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Intergenerational Economic Mobility in Mexico

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Abstract

This article documents several measures of intergenerational economic mobility in Mexico. We employ census data available for 1990 to 2015 that provides data on earnings. Since censuses do not link individuals over time, the empirical strategy follows a synthetic approach by matching individuals with synthetic family earnings by the state where they were born and their birth cohort. The aggregate estimate indicates an intergenerational elasticity (IGE) of 0.50 for Mexico, adjusted for cross-country comparison. From this perspective, intergenerational mobility is low in comparison with advanced economies. Results also suggest a higher intergenerational mobility for younger cohorts. For regional comparisons, estimates show that people born in southern Mexico are more likely to have a lesser degree of intergenerational mobility.

Keywords: Intergenerational mobility, earnings, inequality, Mexico.
JEL: D63; J62; N36; O54; R10.

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1. Introduction

Recent studies suggest that a high degree of income inequality strengthens the role of family background in determining children's life outcomes (Corak 2013; Krueger 2012; Solon 1992). The present work seeks to provide a descriptive yet structured discussion of intergenerational economic mobility in the highly unequal context of Mexico: its trends, its regional variability, and its plausible relationship with income inequality.

Our research question is based on the economic literature that focuses on income persistence across generations, particularly in studies of the United States (Solon 1992, 1999, 2002; Mazumder 2005).¹ The U.S. has relatively low mobility in comparison to other advanced economies, but greater mobility than developing countries (Mazumder 2018; Corak 2013; Delajara, Campos-Vázquez, and Vélez-Grajales, 2020).

Notwithstanding extensive interest in the topic, the literature examining income mobility in developing countries remains limited because of the lack of high-quality datasets linking adult children's income with that of their parents (Rojas-Valdés 2012).² To overcome this challenge, recent work relies on analyzing the broader concept of social intergenerational mobility through socioeconomic or wealth indexes (e.g., Torche and Spilerman 2010; Torche 2010, 2014).³ Although we do not deny that such an approach allows the inclusion of aspects of intergenerational mobility other than the economic one, a significant limitation of this approach is the underlying assumption of homogenous individual preferences across time and place toward certain assets.⁴

¹ This literature suggests that intergenerational income mobility can be approached by a regression coefficient, where the dependent variable is adult children's income and the independent variable is parents' income (e.g., Solon 1999).

² The lack of this type of data can be explained mainly by the difficulty of gathering income-related data in Latin America (Torche 2009).

³ There have been some efforts to describe intergenerational mobility in Mexico based on dimensions other than income, such as education (e.g., Torche 2020) and socioeconomic status or wealth (e.g., Torche and Spilerman 2010).

⁴ See Vyas and Kumaranayake (2006) for issues related to socioeconomic status. There is also a discussion on what these indexes really measure. For a discussion on this topic see Bradley and Corwyn (2002). Social scientists often interpret these indexes as proxies for household wealth (e.g., Filmer and Pritchett 2001), permanent income (e.g., Ferguson, Tadon, Gakidou, and Murray 2003),

In the present study, the key issue is to compute family earnings while children are growing up. In the Mexican census, parents' and children's earnings are not linked. We therefore follow previous literature to define synthetic families (Aronson and Mazumder 2008). First, we compute parents' earnings for children in earlier censuses by relevant birth cohort, the state in which they were born, and census year. In later censuses, the adult children report their earnings. Second, we obtain the average of parents' earnings by birth cohort, the state where they were born, and census year. Third, when parents' earnings are available for a particular birth cohort and state of birth for more than one census year, we calculate a multi-year average as a way to address short-term shocks in family earnings (Mazumder 2005). In this way, we are able to match grown children with synthetic families, and their synthetic earnings by cohort and the state where they were born. For example, individuals reporting earnings in 2015 who were born in Mexico City between 1986 and 1990 are matched with the average earnings of families whose children were born in the same years in Mexico City. Our measures of intergenerational economic mobility thus account for the extent to which the earnings of adult children differ from synthetic family earnings.

As a first step, this work presents aggregate estimates of intergenerational economic mobility at the national level. The empirical strategy follows previous literature (e.g., Aaronson and Mazumder 2008; and Lee and Solon 2009), regressing the log of adult children's earnings on the log of synthetic family earnings, with different sets of controls. The regression coefficient is the intergenerational elasticity (IGE), and it describes the extent to which family economic background persists over generations. A previously reported IGE for Mexico is 36 percent lower than ours (Rojas-Valdés 2012).

The empirical strategy allows for both time-invariant and time-variant estimates. An initial result without controls shows that a 1 percent increase in synthetic family earnings yields a 0.45 percent increase in adult children's earnings. Controlling for cohort fixed effects, year fixed effects, region of birth fixed effects,

or living standards (McKenzie 2005), even when they consider similar approaches to compute them (Torche 2020).

age, and earnings profile, the same increase yields a 0.47 percent increase in adult children's earnings. Our estimate that is most comparable to the U.S. estimate reported in Aaronson and Mazumder (2008) shows an IGE coefficient for Mexico that is 16 percent greater than the American one.

We conducted several robustness checks to test the stability of our estimates, and analysis of different sample characteristics considered in previous studies showed no major changes. The estimates are robust with restrictions on the age of adult children (25 or older and 30 or older) and parents (between 40 and 50 years). We also examine synthetic fathers' earnings as an alternative independent variable, which yields a similar IGE estimate. Furthermore, the stability of our baseline estimate provides a certain degree of confidence in our empirical strategy.

The time-variant estimates, which included interaction terms of synthetic family earnings with birth cohorts and census years, depict the intergenerational economic mobility trend between 1995 and 2015 (Almond and Mazumder 2005; Aaronson and Mazumder 2008). If we restrict the specification to account only for the interaction between family earnings and year, there is a decrease in IGE that is significant only over a long period. If we restrict it to account only for the interaction between birth cohort and family earnings, the IGE also decreases across birth cohorts. The less restrictive specification, which includes both year and birth cohort estimates, confirms an increase in mobility from 1995 to 2010 and from 1995 to 2015, and the increase is driven by the census year interaction terms rather than birth cohort interactions. These patterns are robust to changes in sample features and alternative dependent and independent variables, and are consistent with the decline that has been found in returns to schooling and in inequality in Mexico (Campos-Vázquez, Esquivel, and Lustig 2012). However, future research also needs to address whether measurement error is affecting the estimates' magnitude.

We also compute the IGE estimates by region. These suggest the presence of an important geographical variation in intergenerational mobility across regions of birth. People born in the south face the lowest degree of relative intergenerational mobility and those in the north face the highest. These results are consistent with

recent efforts to estimate social mobility across Mexican states (Delajara, Campos-Vázquez and Vélez-Grajales, 2020).

Finally, we compute a comparison of the Mexican IGE with other countries, which provides a broad portrait of the underlying factors determining children's outcomes as adults (Solon 2004; Corak 2016). The heterogeneity found confirms that Mexico has a lower degree of intergenerational mobility than more advanced economies.

The rest of this paper is structured as follows. The next section describes the data and our synthetic approach, and it presents our empirical strategy. Section III presents the main results and robustness checks, and Section IV offers some conclusions.

2. Methods

2.1. Data

This study employs micro-level data from Mexican censuses conducted by the National Institute of Statistics and Geography (INEGI) in 1990, 1995, 2000, 2010 and 2015; these data are available on the IPUMS International web site (<https://international.ipums.org/international>). The sample fraction available is 10 percent for 1990, 0.4 percent for 1995, 10.6 percent for 2010, and 9.5 percent for 2015. The universe for all samples is individuals aged 12 and above. Data on earnings from the 1970 census are not comparable to earnings reported in the selected censuses, and the 1980 census microdata is no longer available since it was lost in the 1985 Mexico City earthquake.⁵

The censuses collect data on labor income and earnings for the previous month. These earnings include wage income from businesses and farms, and other sources. One of the main advantages of focusing on earnings is that earnings capacity, such as that represented by skills and effort, is transferred from parents to children differently than other assets. Earnings capacity can be transferred through investment in human capital (Becker, Kominers, Murphy and Spenkuch 2018), while

⁵ For comparing earnings across generations, we deflate earnings using the 2010 deflator for Mexico published by the World Bank, and all earnings are converted to New Mexican Pesos (MXN), which were introduced in 1993.

other assets are transferred directly from parents to children (Becker and Tomes 1986). In this sense, earnings provide the best proxy for opportunities related to individual merit (Mazumder 2005).

Mexican censuses do not link individuals across years. We thus follow the synthetic approach of Aaronson and Mazumder (2008), which requires a core sample that clearly distinguishes between adult children and synthetic families, allowing us to compare how much adult children's earnings differ from their synthetic family earnings. We define adult children as men who are 20 years old in the 1995-2015 censuses; these individuals are old enough to report earnings.⁶ Synthetic families are defined as representative family units where adult children are likely to be members, as determined by two variables: the state in which they were born and their birth cohort. The earnings of such representative families are the synthetic family earnings. With these definitions, synthetic families are observed in the 1990, 1995, and 2000 censuses, and adult children are observed in those of 1995, 2000, 2010, and 2015. For example, a 30-year-old man born in Mexico City who reports earnings in the 2010 census is virtually matched with a Mexico City family reporting earnings in the 1990 census, whose children were approximately 10 years old at that time. For the purposes of this study, we consider four birth cohorts: 1971-75, 1976-80, 1981-85, and 1986-90. We take the state where they were born, as reported in the censuses; since there are 32 states, the number of representative families is 128.

Once we have defined the core sample and the linkage between individuals and families across censuses, we compute synthetic family earnings. First, for the 1990-2000 censuses, we assign cohorts to children born in Mexico. During this time, children live with their parents; hence, by assigning a birth-cohort we are identifying potential families of future generations. This task is conditional on the available information. For instance, in the 1990 census, we can identify individuals from all birth cohorts, as shown in Table 1, column (1); in other words, all men born between 1971 and 1990 are children in the 1990 census. Column (2) shows their age.

⁶ We restrict the definition to men since women's labor force participation is lower than men's, and shows an increasing trend during the period of study (Ermisch et al. 2006). However, we perform a robustness check accounting for spousal earnings.

However, for the 1995 and 2000 censuses we can only assign the 1981-85 and 1986-90 birth cohorts, since individuals born in prior cohorts have become adult children by the time of those censuses, as shown in column (4). By the time of the 2010 and 2015 censuses, all of the children have become adults and no families are observed.

Once children are assigned to a birth cohort, we add the earnings of household heads and spouses to compute parental earnings in each census year. We also assign these earnings to children. In the case of families with children belonging to different cohorts or who were born in different states, the same parental earnings are assigned to each one. We assign family earnings regardless of other family characteristics (such as family size, children's gender, or parents' marital status). As a final step, we compute synthetic family earnings (SFE). These are the average parental earnings assigned to children i that were born in state s , where $s = \{1, \dots, 32\}$; in birth cohort c , where $c = \{1971 - 75, 1976 - 90, 1981 - 85, 1986 - 90\}$; observed in census year t , where $t = \{1990, 1995, 2000, 2010\}$. This can be written as follows:

$$SFE_{c,s,t} = \sum_{i=1}^{N_{c,s,t}} \frac{Parent\ Earnings_{i,c,s,t}}{N_{c,s,t}} ; \forall c, s, t \quad (1)$$

This definition allows us to compute family earnings for the same cohort at different points in time. For example, in Table 1, column (1), we can observe that for the birth cohort 1981-85 it is possible to estimate the SFE in 1990, 1995, and 2000. In such cases, we calculate the period average to smooth cyclical variation in the family's earnings (Mazumder 2005). This results in an SFE for each birth cohort and state of birth. Table 1, column (3) shows the SFE for each cohort. These earnings turn out to be very similar for the 1971-75, 1976-80 and 1981-85 birth cohorts, just above MXN 5,600 per month, while for the 1986-90 birth cohort the SFE is around MXN 5,800 per month. Column (6) shows the mean of adult children's monthly earnings, including those individuals reporting zero earnings. This amount ranges from MXN 2,795 to MXN 6,381. Column (7) reports the number of observations per cohort in every census. The total sample has approximately 2.6 million observations.

Table 1: Core Sample

Cohort	<i>Family</i>			<i>Adult Children</i>			
	Census Year	Age	Mean earnings	Census Year	Age	Mean earnings	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1971-75	1990	15-19	5,653	1995	20-24	2,795	14,261
				2000	25-29	4,714	365,869
				2010	35-40	6,429	352,873
				2015	41-45	6,381	258,422
1976-80	1990	10-14	5,620	2000	20-24	2,852	403,698
	1995	15-19		2010	30-34	5,760	365,882
				2015	35-40	5,997	277,253
1981-85	1990	5-9	5,677	2010	25-29	4,798	381,373
	1995	10-14		2015	30-34	5,845	286,604
	2000	15-19					
1986-90	1990	0-4	5,804	2010	20-24	2,865	458,567
	1995	5-9		2015	25-29	5,251	289,102
	2000	10-14					

Notes: Column (1) shows the correspondence between birth cohorts and the census year in which families are virtually observed, column (2) the age of individuals when they lived with their families, column (3) synthetic family earnings (monthly labor income in 2010 MXN), column (4) the years when adult children (men) are observed, column (5) their ages, column (6) their average earnings (monthly labor income in 2010 MXN), and column (7) the number of observations in each census. Synthetic family earnings consider parents with zero earnings. Average earnings of adult children includes those with zero earnings.

2.2 Empirical Strategy

The empirical strategy follows the existing literature for estimating intergenerational economic persistence by allowing for time-varying estimates (e.g., Aaronson and Mazumder 2008; Lee and Solon 2009). The basic specification can be written as follows:

$$\log(GCE_{i,c,s,t}) = \alpha + \pi_c + \lambda_t + \phi_r + \beta \log(SFE_{c,s}) + \rho_t \log(SFE_{c,s}) + \delta_c \log(SFE_{c,s}) + X'_{i,c,s,t} \Omega + \varepsilon_{i,c,s,t} \quad (2)$$

where $\log(GCE_{i,c,s,t})$ is the log of monthly earnings (in 2010 MXN) for a grown child i , belonging to birth cohort c , born in state s , reporting earnings in census year t . The key independent variable is $\log(SFE_{c,s})$, which indicates a multi-year average, for some cohorts, of monthly synthetic earnings of families whose children were born in cohort c and state s .⁷ The specification also includes the log of family earnings interacting with census years and birth cohort to measure intergenerational mobility over time. Although a large body of the literature has focused on fathers' earnings (see Solon 1999), we use family earnings, since these provide a broader measure of the family resources for children's opportunities (Chadwick and Solon 2002; Mazumder 2005; Mayer and Loopo 2005).⁸

The coefficients of interest are β , ρ_t , and δ_c . Since both adult children's earnings and family earnings are expressed in logarithmic form, these coefficients are the intergenerational income elasticity (IGE).⁹ They provide different descriptive measures of IGE depending on the restrictions set into the specification. If we set $\rho_t = 0$ and $\delta = 0$, the resulting estimate $\hat{\beta}$ is the time-invariant IGE estimate, and it refers to a descriptive measure of economic mobility at the national level. If $\delta_c = 0$ and $\beta = 0$, the resulting estimates $\hat{\rho}_t$ are time-variant, allowing the IGE to vary across census years: this is a time-trend IGE. Changes in the IGE time trend may reflect changes in childhood investment over time in line with changes in returns to skills. If $\rho_t = 0$ and $\beta = 0$, the resulting estimates $\hat{\delta}_c$ are cohort-variant, allowing the IGE to vary across cohorts.¹⁰ This trend is likely to capture changes if cohorts were

⁷ Mazumder (2005) shows that intergenerational estimates for the U.S. that do not account for a multi-year measure of family earnings are downward biased.

⁸ Due to lack of consistent information across censuses, it is not possible to include sources of income other than earnings.

⁹ In general, if the IGE is close to one, then mobility is relatively low: individuals can improve or diminish their economic status only minimally with respect to their parents. If the IGE is close to zero, then mobility is relatively high: individuals can easily improve or diminish their economic status with respect to their parents.

¹⁰ This specification has been used to identify long-term health outcomes across cohorts (Almond and Mazumder 2005).

exposed to different policies (Nyblom and Stuhler 2013).¹¹ For example, younger cohorts in Mexico were eligible for social policy programs that broadened their access to higher education, so these individuals were likely to show higher intergenerational mobility than those in older cohorts. If there are no restrictions, it is possible to estimate a general intergenerational economic mobility trend. In this case, we combine both census year and cohort effects.¹²

Specification (2) also accounts for additional factors that, according to the literature, could bias the results. The vector $X_{i,c,s,t}$ controls for age profile and heterogeneous age-earnings profiles to reduce plausible biases (Lee and Solon 2009). It includes a quadratic polynomial for individuals' age centered at 40 (Altonji and Williams 2005; Haider and Solon 2006) and its interaction with family earnings (Böhlmark and Lindquist 2006; Lee and Solon 2009).¹³ Additionally, π_c , λ_t , and ϕ_r are cohort, year, and birth region fixed effects. Cohort fixed effects control for time-invariant characteristics across cohorts, while census year fixed effects capture global trends that affect all individuals similarly. We also consider four birth regions, so that ϕ_r controls for time-invariant factors that could determine intergenerational mobility at the time of birth.

Specification (2) is similar to one employing state of birth and birth cohorts as instrumental variables (Aaronson and Mazumder 2008). If these variables exogenously determine family earnings from previous generations, it is possible for the OLS estimate for $\hat{\beta}$ to be consistent. In this sense, our estimate is similar to a two-sample instrumental variable estimator (Klevmarken 1982; Angrist and Krueger 1992). One issue with our estimates is the presence of non-observable characteristics that are correlated with synthetic family earnings. However, if the

¹¹ This specification requires observing birth cohorts in multiple census years to avoid perfect collinearity between age controls, birth-cohort fixed effects, and census-year fixed effects (Almond and Mazumder 2005). Our cohorts allow us to do this.

¹² In this case, we have to exclude one census year interaction and one birth cohort interaction to identify the IGE trend. The coefficient then refers to the omitted group. We add or subtract c or t to measure IGE in year t for an individual in birth cohort c .

¹³ Haider and Solon (2006) find that estimates of intergenerational economic mobility are sensitive to heterogeneous patterns in the life-cycle earnings profile. The estimates can be biased downward when adult children's income is measured at a relatively young age, or biased upward when their income is measured when they are older. This bias is reduced, they find, if adult children's earnings are measured around the age of 40.

direction of the bias and its magnitude is constant over time, the bias should not affect the general pattern reflected in our estimates (Aaronson and Mazumder 2008).¹⁴

One concern is that specification (2) does not allow us to analyze the importance of birthplace in determining adult children's outcomes. Since part of the exogenous source of variation in synthetic family earnings is the state of birth, that variation is lost in the analysis of intergenerational mobility across states of birth. However, we overcome this problem by allowing synthetic family earnings to vary across regions of birth. We consider the four regions defined by the Mexican central bank (Banxico, 2016): north (Baja California, Sonora, Chihuahua, Coahuila, Nuevo León, and Tamaulipas), north-center (Sinaloa, Durango, Zacatecas, San Luis Potosí, Nayarit, Tlaxcala, Aguascalientes, Jalisco, Colima, and Michoacán), center (Mexico City, Estado de México, Morelos, Puebla, Tlaxcala, Hidalgo, Querétaro, and Guanajuato), and south (Guerrero, Oaxaca, Chiapas, Veracruz, Tabasco, Campeche, Yucatán, and Quintana Roo). Since each of these regions contains several states, it is possible to rely on some variation to compute IGE estimates by region of birth. For this task, we use the following specification:

$$\log(GCE_{i,c,s,t}) = \alpha + \pi_c + \lambda_t + \pi_r \log(SFE_{c,s}) + X'_{i,c,s,t}\Omega + v_{i,c,s,t} \quad (3)$$

Specification (3) estimates the time-invariant IGE for each birth region, and π_r captures the place-based factors determining family background when individuals were children, such as public investment within a region, or policies that enhanced human capital, like child care systems or scholarship programs. The specification also includes cohort fixed effects, census-year fixed effects, and life-cycle controls. It is important to mention that these estimates are merely qualitative, given the limited data.

¹⁴ We would emphasize that our approach, which can be classified as a synthetic pseudo-panel, has some advantages with respect to surveys following parents and children. It avoids the problem of nonrandom attrition, and it addresses measurement error by eliminating measurement errors in individual earnings by taking averages across cohorts and considering differences in measurement error over time (Antman and McKenzie 2005). However, it does not completely solve the problems of empirical strategies comparing the earnings of children and parents using a balanced panel.

A second concern is the cross-country comparability of our time-invariant IGE estimate, which is crucial to understanding the underlying factors driving intergenerational economic mobility (Corak 2016; Solon 2004). To address this problem, we follow the framework proposed by Corak (2006) for cross-country comparison. Employing this framework, the author uses metadata from the literature to select representative estimates for several countries and scale them by a factor that considers the U.S. as reference and a U.S. estimate that would adjust for the difference in sample characteristics and methodologies across countries.¹⁵ The scaling factor is defined as follows:

$$\hat{\beta}_{MX} = \hat{\beta}^* \times \frac{\hat{\beta}_{an}}{\hat{\beta}_{sa}} \quad (4)$$

where $\hat{\beta}^*$ is our preferred estimate. $\hat{\beta}_{an}$ is the U.S. estimate of reference, and $\hat{\beta}_{sa}$ is the estimate adjusted for sample characteristics and methodologies.

3. Results

3.1. Time-Invariant and Time-Variant IGE Estimates

Table 2 presents time-invariant IGE estimates at the national level, in which $\rho_t = 0$ and $\delta_c = 0$. All coefficients are positive and statistically significant at the 1 percent level. Column (1) shows the IGE estimate with no controls, and column (2) adds cohort and year fixed effects. Column (3) shows the results for a quadratic polynomial for age, and column (4) those for the polynomial with each term interacting with family earnings. Column (5) presents the IGE estimate with region of birth fixed effects. Column (6) presents the IGE estimate considering all of the controls specified in equation (2). With no controls the estimate suggests that a 1 percent increase in family earnings is associated with an increase of 0.45 percent increase in adult children's earnings. Columns (2) and (3) suggest that the estimate is barely modified when including fixed effects and the age earnings are measured. Columns (4) and (5), which incorporate all life-cycle controls, suggests that the

¹⁵ We follow specification (2) and use the Panel Study of Income Dynamics (PSID) to estimate an IGE that is likely to be methodologically comparable to ours.

absence of such controls does bias the estimates downwards. Finally, column (6) shows that the IGE estimates decrease by 6.4 percent with respect to those shown in column (5).

A first benchmark for comparison is the baseline IGE estimate for the U.S. reported in Aaronson and Mazumder (2008), which is 0.43. If we consider the main estimate in column (5) to have the most similar specification and sample characteristics, persistence is greater in Mexico. A second benchmark uses the intergenerational income elasticities reported by Rojas-Valdés (2012), and it varies significantly, depending on the type of estimate and sample characteristics. For his two-sample instrumental variable estimate, the IGE is about 0.31, which is 36 percent lower than the estimate in column (5), while his estimate for a pseudo-panel sample yields a value of 0.6, which is 20 percent higher than our estimate.

One concern here is the extent to which our IGE time-invariant estimates are robust to sampling changes. There are four alternative samples of interest: 1) families whose children belong to the same birth cohort (Aaronson and Mazumder 2008), 2) adult children aged 25 or older (e.g., Solon 1992), 3) adult children aged 30 or older (e.g., Mazumder 2001), and 4) synthetic families with parents aged 40-50 and children 30 or older (e.g., Zimmerman 1992). Following specification (2) and the appropriate restriction to estimate the IGE, Figure 1, panel A shows the resulting OLS estimates for this robustness check, with the estimates indicated by blue squares with 95 percent confidence intervals. The estimates are similar for most of the sample. Restricting the sample to families whose children are in the same birth cohort yields an estimate of 0.26, 44 percent lower than the baseline estimate. If the age of adult children is restricted to 25 years or older, the estimate increases to 0.486, and if it is restricted to 29 years or older, it increases to 0.499. Restricting both children's and fathers' age leads to an estimate of 0.479, suggesting that considering children between 20 and 24 years old does not substantially decrease the baseline estimate (as suggested by Haider and Solon 2006).

Table 2: Time-Invariant IGE Estimates

	<i>Dependent variable: log of adult children's earnings</i>					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>log(SFE)</i>	0.451*** (0.036)	0.500*** (0.038)	0.459*** (0.038)	0.479*** (0.037)	0.500*** (0.038)	0.468*** (0.033)
Cohort F.E.	No	Yes	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	Yes	Yes	Yes
Region of Birth F.E.	No	No	No	No	No	Yes
Age	No	No	Yes	No	Yes	Yes
Earnings profile	No	No	No	Yes	Yes	Yes
Observations	2,641,109	2,641,109	2,641,109	2,641,109	2,641,109	2,641,109
R ²	0.05	0.11	0.11	0.11	0.112	0.11

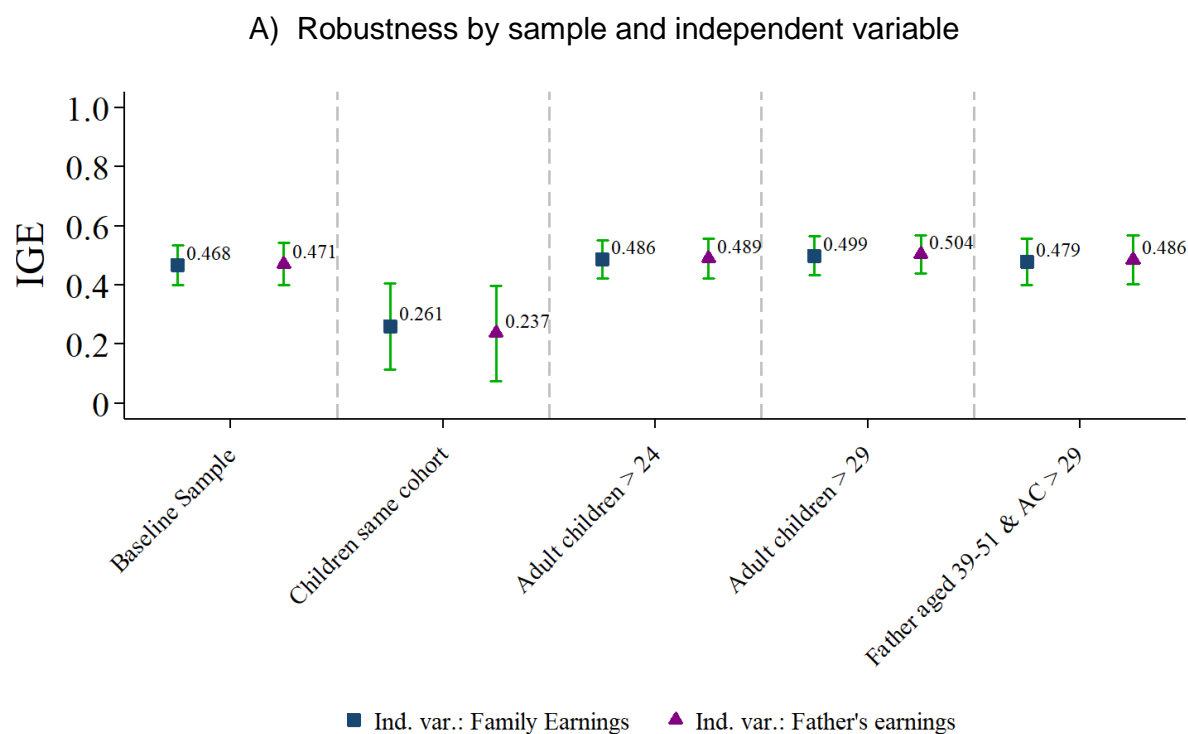
Notes: OLS estimates for the time-invariant intergenerational elasticity. The dependent variable is the log of adult children's monthly earnings. The independent variable is the log of average monthly synthetic family earnings by state of birth and birth cohort of previous generations. Standard error adjusting for clustering within state of birth in parentheses. Columns report results for different sets of controls. These controls are cohort fixed effects, census year fixed effects, region of birth fixed effects, a quadratic polynomial for age, and a quadratic polynomial for age where each term interacts with synthetic family earnings. Coefficients statistically different from zero at the following significance levels: * 10 percent, ** 5 percent, and *** 1 percent.

A substantial part of the literature has focused on studying fathers' rather than family earnings (Solon 1999). We thus test the robustness of our estimates by using synthetic fathers' instead of family earnings, while also considering different sample characteristics. Figure 1, panel A indicates the corresponding IGE estimates with triangles, along with their 95 percent confidence intervals: considering fathers' earnings slightly increases the estimates. The IGE estimate with the baseline sample shows that a 1 percent increase in fathers' earnings is associated with a 0.47 percent increase in adult children's income. The estimate across samples also remains similar, reaching a maximum value of 0.50 if the sample is restricted to children aged 30 years or older, with a value of 0.49 if fathers' age is restricted.

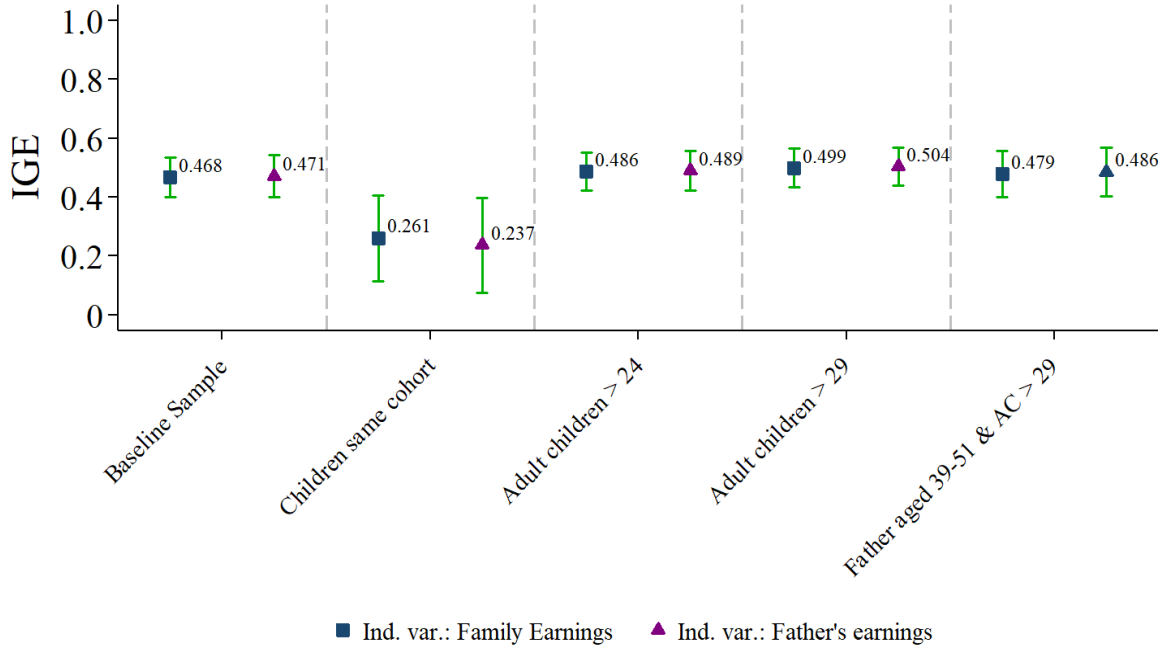
A second concern about our IGE estimates is the extent to which economic persistence takes place in family earnings rather than in adult children's earnings. For this robustness check, we use specification (2), changing the dependent variable

to the log of family earnings, that is, adding the earnings of adult children and their spouses. Figure 1, panel B plots these IGE estimates along with their 95 percent confidence intervals across different samples and independent variables. In the baseline sample, the estimates increase substantially, by 22.8 percent with respect to the baseline estimate. The increase is consistent across different samples, with slight differences due to adult children's age or the use of father's instead of family earnings as the key independent variable. Although we are not able to formally test the factors driving the IGE upwards, it may be that marital sorting factors lead to a higher level of economic persistence across generations (Chadwick and Solon 2002; Ermisch et al. 2006). In this sense, intergenerational mobility in Mexico has an important component derived from marriage decisions.

Figure 1. Robustness checks on time-invariant IGE estimates



B) Robustness by outcome variable, sample, and independent variable



Notes: The figure shows IGE estimates for different samples along with their clustered (within state of birth) confidence intervals at the 95 percent level. The first sample is the baseline, the second focuses on families whose children belong to the same birth cohort to compute family earnings, the third and fourth restrict the age of adult children, while the fifth also restricts the sample to fathers within a specific age range. Panel A employs adult children's earnings as the outcome variable, while Panel B employs family earnings of adult children as the outcome variable. There are two independent variables: family earnings (squares) and father's earnings (triangles).

3.2. Time-Variant and Cohort-Variant IGE Estimates

Table 3 reports time-variant (census year) and cohort-variant (birth cohort) IGE trends for the period 1995-2015. As mentioned above, we obtain a census-year trend after setting $\beta = 0$ and $\delta_c = 0$, allowing us to estimate the interacting terms between family earnings and census year. Columns (1) and (2) show the census-year trend. Column (1) incorporates only fixed effects for census year, birth cohort, and region of birth, and column (2) also includes life-cycle controls. We also compute a cohort trend, setting $\beta = 0$ and $\rho_t = 0$, which allows us to estimate the interacting terms between family earnings and birth cohorts. The birth cohort trends are shown

in columns (3) and (4), where the latter includes life-cycle controls. Column (5) shows the results for our most flexible specification.

In general, Table 3 shows a decreasing pattern in the intergenerational elasticity across census years and cohorts. This would suggest that relative intergenerational mobility increased between 1995 and 2015. Most coefficients are positive and statistically significant at the 1 percent level, allowing us to compute IGE estimates for different points in time and for specific birth cohorts. With respect to the census-year trend, column (1) and column (2) show a similar decreasing pattern in the time-variant IGE estimate, where the main difference is that the absence of life-cycle controls yields estimates that are likely to be biased downward. The preferred census-year estimate, shown in column (2), suggests that the IGE decreases from 0.77 in 1995 to 0.67 in 2000, and decreases more in 2010, to 0.47. After that it remains at a similar value for 2015. In fact, by computing confidence intervals at the 95 percent level, it turns out that the decrease in the IGE estimates is particularly significant when comparing estimates for 1995 or 2000 with those for 2010.

For the birth cohort estimates, columns (3) and (4) also show a decreasing pattern, and life-cycle controls play a less important role in their magnitude. The preferred birth cohort estimate, reported in column (4), suggests that the IGE for individuals in the 1971-75 birth cohort is 0.5. The estimate decreases to 0.4 for those in the 1976-80 cohort, and to approximately 0.3 for those in the 1981-85 and 1986-90 birth cohorts. It should be noted that with confidence intervals at the 95 percent level for the point estimates, the IGE differences are statistically significant only when comparing the oldest and youngest cohorts. These results are in line with the census-year trend result, where younger generations have a higher degree of intergenerational mobility.

The last column, which considers our most flexible specification, also supports the argument that intergenerational mobility has increased in recent times, and enables us to determine whether the increase is driven by census-year or birth-cohort effects: the prevailing effect is the one observed across census years. Interpretation of these estimates suggests that people in the 1971-75 birth cohort

have an estimated IGE of 0.8 in 1995. This estimate decreases to approximately 0.5 in 2010 and 2015; the estimate for 2000 is not statistically significant. The fact that interactions between cohort and family earnings are not statistically significant indicates that all cohorts follow the same trend.

These results appear to be similar to those from a recent estimate by Torche (2020), who builds a socioeconomic index accounting for a family's durable goods, assets, and services as a proxy for economic persistence across birth cohorts, and finds that intergenerational economic association increases for individuals born between 1950 and 1970, but decreases for younger cohorts.

We also perform robustness checks to test the sensitivity of our preferred IGE estimate, reported in column (2) of Table 3. First, we randomly assign a birth state to individuals before computing the IGE estimates; as expected the coefficients are very close to zero. Second, we use the log of fathers' earnings as the key independent variable, and find similar estimates, with the same pattern in the IGE estimates. Third, we regress the log of family earnings of adult children on the log of synthetic family earnings. These estimates substantially increase with respect to baseline estimates, but the pattern remains similar. Although further research is needed to account for alternative sources of variation, the evidence points to a slight improvement in relative intergenerational economic mobility (that is, lower persistence) in Mexico from 1995 to 2010-2015.

Table 3. Time-Variant and Cohort-Variant IGE Estimates

<i>Dependent variable: log of adult children's earnings</i>					
	(1)	(2)	(3)	(4)	(5)
<i>log(SFE)</i>	—	—	—	—	0.468*** (0.033)
<i>x census year</i>					
1995	0.551*** (0.048)	0.770*** (0.058)	—	—	—
2000	0.514*** (0.061)	0.673*** (0.053)	—	—	-0.095 (0.080)
2010	0.322*** (0.037)	0.470*** (0.040)	—	—	-0.333*** (0.073)
2015	0.417*** (0.029)	0.474*** (0.033)	—	—	-0.345*** (0.085)
<i>x birth cohort</i>					
1971-75	—	—	0.525*** (0.034)	0.504*** (0.037)	—
1976-80	—	—	0.424*** (0.031)	0.390*** (0.031)	-0.024 (0.023)
1981-85	—	—	0.379*** (0.034)	0.326*** (0.051)	.003 (0.035)
1986-90	—	—	0.324*** (0.031)	0.290*** (0.053)	0.048 (0.041)
Cohort F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Region of birth F.E.	Yes	Yes	Yes	Yes	Yes
Age	No	Yes	No	Yes	Yes
Earnings profile	No	Yes	No	Yes	Yes
Observations	2,641,109	2,641,109	2,641,109	2,641,109	2,641,109
R ²	0.10	0.11	0.10	0.11	0.11

Notes: OLS estimates for time-variant and cohort-variant intergenerational elasticities. The dependent variable is the log of adult children's monthly earnings. In columns (1)-(2), the independent variables are the log of average monthly synthetic family earnings interacting with dummy variables indicating the year adult children's earnings are observed. In columns (3)-(4), the independent variables are the log of average monthly synthetic family earnings interacting with dummy variables indicating the relevant birth cohort. In column (5), all interactions are included. Standard errors adjusting for clustering within state of birth in parentheses. Columns report results for different sets of controls. Columns (1) and (3) include census-year fixed effects, cohort fixed effects, and region of birth fixed effects. Columns (2) and (4) include a quadratic polynomial for age and a quadratic polynomial for age where each term interacts with the log of synthetic family earnings. Coefficients statistically different from zero at the following significance levels: * 10 percent, ** 5 percent, and *** 1 percent.

3.3. Regional-Variation of the IGE Estimate

Table 4 shows the results for IGE by region of birth. As previously explained, we consider four regions: north, center, north-center, and south. Column (1) reports the IGE estimates for the north, column (2) for the center, column (3) for the north-center, and column (4) for the south. All estimates account for census-year fixed effects, birth-cohort fixed effects, and lifecycle factors. In general, the estimates suggest that region of birth plays an important role in intergenerational mobility, and that there is heterogeneous mobility across regions. The highest level of intergenerational mobility is in the north, followed by the center, then the north-center, and finally the south. A 1 percent increase in synthetic family earnings is associated with a 0.43 percent increase in adult children's earnings in the north, 0.49 percent in the center, 0.52 percent in the north-center, and 0.53 percent in south. Unfortunately, there is not enough data to identify statistical differences between regions.

These results are in line with recent evidence, coinciding mainly in the fact that the southern region has the lowest level of intergenerational mobility in the country. Delajara and Graña (2018) and Vélez-Grajales, Minor-Campa and Stabridis-Arana (2018) used the 2011 ESRU Social Mobility Survey in Mexico to compute relative intergenerational social mobility with a wealth index for the same regions. They find the lowest relative mobility in the south and the highest in the north-central region. More recently, Delajara et al. (2020) employed the 2017 edition of the same survey to estimate social mobility across the states of Mexico and across wealth ranks. These authors find that southern states have the lowest degree of social mobility (absolute upward mobility), while northern states have the highest (relative and absolute upward mobility).

The robustness checks for these estimates were limited. The first was to consider specification (2). In this case, we examine the interaction between synthetic family earnings and region of birth, with the restrictions $\beta = 0$, $\delta_c = 0$, and $\rho_t = 0$. The estimates were similar to those in Table 4. The second varied both the dependent and independent variables in equation (3) with no major changes. The

third considered clustered standard errors, and only the estimate for the southern region turned out not to be statistically significant, which is mainly due to the lack of variation already noted.¹⁶

Table 4: Region-Invariant IGE Estimates

	<i>Dependent variable: log of adult children's earnings</i>			
	<i>North</i>	<i>Center</i>	<i>North-center</i>	<i>South</i>
	(1)	(2)	(3)	(4)
<i>log(SFE)</i>	0.434*** (0.025)	0.496*** (0.008)	0.515*** (0.14)	0.534*** (0.025)
Cohort F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Region of Birth F.E.	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes
Earnings profile	Yes	Yes	Yes	Yes
Observations	326,641	909,552	560,137	844,779
R ²	0.07	0.10	0.08	0.06

Notes: The table reports OLS estimates for the time-invariant intergenerational elasticity. The dependent variable is the log of adult children's monthly earnings. The independent variable is the log of average monthly synthetic family earnings by state of birth and birth cohort of previous generations. Robust standard errors in parentheses. Columns report results for different sets of controls. These controls are cohort fixed effects, census year fixed effects, region of birth fixed effect, a quadratic polynomial for age, and a quadratic polynomial for age where each term interacts with synthetic family earnings. Coefficients statistically significant different from zero at the following significance levels: * 10 percent, ** 5 percent, and *** 1 percent. Supplementary materials documents these results with a map of Mexico and its regions.

3.4. Cross-Country Differences, Mexico, and the Great Gatsby Curve

Cross-country differences can shed light on the role of three fundamental factors in determining children's economic outcomes: family background, labor markets, and the role of the state (Solon 2004). Corak (2016) argues that cross-

¹⁶ We did not compute rank-rank slopes in these cases, since the region of birth is very likely to determine children's position in the national earnings distribution, to some extent invalidating the estimates (Chetty et al. 2014a). Recent literature has addressed this issue by using intergenerational mobility surveys and considering smaller regions, such as states (e.g., Delajara et al. 2020). Further research would need to consider even smaller regions (e.g., Chetty et al. 2014a) to fully determine the geographic variation of intergenerational mobility within México.

country differences are related to differences in the transmission of inequality due to differences in the investments in children made by different societies, and the return on those investments. These processes include family background (i.e., investment in human capital), labor markets (i.e., returns to education), public policy (i.e., progressive reforms like increasing education and health care for the poor) and their interactions. By understanding how these factors influence intergenerational earnings mobility in Mexico and its differences with other countries, we can understand better what is needed to change the ways in which inequality is transmitted from one generation to the next.¹⁷

To examine the case of Mexico in a cross-country framework, we follow the methodology proposed by Corak (2006), which scales the most reasonable IGE estimates for different countries to a representative (anchor) estimate for the U.S., adjusting also for differences in sample characteristics and methods. The anchor is 0.462 for countries other than the U.S., Canada, and the U.K. (Corak 2006). For Mexico, we consider the IGE estimate based on regressing the log of adult children's earnings on the log of synthetic fathers' earnings, controlling for all the factors specified in equation (2) except birth region. This estimate is 0.52. Then, by following a similar specification with PSID data, we estimate an IGE of 0.479, which is similar to the estimate obtained by Grawe (2004) for the U.S. Finally, by using equation (4) we obtain an IGE of 0.5 for Mexico.

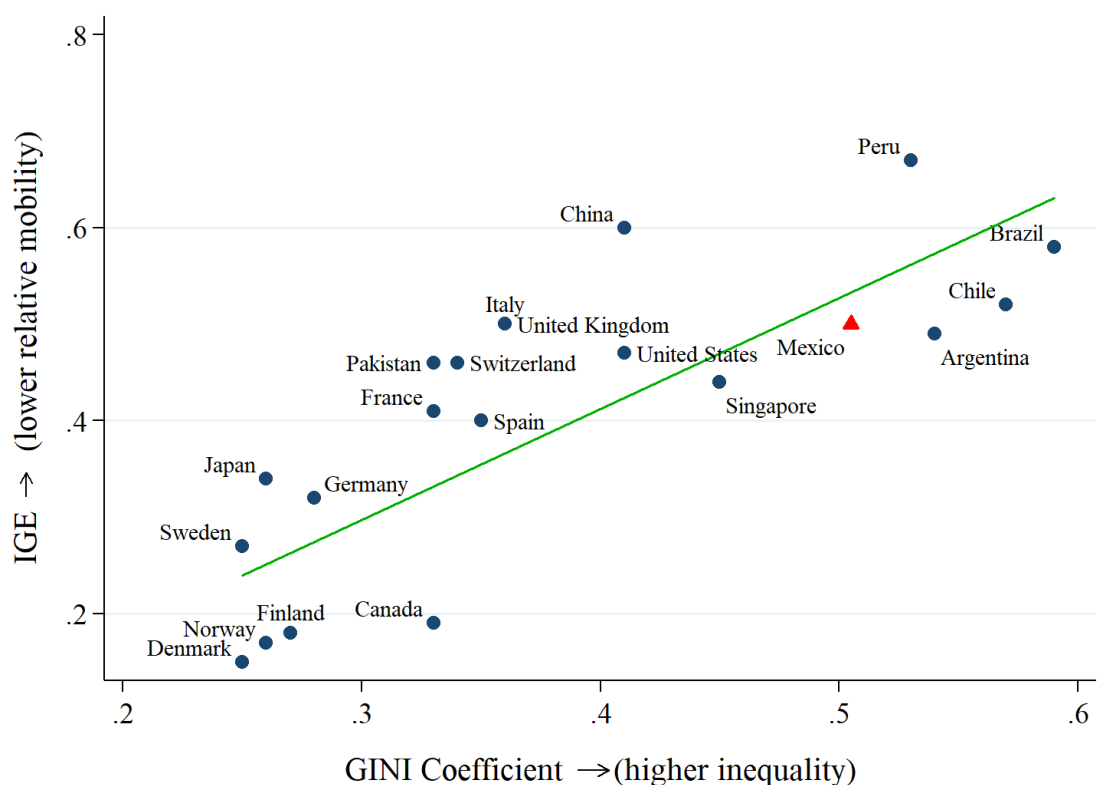
Figure 2 is the “Great Gatsby curve” that shows how Mexico compares with other countries in terms of intergenerational economic mobility (x-axis) and inequality (y-axis), (Corak 2016; Krueger 2012). In general, the graph suggests a relationship between the transmission of inequality and intergenerational economic mobility (Corak 2016); it shows that our estimate is similar to those observed for Italy (0.50) and the United Kingdom (0.5), just above Argentina (0.47) and the United States (0.40), and below Chile (0.52) and Brazil (0.58). Mexico shows a low level of economic intergenerational mobility compared with advanced European economies,

¹⁷ IGE differences provide only a descriptive framework of the determinants of children's opportunities, and should not be taken alone for policy recommendations. There have been recent efforts to understand within-country variation in social mobility in Mexico and its main correlations as part of the discussion about policies to enhance social mobility (Delajara et al. 2020).

although it is reasonable for its level of income inequality. However, among similar economies (Argentina, Chile, Brazil, and Peru), Mexico is the least unequal country and has the second highest level of intergenerational mobility.

This result needs to be interpreted with caution. With the limited available data on earnings, synthetic family earnings are not observed long enough to completely solve the problem of measurement error and attenuation bias (Mazumder 2005). Better estimates could be computed if data on children and parents were available in the form of surveys or administrative records. However, given the current level of inequality in Mexico, our estimate suggests a reasonable lower bound of intergenerational economic mobility.

Figure 2. International Comparison: Great Gatsby Curve



Note: IGE estimates collected by Corak (2006) and Corak (2016), with the authors' estimation for Mexico (y-axis), versus the Gini coefficient (x-axis) reported by the World Bank. For Mexico, the graph displays an average of available GINI coefficients. The straight line shows the fit to a linear regression.

4. Conclusion

This study provides different measures for intergenerational economic mobility for Mexico, using earnings as a measure of the extent to which society rewards people's merit (Mazumder 2005) in a context of high inequality. It documents three main findings. First, the aggregate IGE estimate for Mexico is around 0.5, which is above the IGE for advanced economies and similar to countries like Argentina and Chile. Second, younger generations are more likely to experience higher degrees of mobility. Although future research needs to validate this finding, and discard it is driven by measurement error. Third, intergenerational variation across regions of birth suggest that people who were born in the southern part of Mexico experience the lowest degree of intergenerational mobility.

Although the estimates are stable to different robustness checks, it is necessary to interpret these results with caution. Our synthetic approach addresses the issue of measurement error by considering multi-year averages of synthetic family earnings by cohort and state of birth (e.g., Antman and McKenzie 2007), but the available data does not allow us to fully address attenuation bias (Aaronson and Mazumder 2008; Mazumder 2005). However, our aggregate IGE estimate is very likely to be an accurate lower bound, and the overall portrait of income inequality in Mexico suggests a rigid society that does not fully compensate people for their effort.

Further research should seek data sources that allow for the comparison of parents' and children's earnings and income, examine spatial variation of intergenerational mobility at the most disaggregated level, and deepen its focus on the economic factors influencing intergenerational mobility in Mexico, including investment in human capital, returns to skills, labor market inequalities, and public policy (Corak 2016, Solon 2004).

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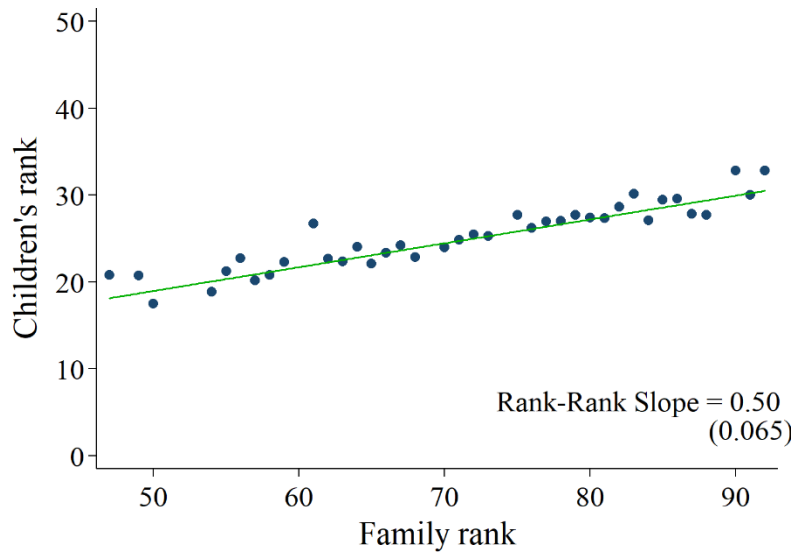
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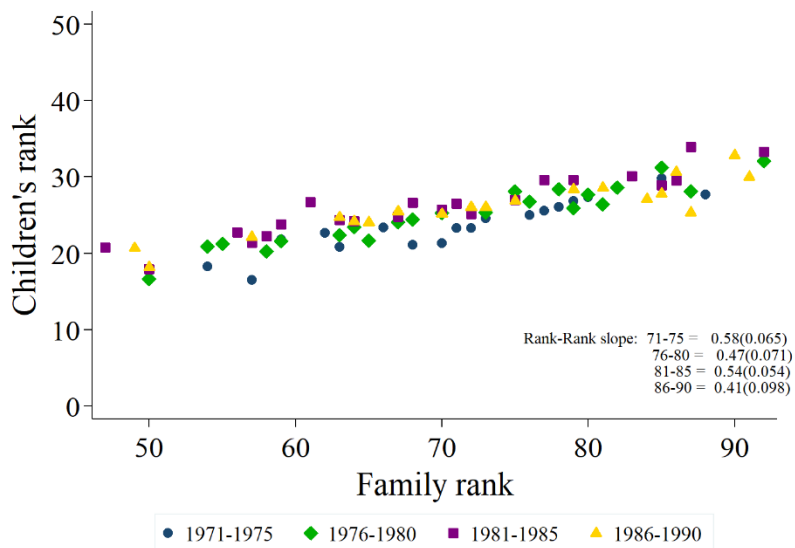
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Appendix I. Synthetic Rank-Rank Estimates

A. Time-Invariant Rank-Rank Estimate



B. Cohort-Variant Rank-Rank Estimates



Notes: The figure displays two binned scatter plots showing the relationship between children's and family earnings percentile ranks: synthetic rank-rank estimates. For these estimates, we divide adult children into groups or bins of equal size and assign a rank to each bin by birth cohort. For family earnings, we assign a percentile earnings rank as if earnings were observed in the corresponding distribution of family earnings in a particular cohort (for this reason we are only able to rank families from particular earnings percentiles). Panel A summarizes rank-rank relationships in 37 groups of equal size; these bins report an average of children's ranks for a particular family rank. It also shows the time-invariant rank-rank estimate: the constant is 13.83. Panel B displays rank-rank estimates for every relevant cohort; it also shows the cohort-variant rank-rank estimate; the constants are 8.6 (1971-75), 16.28 (1975-80), 11.79 (1981-85) and 17.85 (1986-90).

Appendix II. Regional Variation of IGE Estimates



Notes: This figure shows the spatial variation of intergenerational economic mobility in Mexico. We consider four regions of birth that have been previously defined by the Bank of Mexico (2016). We perform a linear regression to estimate the IGE for each region, controlling for census-year fixed effects, birth-cohort fixed effects, age controls, and earnings profile controls. The results show differences between regions: north (0.43), center (0.49), north-center (0.52), and south (0.53).