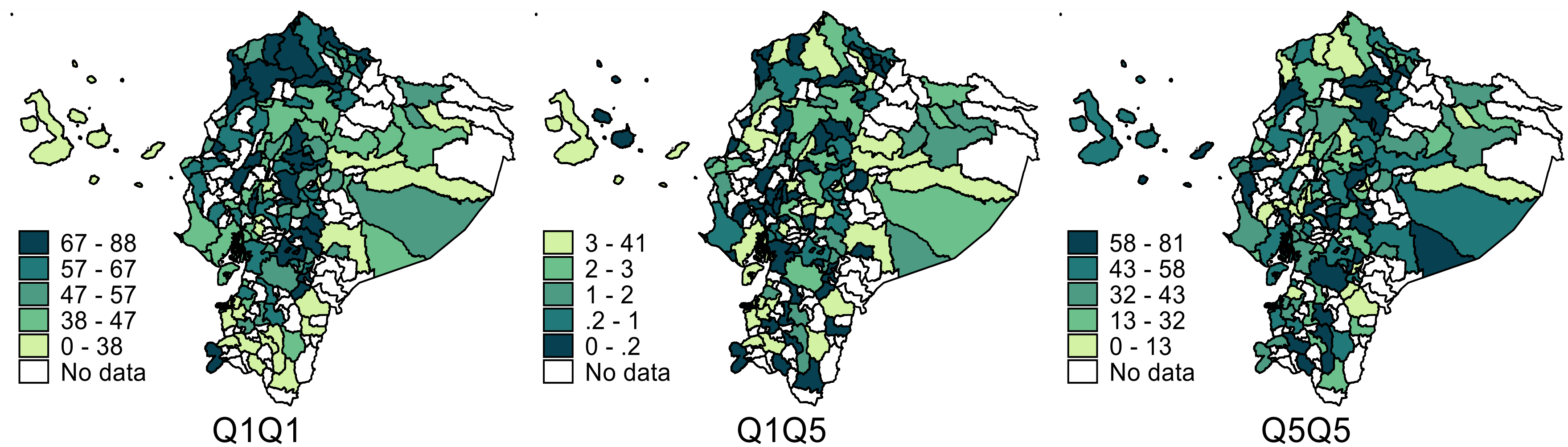


Figure 3. Positional measures of schooling mobility: Canton level



Source: Own estimates based on Encuesta de Condiciones de Vida (INEC, 1998–2014). Notes: Origin dependence measures depict darker areas where origin dependence is higher. Positional measures depict darker areas where Q1Q1 and Q5Q5 probabilities are higher and Q1Q5 are lower. Therefore, in all measures, darker areas represent lower mobility according to the different concepts.

Although a full comparison with other countries is difficult due to the diverse nature of the datasets and measures used, if we do some comparisons, we also uncover steeper persistence than in other contexts. The best-case scenario is Switzerland (Chuard & Grassi, 2020), where the probability of a Swiss person being born and staying in the bottom quintile is less than half that of an Ecuadorian (24 per cent), while the probability of being raised and staying in the top quintile is 30 per cent on average. Other available estimates for Canada (Corak, 2020) and Italy (Acciari et al., 2022) also show great divergence with our estimates, which is partially expected given that these are characterised as largely open societies.

On the other hand, the results of the Q1Q5 measure are rather small. While in Switzerland, Canada and Italy, a child from the bottom of the distribution can rise to the top quintile with a probability of nearly 10 per cent, in Ecuador, this probability stands at an approximate average of 3 per cent. Only three out of 124 cantons approach this international reference. The Latin American average for the Q1Q5 measure using quartiles is approximately 13 per cent (Torche, 2021). In terms of the heterogeneity observed, our estimates are quite similar to the subnational patterns in other Latin American countries such as Mexico (Delajara et al., 2021) and Chile (Cortés Orihuela, 2022).

5.2. Explaining geographical differences in intergenerational mobility

In this section, we present the exploratory analysis of the spatial dependence of mobility. Once we find that there is a spatial correlation, we move on to find the best-fitting specification and decompose the spatial direct and indirect effects. We focus on the β coefficient (Tables 1 to 3), as it is the most studied measure in the literature. It should be noted that this index of mobility is larger where there is more origin dependence; hence, it can be read as intergenerational persistence. To complement the results on β, we also provide the best-fitting spatial model for each mobility measure obtained in Section 5.1 (Table 4). Given the exclusion of cantons with reduced samples when measuring mobility, we are left with some islands that are discarded for the spatial analysis in this section, resulting in 111 cantons in all regressions.

Exploratory analysis of the spatial dependence of β resulted in a statistically significant global Moran's I statistic of 0.30, meaning that cantons where intergenerational mobility is low (high) are surrounded by similarly low (high) mobility cantons. As presented in Figure A.3, the local statistic also reported significant values at the cantonal level. These results remain unchanged when incorporating the cantons excluded due to reduced samples.

As a result, we next apply the combined approach developed by Elhorst (2010) to ascertain the best fitting spatial specification. Three spatial models for β with different spatial spillovers to account for the correlations are presented in Table 1. Firstly, the spatial autoregressive (SAR) and spatial error model (SEM) specifications are studied, where, through robust Lagrange multiplier (LM) tests, we find evidence of a spatially lagged dependent variable at the significance level of 5 per cent ($\rho \neq 0$). Then we study the SDM and, by means of a likelihood ratio test on $\theta = 0$, we find no evidence that the spatial lag on the independent variables is statistically different from zero. This favours the SAR as an appropriate simplification of the SDM, backed up by the Akaike information criterion (AIC) and Bayesian information criterion (BIC) measures.

Table 1. Spatial models of intergenerational persistence (β)

	Intergenerational persistence β		
	SAR	SEM	SDM
Indigenous	0.1380***	0.1408**	0.0680
Migration	-0.2339***	-0.2313***	-0.2246***
Schooling	-0.0346***	-0.0344***	-0.0376***
Gini education	0.8708**	0.9255**	0.9654**
Agriculture	-0.3616***	-0.3565***	-0.3389***
Family self-empl.	-0.4420***	-0.4044**	-0.4915***
Oil activity	-0.0459*	-0.0638**	-0.0631
ρ	0.2872***		
λ		0.2575**	
θ-Indigenous			0.1867*
θ-Migrant			-0.1304
θ-Education children			-0.0146
θ-Gini education			-0.3376
θ-Agriculture			-0.1625
θ-Family-owned b.			-0.2824
θ-Oil activity			0.033
N	111	111	111
AIC	-146.6542	-142.3022	-139.9171
BIC	-119.5589	-115.2069	-93.85512
R^2 Adjusted	0.3730	0.3327	0.3740
LM-Error test (λ=0)		3.2160*	1.3860
LM-Lag test (ρ=0)	8.5510***		2.1098
Robust LM-Error test		2.6254	1.604
Robust LM-Lag test	7.9610***		2.3278
Wald (ρ=0) (λ=0)	9.0440***	4.24**	16.90**
LR test (ρ=0)	8.2910***		2.3876
LR test (λ=0)		3.9390**	
LR test (θX's=0)			7.3810

* p<0.10, ** p<0.05, *** p<0.010.

We now proceed to the decomposition of these coefficients into direct and indirect spatial effects. At first glance, we see in Table 2 that the signs of the effects echo those of the coefficient estimates and that the direct effects are also similar in magnitude. The direct impacts show, for instance, that intergenerational persistence decreases with migration, schooling, agriculture, family self-employment and oil activity. On the other hand, inequality and the percentage of indigenous people increase intergenerational persistence. The indirect effects also display interesting information in the same direction as the direct effects, with the difference that the Gini coefficient and oil activity dummy become not significant.

Starting with the demographic variables, these are in line with the literature and show that internal migration reduces persistence and so increases social mobility. This would reflect the moving to opportunity behaviour discussed by Berger et al. (2023), where people may be migrating to cantons with better economic opportunities; this would exert a local effect as well as spillovers to neighbouring cantons. In Ecuador, internal migration is an important phenomenon and it is associated with the formation of a multipolar economic development scenario in the country (Royuela & Ordóñez, 2018), which could in turn be linked to its power to improve intergenerational mobility.

On the other hand, the share of indigenous population increases persistence. As stated by the UNDP (2021), indigenous groups are known to be subject to structural disadvantages in numerous respects; hence the fact that these disadvantages may be passed on through generations represents an additional constraint. Previous calculations show that indigenous groups in Ecuador are approximately 9 per cent less likely to overcome income poverty than non-indigenous populations (UNDP, 2016). The impact of indigeneity on neighbouring cantons reflects what we observed at a descriptive level, where the lowest intergenerational mobility rates form an important cluster in the Central Andes cantons in those territories with the largest proportions of indigenous people. An explanation for the feedback effect is that these ethnic groups tend to inhabit the most impoverished and institutionally underdeveloped areas and are prone to being geographically concentrated (UNDP, 2021). The disadvantageous social mobility experienced in places with larger shares of disadvantaged ethnic groups is not new and has been tested in a variety of contexts (Chetty et al., 2014; Connolly et al., 2019; Cortés Orihuela et al., 2022; Deutscher & Mazumder, 2020).

In regard to the variables capturing the human capital structure of the country, as expected, the findings suggest that better performance in these indicators is associated with better mobility prospects. The result of the variable that captures schooling is in line with Benabou's (1993) notion that schooling creates contagion effects, which could be through the spread of opportunities (Connor & Storper, 2020). The impact of the Gini coefficient is in line with that reported in the literature and reflects the existence of the Great Gatsby curve; it is in fact the largest of impacts showing that a society with higher inequality is correlated with a lower capacity to provide equal opportunities to all. Durlauf and Seshadri (2018) have developed a model in which it is argued that multiple mechanisms underlie this relationship. However, the key aspect is that greater inequality causes greater segregation across space (neighbourhoods) and this in turn affects mobility.

Table 2. Decomposition of spatial effects on intergenerational persistence (β)

	Direct effects		Indirect effects		Total effects	
	Coefficients	z-values	Coefficients	z-values	Coefficients	z-values
Indigenous	0.1416***	2.77	0.0521**	2.03	0.1937***	2.84
Migration	-0.2399***	-3.60	-0.0883**	-2.00	-0.3282***	-3.40
Schooling	-0.0354***	-3.25	-0.0130*	-1.85	-0.0485***	-3.00
Gini education	0.8930**	1.99	0.3287	1.48	1.2217*	1.92
Agriculture	-0.3708***	-3.76	-0.1365**	-1.98	-0.5073***	-3.46
Family self-empl.	-0.4533***	-2.78	-0.1669*	-1.71	-0.6202**	-2.58
Oil activity	-0.0471*	-1.88	-0.0173	-1.59	-0.0644*	-1.90

* p<0.10, ** p<0.05, *** p<0.010.

Turning our attention to the labour market structure variables, we find that the concentration of agricultural employment increases intergenerational mobility through both local and spillover effects. Though this is contrary to the evidence in countries such as Canada or England (Granström & Engzell, 2023), as Iversen et al. (2019) discusses, the relationship between mobility and sectoral composition could present contrasts, especially in developing countries where agriculture and the informal sector absorb most of the workforce. Furthermore, there is a strand of literature arguing that agriculture can play a positive role in reducing poverty traps, especially in low- to middle-income and resource-rich countries and, moreover, when agricultural employment is associated with poor workers (Christiaensen et al., 2011; Fan & Cho, 2021). Although delving more deeply into this is not our aim, we argue that it could be one of the underlying mechanisms behind our results, as in Ecuador approximately one in two poor workers is employed in agriculture and this trend has remained the same for at the least the past two decades for which we have information (INEC, n.d.).

Furthermore, family self-employment is associated with increases in social mobility. This is in line with the discussion in Section 2. By definition, we know that such individuals are not in self-employment because of necessity or due to a lack of opportunities; hence, to delve deeper into this, we looked at the information reported by those self-employed due to family tradition. We find that in general they have a higher probability of being in formal business and report larger monthly revenues and a larger trajectory (almost doubling the trajectory of businesses established out of necessity). According to García and Burbano (2021), many go into self-employment due to the lack of opportunities in Ecuador, but this then turns into a family habit as they find in it an escape route from poverty (García & Burbano, 2021). Laferrère (2001) adds that self-employment in the family could have positive effects, since the sons of self-employed parents could be exposed to less binding liquidity constraints. In this sense, it is natural to think that the characteristics of family self-employment may be related to jobs being better at promoting mobility, hence decreasing social persistence.

With respect to the variable of oil activity, as found by Alesina et al. (2021), the effects of the exploitation of natural resources on mobility could be both positive and negative, resulting in a null impact. When positive, it may be a sign that resource exploitation can promote human capital and structural transformation in the territories in which it takes place, which may be the reason for our results.

To conclude this section and assess the sensibility of our results to the spatial weights matrix, we estimated the SAR model for β using different specifications. We have considered different contiguity matrices involving first- and second-order neighbours and different distance-based measures (inverse of distance, inverse of the squared distance, and the four nearest neighbours). Table 3 shows that similar results can be obtained.

Table 3. SAR model of β: Different spatial weights matrix specifications

	Queen contiguity matrix		Haversine distance matrix		
	First- order neighbours	Second-order neighbours	Inverse distance	Inverse squared distance	Knn −4
Indigenous	0.138***	0.160***	0.167***	0.179***	0.154***
Migration	-0.234***	-0.246***	-0.256***	-0.297***	-0.231***
Schooling	-0.035***	-0.034***	-0.034***	-0.031**	-0.031***
Gini education	0.871**	0.909**	0.863*	0.428	0.875*
Agriculture	-0.362***	-0.372***	-0.377***	-0.498***	-0.343***
Family self-empl.	-0.442***	-0.454***	-0.440***	-0.629***	-0.438***
Oil activity	-0.046*	-0.056**	-0.056**	-0.062**	-0.049*

ρ	0.287***	0.218***	0.555	0.525	0.232**
N	111	111	111	111	111
AIC	-146.65	-140.65	-140.11	-126.84	-142.42
BIC	-119.56	-113.55	-113.02	-99.75	-115.33
LM-Lag test (ρ=0)	8.55***	2.99*	1.83	1.18***	4.24**
Robust LM-Lag test	7.96***	3.67*	3.02*	1.05***	
LR test	9.04***	2.38	2.48	2.09	4.06**

* p<0.10, ** p<0.05, *** p<0.010.

Lastly, we tested the global and local spatial correlation for the remaining mobility measures, identifying such correlations in seven out of eight measures. Only the rags-to-riches measure (Q1Q5) could not be considered a spatial phenomenon in our case study. When the global Moran's I is statistically significant (see Table 4), it is always positive, implying that mobility behaves in the same direction between adjacent territories. The local statistic also reported significant spatial correlations at the canton level in several jurisdictions, showing different clusters across the country depending on the measure (Figure A.3 in the Supplementary Material). One pattern that stands out is the spatial correlation of persistence in cantons in the Central Andes.

Accordingly, the best model is identified for the seven indicators where correlations were found. Table 4 presents a summary of these results. For simplicity, we include the sign of the covariates' correlations with intergenerational mobility only when significant. Detailed results are available upon request. In general, the results show consistency with Table 1. In line with the literature, we find that migration is the most robust predictor of intergenerational mobility regardless of the mobility measure we analyse. However, we also observe that the set of covariates chosen may better explain the relative measures of mobility that depict origin dependence (β, ρ, b).

Table 4. Best-fitting model and covariates' effect on intergenerational mobility measures

	β	**ρ**	**b**	**α**	**α**	**Q1Q1**	**Q5Q5**
Global Moran's I	0.304***	0.164***	0.283***	0.182***	0.162**	0.369***	0.088*
Spatial specification	SAR	SDM	SAR	SLX	SLX	SAR	SLX
Direction of the covariates' relationship							
Indigenous	+		+	-	-		
Migration	-	-	-	-	-		-
Schooling	-			-	-	-	+
Gini education	+	+	+	+	+		+
Agriculture	-	-	-	-		-	
Family self-empl.	-	-	-				-
Oil activity	-		-	-			-
θ-Indigenous		+			+		
θ-Migration							
θ-Schooling							
θ-Gini education							
θ-Agriculture		-					
θ-Family self-empl.							
θ-Oil activity							+

Note: A model for Q1Q5 has been run through the ordinary least squares method, but none of the covariates we selected have been found to correlate with it; hence, it has been omitted from this table (*p<0.10, **p<0.05, ***p<0.010).

6. Conclusions

In this study, we calculate intergenerational education mobility across cantons using different concepts. We then test whether mobility has a significant spatial dimension and identify its correlates. The study is correlational and presents a snapshot of intergenerational mobility in time and space in line with recent literature such as that by Connor and Storper (2020), Tan (2023) and Ward (2023), among others.

For a small country such as Ecuador, one should not expect much regional variation; however, this proves not to be the case. We find heterogeneity in the estimates not only across territories, but also across concepts of mobility. We observe that using different concepts provides a richer view of the phenomenon and helps distinguish the Ecuadorian case from other contexts for which subnational evidence is available. In fact, we find few coincidences between the different concepts and mostly observe that cantons where children's outcomes are barely tied to those of their parents are not necessarily places that provide better opportunities for upward mobility. Hence, depending on the context, a general perspective on intergenerational mobility may not only be difficult to establish but misleading. For instance, we also find that average schooling is higher in the capital cantons of the country while intergenerational mobility is not. In fact, some capitals exhibit the highest transmission of status across generations. This may sound counterintuitive as capitals are characterised by economic dynamism and access to health and education, which should be expected to improve social mobility (Daude & Robano, 2015). However, if these opportunities are not guaranteed for all, low social mobility could be the result.

The spatial techniques that we apply help conclude that intergenerational mobility can be treated as a spatial phenomenon, as expected by the theoretical models on which we base our work. This suggests that analysis of the drivers of mobility should consider spatial correlations to avoid bias in the results. Furthermore, as Chetty (2014) pointed out, the subnational estimates highlight that to address intergenerational mobility more efficiently, place-based public policy should be developed rather than national-level efforts. Specifically, our results suggest that this can be focused in the areas where significant clusters of persistence are found. In this study, this area is composed of the cantons in the Central Andes.

The analysis of the drivers of mobility allows some concluding remarks with regard to the findings for the indigenous and migrant populations. Regarding the former, two important aspects should be considered. Firstly, the inclusion of ethnic minorities tends to increase the estimated level of mobility (Ward, 2023). Secondly, a large share of the indigenous populations in Ecuador are in rural areas, where recent literature has found that there is an advantage (Connor, Hunter, et al., 2023). Therefore, a deeper analysis of mobility for these groups could be a new direction in further work.

Secondly, the effect of migration on mobility aligns with prior work and poses a key consideration when public policy is to be developed. As migration entails costs for both the individuals and places involved, these may be better addressed by knowing that there can be spillover effects and so by coordinating public policymaking across the cantons where these spillovers take place.

Finally, our findings may help with a better understanding of intergenerational mobility in other Latin American countries similar to Ecuador and to advance study of the concept. The relevance of this should not be understated as this had previously been a difficult task due to data limitations in these countries. More importantly, in this context, our work contributes to the debate on the high inequality and low growth trap in which the region is embedded, where intergenerational mobility has a major role (UNDP, 2021).

Notes

1. Also called 'space of mobility' (Jäntti & Jenkins, 2015). We avoid using this term and reserve it for addressing the spatial econometric analysis of mobility.

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