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Abstract

Intergenerational mobility is a growing concern among academics and policymakers. However, due to the absence of information on earnings for successive generations, little evidence is available for developing countries. This paper adds to this scarce body of evidence by studying intergenerational mobility of earnings for Mexico. I rely on the Two-Sample Two-Stage Least Squares approach to estimate the intergenerational elasticity of earnings and the rank-rank coefficient at the national, urban and regional levels, considering the attenuation and life-cycle biases suffered by the estimators. The key results show less mobility than previously suggested. On average, 70.9% of the relative difference in father's earnings is transmitted to their children. Moreover, a 10 percentile point increase in the father's earnings rank is associated with a 3.15 percentile point increase in the son's earnings rank. At the regional level, strong intergenerational persistence is found in the South; whilst the North presents the highest intergenerational earnings mobility.

Keywords: Inequality, Intergenerational earnings mobility, Rank-rank coefficient, Two-Sample Two-Stage Least Squares, Mexico.
JEL: D31, D64, J62, C20.

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1 Introduction

During the last twenty years a vast amount of research has demonstrated that the ways resources are allocated across parents generations influence social welfare for children generations. Children from disadvantaged backgrounds have less chances to climb the social ladder and improve their conditions. The socioeconomic status has a significant effect on education, employment prospects, job quality, health outcomes, access to networks and other opportunities that matter for people's well-being. The combination of poor educational opportunities, low skills and limited employment possibilities usually increases inequality and traps people in vulnerable situations where they are more exposed to environmental hazards and violence (OECD, 2018).

One of the main purposes of the empirical literature on intergenerational mobility has been to estimate the association between the social origin and the social destination of the individual. Different approaches to measure this association have been proposed using either ordered categorical variables such as social and economic class positions or continuous monetary variables, such as income or earnings.[1] Respecting intergenerational mobility of income, most of this literature has been focused on the analysis of developed countries given the ample availability of longitudinal datasets (e.g. Björklund and Jäntti, 1997; Nicoletti and Ermisch, 2008; Chetty et al., 2014b). Nevertheless, the pervasive consequences of the lack of social mobility are more notorious in poor and highly unequal developing countries, for which it might be even more relevant to measure the inequality of opportunities (Narayan et al., 2018; OECD, 2018). Unfortunately, the availability of long run longitudinal data is almost null in these countries, a fact that imposes restrictions to achieve this goal.

This paper contributes in filling this gap in the empirical literature by estimating the strength of the association between parents' and son's earnings for the case of Mexico, its urban area, and its main geographical regions. Since data regarding earnings information for two subsequent generations is not available, but other characteristics such as parents' education and occupation are observable, I follow the Two Sample Two Stage Least Squares (TSTSLS)[2] methodology (e.g. Björklund and Jäntti, 1997; Nicoletti and Ermisch, 2008), which relies on the use of retrospective information to link the socioeconomic circumstances during the childhood and the adult destination of offspring, to estimate the intergenerational persistence of earnings and provide a measure of intergenerational social mobility for Mexico. In contrast to Cuesta et al. (2011); Rojas (2012) and Campos-Vázquez et al. (2020), I take careful consideration of the attenuation and the life-cycle biases suffered by the estimators of mobility when point-in-time measures of

[1]For a review on these approaches see Björklund and Jäntti (2000); Erikson and Goldthorpe (2000); Blanden (2013) and Torche (2013).

[2]The TSTSLS estimator is a variation of the Two Sample Instrumental Variables TSIV estimator presented by Angrist and Krueger (1992). Inoue and Solon (2010) state that despite both estimators (TSTSLS and TSIV) being consistent, the TSTSLS is the most efficient estimator.

earnings are used, which tends to highly underestimate the measure of permanent income, affecting the consistency of the estimator of the intergenerational persistence of earnings (Solon, 1992; Zimmerman, 1992).

I contribute to the analysis of intergenerational earnings mobility in developing countries and extend the evidence for Mexico in new multiple ways. Foremost, I manage to construct a closer measure of the permanent income of the parents through a sample of "pseudo-parents" using the National Survey of Urban Employment (ENEU) for the period 1987-1991 as the base to predict parents' earnings from retrospective information provided by the sons in the ESRU Survey on Social Mobility in Mexico 2011 (ESRU-EMOVI 2011), which allows me to provide a more consistent estimator of the intergenerational elasticity of earnings for Mexico. Moreover, for the first time in the case of Mexico, I estimate the earnings-based rank-rank coefficient which measures the correlation between the child's and the parents' earnings positions within their respective distribution of earnings, using the imputed parents' earnings from the first stage of the TSTSLS estimation approach.

I also enrich the analysis of the intergenerational persistence of earnings in Mexico in two new directions. First, I quantitatively illustrate the sensitivity of the IGE and the rank-rank coefficient to the attenuation bias, the life-cycle bias and alternative earnings definitions. I explicitly consider two different measures of earnings –father's and parents' earnings– to provide contrasting evidence regarding father's and family's resources in childhood. Second, I present new evidence for Mexico at the urban and regional level. The latter is build upon cross-regional comparisons of the estimated IGE and the rank-rank coefficient for four big regions, which are aggregations of federate states as defined by Banco de México (2016).

The estimates show that intergenerational earnings persistence in Mexico is 0.709, as measured by the IGE, and it is 0.315, as measured by the rank-rank coefficient. However, when the total earnings of parents are considered as the measure of permanent parental income these figures are slightly lower. The value of the IGE is 0.638, whilst the rank-rank coefficient is equal to 0.296, indicating less intergenerational mobility in earnings than that suggested by previous research. The estimated IGE for the urban area is 0.661, whilst the value of rank-rank coefficient is 0.291. These lower values are evidence of the low level of intergenerational mobility of earnings in the non-urban areas. At the regional level, strong intergenerational persistence is found in the South region (0.974); meanwhile, the North region (0.371) presents the highest intergenerational earnings mobility, showing an association between income inequality and intergenerational persistence of earnings among the Mexican regions.

Both the attenuation bias and the life-cycle bias affect significantly the estimation of the intergenerational earnings persistence in Mexico. In the case of the former, when point-in-time measures of parental income are considered, the IGE is approximately reduced by 10.3%, whilst the latter is evidenced in a decrease of 24.9% in the baseline estimated valued of the IGE computed from a subsample of sons aged 35 to 45. The observed pattern for the rank-rank coefficient is rather similar but less pronounced, which implies that these biases are driven mainly by a scale issue instead of a positional accuracy issue. This analysis remains valid when only the urban sample is used to generate the estimated values.

These results are a complement to previous findings for the case of Mexico in Daham and Gaviria (2001); Behrman et al. (2001) and Binder and Woodruff (2002), which by performing cohort analysis show evidence of high persistence in the association between parents' and child's educational level; and are particularly close to those in Behrman and Vélez-Grajales (2015); Torche (2015) and Yalonetzky (2015) which, by using ESRU-EMOVI 2011, find that children with less educated parents have the same likelihood of getting their parents educational level than children with more educated parents, and observe that new generations have less relative intergenerational mobility in terms of economic wealth than older generations.

The regional results are in line with those in Vélez-Grajales et al. (2017) and Delajara and Graña (2017) which analyse intergenerational mobility at the regional level using a wealth index, and with Campos-Vázquez et al. (2020) which uses earnings. They observe heterogeneous patterns of intergenerational mobility among regions of Mexico, with a negative correlation between poverty and intergenerational social mobility. In particular, Delajara and Graña (2017) describes a "regional gradient" also present in the analysis of intergenerational mobility of earnings: South - Central - North Central - North (From lowest to highest intergenerational mobility).

This paper now proceeds as follows. An overview of the empirical methodology is presented in section 2. Data sources, samples, and variables used in the empirical analysis are described in section 3. The main results and the consistency analysis of the estimators of relative intergenerational mobility, are presented and discussed in section 4. Conclusions are presented in section 5.

2 Methodology

I estimate social mobility based on earnings for the case of Mexico. Since most measures of earnings are directly related to the status of the individual in the labour market, and given the considerable number of women who are not employed in Mexico[3], I avoid selection issues regarding female labour market participation, in line with the vast majority of literature, by focusing the analysis on sons. The reference measure of permanent parental income will be the earnings of the father. However, since recent studies have emphasized the use of family resources as a measure of permanent earnings (Chetty et al., 2014a; Jäntti and Jenkins, 2015; Gregg et al., 2017), which provides a more complete view of the childhood circumstances and the family-level dynamics, such as assortative mating and intra-household division of labour, I also consider the total earnings of parents as an

[3] In 2011, 40.6% of women and 74.4% of men in working age were employed in Mexico (ILO, 2019).

alternative measure of permanent parental income.

The degree of intergenerational mobility is measured as the association between the socio-economic status of the father/parents throughout an individual's childhood, and their socio-economic status as an adult. To estimate this association the empirical intergenerational mobility equation is defined as:

$$y_i^{son} = \alpha + \beta y_i^{parent} + u_i \tag{1}$$

where y_i^{son} is the logarithm of the permanent income of the male individual in adulthood and y_i^{parent} is the logarithm of the permanent income (earnings) of his father or parents[4] throughout the individual's childhood. If y_i^{son} and y_i^{parent} are observed for any random sample of son-parent pairs, the intergenerational elasticity (IGE) coefficient β could be estimated by applying ordinary least squares (OLS). However, in many countries, the lack of surveys with information on earnings for both the sons and their parents, impedes to estimate the IGE using a simple OLS regression.

The Two-Sample Two-Stage Least Squares (TSTSLS) procedure, initially presented in Björklund and Jäntti (1997), attempts to solve this problem using information from two different datasets to impute the unobserved parent's earnings. The "main dataset" is a random sample of son-parent pairs with information on the sons' earnings and retrospective information of the parents, such as education and occupation status. The "auxiliary dataset" is an independent random sample that contains earnings and a set of characteristics (e.g. age, education, occupation status) of "pseudo-parents", which are not the observed parents in the main dataset but individuals sharing the same characteristics. Based on these two independent random samples, the IGE can be estimated by making an imputation of the parent's earnings using the pseudo-parent's characteristics from the auxiliary dataset (Björklund and Jäntti, 1997; Nicoletti and Ermisch, 2008; Jerrim et al., 2016).

More precisely, the estimation of the IGE is done in two steps. In the first step, a log-earnings equation is estimated using the pseudo-parent's characteristics (e.g. education and occupation) as a vector Z of k imputer explanatory variables, following the equation:

$$y_i^{parent} = \delta_0 + \sum_{j=1}^{k} \delta_j Z_{ij} + v_i \tag{2}$$

In the second step, the equation (1) is estimated by using the main dataset and replacing y_i^{parent} by its predictor ($\hat{y}_i^{parent}$), which is obtained as the combination of the coefficient vector estimated in the first step, and the set of parent's characteristics observed in the main sample ($Z\hat{\delta}$). The estimated parameter ($\hat{\beta}$) measures the IGE or the level of association between parental resources during childhood and the individual's lifetime adult earnings. Therefore, the higher the IGE, the lower the degree of intergenerational economic

[4] I define parents' earnings as the sum of the father's earnings and the mother's earnings.

mobility.

The parameter also combines both components into which the joint distribution of parent and child earnings can be decomposed. The first is the copula or the joint distribution of parents' and children's percentile ranks, which captures the extent of the re-ordering among generations, and the second is the marginal distribution of parents' and children's earnings, which captures inequality within generations (Chetty et al., 2014b; Gregg et al., 2017). This estimate is quite sensitive to the regression specification. In particular, the way in which zero earnings are treated affect significantly the IGE.[5]

An alternative measure to the IGE is the correlation (ρ) between the child's and parent's "ranks" within their respective distribution of earnings (rank-rank coefficient):

$$Rank_i^{y^{son}} = c + \rho Rank_i^{\hat{y}^{parent}} + e_i \tag{3}$$

$Rank_i^{y_{son}}$ is the child's percentile rank in the distribution of earnings of sons and $Rank_i^{\hat{y}_{parent}}$ is the parent's percentile rank in the predicted distribution of earnings for parents. Following equation (3), the rank-rank coefficient ρ, is estimated by an OLS regression, and measures the association between the son's position and his parent's position within their own earnings distribution.

Both the IGE and the rank-rank coefficient are measures of relative mobility. Nevertheless, the latter depends purely of the joint distribution, which implies that differences between the two estimators are given by differences in inequality (Chetty et al., 2014a,b). Moreover, the rank-rank estimation provides a more robust estimator and is less sensitive to measurement issues (Chetty et al., 2014a; Gregg et al., 2017). By estimating these two measures of relative social mobility using the father's and the parents' earnings as measures of parental permanent income, I provide a more complete analysis of the intergenerational earnings mobility in Mexico.

Consistency of the estimators

By using the TSTSLS method, the intergenerational mobility measures (IGE or rank-rank coefficient) are estimated using the prediction of parent's earnings instead of a measure that has been directly observed. This procedure can be considered as a "cold-deck" linear regression imputation or a "generated regressor" approach (Nicoletti and Ermisch, 2008; Jerrim et al., 2016), instead of an instrumental variable (IV) method. Inoue and Solon (2010) state that in the two-sample context, unlike the single-sample framework, the estimators from TSLS and IV are different; and the TSTSLS approach is more efficient since it corrects for differences in the empirical distribution of the imputer variables between the "main" and the "auxiliary" samples.

According to the literature (Solon, 1992; Björklund and Jäntti, 1997; Nicoletti and Ermisch, 2008; Jerrim et al., 2016), the TSTSLS estimator is consistent if either: the son's

[5]See Chetty et al. (2014a) and Gregg et al. (2017), for a full discussion

earnings are not affected directly by the imputer variables, or the variance explained (R^2) in the equation used to predict parent's earnings (equation (2)) equals one. However, due to data restrictions, the choice of imputer variables and measurement error problems are two potential sources of inconsistency.

To obtain the best prediction of parent's earnings, most of the studies use parent's education and occupation as imputer variables. However, these are likely to be positively related to the son's earnings[6] and are not perfect predictors of parent's earnings (Solon, 1992; Nicoletti and Ermisch, 2008). As a result, the son's earnings are affected directly and indirectly (through parent's predicted earnings) by the parent's characteristics, generating an upward-bias of the TSTSLS estimator, i.e. If the parent's education and occupation characteristics (Z) affect directly and indirectly the son's earnings, the intergenerational mobility equation would be:

$$y_i^{son} = \alpha + \beta y_i^{parent} + \sum_{j=1}^{k} \delta_j Z_{ij} + w_i = \alpha + \beta y_i^{parent} + \lambda_2 \hat{y}_i^{parent} + \mu_i \tag{4}$$

and the magnitude of the inconsistency of the estimator of the IGE would be $\lambda_2(1 - R^2)$.[7] This inconsistency is mainly driven by the incorrect estimation of the variability in parent's predicted earnings. Hence, the auxiliary variables chosen need to be those with less correlation with the error in the intergenerational mobility equation, and with the maximum multiple correlation with the parent's earnings (Nicoletti and Ermisch, 2008; Jerrim et al., 2016).

Different first stage specifications allow to understand the magnitude of the TSTSLS estimator's inconsistency regarding to imputer variables selection. For instance, when the number of imputer variables increases in the first stage, the value of R^2 increases and the upward inconsistency of the estimator will decrease. However, Jerrim et al. (2016) argue that including additional imputer variables in order to increase the variance explained (R^2) of the first stage regression do not necessarily reduce the inconsistency of the TSTSLS estimator.[8] The authors state that despite the increase of the explained variance, the effect of parent's predicted earnings on son's earnings could increase too, generating the opposite effect (increase the upward inconsistency). Therefore, to reduce the inconsistency of the estimator, losses due to the latter effect have to be offset by gains from the former.

To overcome this potential problem, I follow Lefranc and Trannoy (2005); Nicoletti and Ermisch (2008) and Jerrim et al. (2016), and estimate different specifications using parent's education, occupation and age as imputer variables. However, it should be noticed that since there is not any dataset where I can observe both sons' and parents' earnings

[6]This means that, if parent's education and social status have a positive effect on their son's labour market outcomes, children with less educated parents from lower social status are likely to earn less than children from a more advantaged background, even after controlling for parent's earnings.

[7]Solon (1992); Nicoletti and Ermisch (2008) and Jerrim et al. (2016) explain the process in more detail.

[8]The addition of variables which influence both; the direct effect of parents' earnings on son's earnings and the first stage R^2 can possibly have the opposite effect.

for Mexico, it is not possible to test the potential bias of the TSTSLS estimator. In addition, notice that most of the empirical literature using TSTSLS estimators to measure intergenerational mobility are likely to be affected by a potential endogeneity problem due to the suitability of their auxiliary variables (Jerrim et al., 2016).

Regarding measurement error problems, the literature notes that the social mobility estimators could suffer from three potential biases: Attenuation bias, life-cycle bias and sample selection bias. The first two are related to the general method (OLS) to estimate the intergenerational elasticity (β), whilst the last is mostly related to the TSTSLS method. In contrast, the rank-rank coefficient is less likely to suffer from these biases. This measure captures remarkably well the rank order mobility, which means that the TSTSLS method does not present difficulties placing parents in the wrong distribution of earnings, but in accurately capturing the variance of parent's earnings (Jerrim et al., 2016).

Attenuation bias. Solon (1992) and Zimmerman (1992) observed that the use of point-in-time measures (annual earnings) generates a downward bias of the estimators of social mobility due to transitory error in parental earnings. However, this bias can be reduced if observations of parental earnings are available for several years. More precisely, the inconsistency of the estimators is inversely related to the number of years over which parental earnings are averaged, due to a better approximation of the permanent parental resources during childhood (Björklund and Jäntti, 1997; Mazumder, 2005). In line with this, I construct five-year average measures of parental earnings using data from the ENEU household survey for the period 1987-1991.[9]

Life-cycle bias. The heterogeneity in earnings trajectories across individuals from different backgrounds causes the life-cycle bias (Jenkins, 1987). The direction and magnitude of this bias depends on the age at which the current earnings are observed. If earnings are measured on an early stage of the life-cycle, the current earnings will understate lifetime earnings of those from more wealthy families compared to those from more deprived families (Solon, 1992; D.Grawe, 2006; Böhlmark and Lindquist, 2006). To analyse the sensitivity of the results and to measure the impact of the life-cycle bias, I contrast the estimations from sons between ages 25 and 50 to those from sons between ages 35 and 45.

Sample selection bias. In the TSTSLS method, the consistency of the social mobility estimators also depend on two assumptions: i) the main and auxiliary datasets have to be random samples from the same population; and ii) the auxiliary variables have to be independent and identically distributed across the two datasets (Björklund and Jäntti, 1997; Nicoletti and Ermisch, 2008; Jerrim et al., 2016). In reality, these assumptions are

[9] Solon (1992) finds a significant increment (33%) of the IGE when using five years average instead of one year of data. Five consecutive years of parent's earning is commonly used (Solon, 1992; Chetty et al., 2014a; Jerrim et al., 2016), however more than ten may be needed if there is auto-correlation in the transitory component of earnings over time (Mazumder, 2005). In the particular case of the rank-rank coefficient, Chetty et al. (2014a) find that the estimator remains practically unchanged when more than five years of data are used.

difficult to meet. In the auxiliary dataset, the pseudo-parents (responder) report their own education and occupation, while in the main dataset the offspring reports parent's characteristics. The impact of how the information is collected on the consistency of the estimators, will depend on the nature and magnitude of the measurement error (Jerrim et al., 2016).

To deal with this issue, I select pseudo-parents from the ENUE household survey for the period 1987-1991, with the same characteristics (age, education, occupation) as those reported retrospectively (by the time they were 14 years old) by sons in the ESRU-EMOVI 2011. To adjust the standard error in the second stage subject to sampling variation, I report bootstrapped standard errors as the literature suggest (Björklund and Jäntti, 1997; Nicoletti and Ermisch, 2008; Jerrim et al., 2016).[10]

Regional analysis

A characterisation by region is also provided to understand the dynamics of intergenerational earnings mobility within the country. I analyse four regions (North, North-Centre, Centre and South), to measure the association between geographical conditions during childhood and intergenerational earnings persistence. This helps to identify potential differences in the degree of equality of opportunities faced by children to climb the social ladder and improve their conditions.

The IGE for each region is estimated using the TSTSLS approach based on equations (1) and (2) and the same specification used for the national level. However, the cross-regional comparisons of this estimated elasticities are affected by the cross-regional differences in the distribution of earnings. Unlike the IGE measure, the rank-rank estimation ensures a better cross-regional analysis due to the fact that the ranks of children and parents are based on their positions within their respective national distribution of earnings.

Furthermore, the rank-rank coefficient allows to measure both relative and absolute social mobility. The relative mobility estimates the difference in outcomes between children from top-earnings parents and children from bottom-earnings parents within a region r, and is measured by ρ_r in equation (5):

$$Rank_{ir}^{y^{son}} = c_r + \rho_r Rank_{ir}^{\hat{y}^{parent}} + e_{ir} \tag{5}$$

The absolute mobility estimates the rank achieved by children from parents at any given rank p of the national parents' distribution of earnings , and it is measured by

[10]To calculate the asymptotic variances of the estimators, I first draw separated bootstrap samples of fathers and mothers, from which I estimate the parameters used to generate a son's father's and mother's predicted earnings. Then I draw a sample of sons, for whom I generate predicted father's and mother's earnings. I then estimate both the IGE (β) and the rank-rank coefficient (ρ) for both father's and parents' earnings (i.e the sum of the father's earnings and the mother's earnings) and save the estimates. After repeating these steps 1.000 times, I estimate the standard error of $\hat{\beta}$ and $\hat{\rho}$ as the standard deviation of the bootstrap estimates.

combining the intercept and slope in equation (5) for region r:

$$\hat{Rank}_{ir}^{y^{son}} = c_r + \rho_r p$$

A particular case is “absolute upward mobility”, which measures the expected rank of a child who grew up in the region r with parents whose earnings’ rank (p) is below the median in the national distribution of the parents’ generation (Chetty et al., 2014a). More precisely, this measure describes how children from low-earnings parents, switch rungs on the ladder.

3 Data

I use data from the ESRU Survey on Social Mobility in Mexico 2011 (ESRU-EMOVI 2011), undertook by the Mexican *Centro de Estudios Espinosa Yglesias*, and from the National Survey of Urban Employment (ENEU) for the period 1987-1991, undertook by the National Institute of Statistics and Geograpy (INEGI). The ESRU-EMOVI 2011 survey –main dataset– is based on a probabilistic, multistage and stratified sample design of $11,001$ men and women aged 25-64 years, which is statistically representative of the country population. The survey collects information on respondents’ demographic characteristics, education, employment and occupation, income and assets. It also includes retrospective information about family structure, education, occupation and assets of the respondents’ parents.

The ENEU household survey –auxiliary dataset– uses a probabilistic, multistage and stratified sample design of men and women aged 12 years or more. This survey is one of the first instruments used to understand and measure the labour market indicators in Mexico and, unlike the ESRU-EMOVI; is only representative of the urban population.[11] Among other information, the ENEU collects information on demographic characteristics, education, employment and occupation, and earnings of the respondents. This is an ideal survey to measure the relation between the pseudo-parents’ earnings and their education and occupation.

Main dataset

The main dataset includes sons aged 25 to 50 (born between 1961 and 1986),[12] with employed or self-employed status, who reported earnings from their current job and, conditional on they being 14 years old, retrospectively, reported the age, education and oc-

[11]For the period 1985-1991, the ENEU collected information from 16 cities: Ciudad de México, Guadalajara, Monterrey, Puebla, León, San Luis Potosí, Tampico, Torreón, Chihuahua, Orizaba, Veracruz and Mérida. In 1992 the sample increased to 32 cities and from then on it has been increasing gradually up to 44 cities in 1998.

[12]In contrast to previous literature, I include individuals between 25 and 29 years old to keep a bigger sample. This group represents a 13.64% of the main sample.

cupation of their parents.

In ESRU-EMOVI 2011, the son's earnings information is available in one point in time. If earnings are missing,[13] but earnings intervals are reported, I estimate earnings using interval regression as Steward (1983); Davidson and Mackinnon (2013); and Wooldridge (2016) suggest. This method fits continuous earnings based on information of the interval in which the earnings fall. This does not modify substantially the sons' earnings distribution and allows me to increase the final sample by 36%. Earnings are adjusted to PPP 2011 prices, reported on Pound Sterling for each observation and its logarithm is taken as the measure of earnings at each point.

The final sample keeps 2,455 observations, which represent 41% of men and 22.3% of the total sample in the ESRU-EMOVI 2011 survey (Table 1). To evaluate the effect of the life-cycle bias, the sample is restricted to a tighter age interval (e.g. 35 to 45 years old sons only). However, making such restriction results in a significant reduction of the sample size (707 observations, 29% of the main sample). A more detailed view of the effects of this restrictions on the different subsample sizes is presented in Table A.1 in Appendix A.

TABLE 1
Main Dataset Sample Selection

	Men	%
Original survey	6,011	100%
25-50 years old	4,886	81%
With parents' information (Age, Education, Occupation)	3,413	57%
With father aged 30 to 60 when the child was 14 years old	3,249	54%
With earns/income data	2,455	41%

Source: ESRU-EMOVI 2011.

Regarding the cross-regional analysis, I use information at the level of four big regions defined by Banco de México (2016). The regions are aggregations of the federative states in which children lived at age 14 regardless of whether they left that region afterwards.[14] Since the ESRU-EMOVI 2011 is representative at the national but not at the federative state level, aggregation in the big four regions allows me to have a higher number of observations per region to obtain a better estimate.

[13]The individuals earnings report falls in either of the following possibilities: (i) earnings greater than zero, (ii) do not know, (ii) do not answer or (iii) data is missing; therefore, zero earnings is not a problem to consider in this case.

[14]North: Tamaulipas, Nuevo León, Chihuahua, Coahuila, Sonora, and Baja California. South: Guerrero, Oaxaca, Chiapas, Quintana Roo, Yucatán, Campeche, Tabasco, and Veracruz. Centre: Morelos, Puebla, Tlaxcala, Hidalgo, Guanajuato, Querétaro, State of Mexico and Mexico City. North-Centre: Michoacán, Colima, Jalisco, Baja California Sur, Nayarit, Aguascalientes, Zacatecas, San Luis Potosí, Sinaloa, and Durango.

Auxiliary dataset

The ENEU household survey is used to measure the relationship between earnings, and education and occupation for those identified as parents in the main dataset; to then predict parents' earnings using retrospective information provided by the offspring. According to the literature, the approximate point of prime earnings years, when annual earnings reach their peak, is around age 40 (Baker and Solon, 2003; Jerrim et al., 2016). Having parents' data at that age improves the estimation since parents' earnings are measured at their most productive age, reducing the life-cycle bias (Torche, 2015). In the main dataset, the fathers' average age is 41.6 years when sons' age was 14 (Table 2). Considering this, to measure fathers' earnings around the prime earnings years and close to the fathers' average age when the offspring is 14 years old, the auxiliary dataset needs to include information from 1991 or around. In the case of Mexico, the ENEU provides annual information of education, occupation and earnings; and is the only survey with information available for more than one period in the early 1990's.

TABLE 2
Descriptive Statistics for the Mexican Samples of Synthetic Pairs of Fathers and Sons

Variable	Main Dataset	Auxiliary Dataset	
		Father	*Parents‡*
Log earnings 1987		8.02	7.94
		(0.64)	(0.77)
Log earnings 1988		8.12	8.11
		(0.67)	(0.72)
Log earnings 1989		8.27	8.20
		(0.68)	(0.78)
Log earnings 1990		8.28	8.20
		(0.71)	(0.73)
Log earnings 1991		8.30	8.20
		(0.72)	(0.67)
Log earnings 2011	7.89		
	(0.69)		
Father's age in 1991*	41.59	40.13	
	(7.19)	(7.31)	
Father's age in 2011	64.12		
	(10.23)		
Son's age in 2011	36.53		
	(7.05)		
Observations**	2,455	54,313	2,455

Source: ESRU-EMOVI 2011 and ENEU 1987-1991. *Note:* Standard deviations in parentheses. * Father's age when the son was 14 years old. ** Number of observations reported in 1991. In the previous years the observations were: 50,677 in 1987, 55,535 in 1988, 55,956 in 1989, and 55,537 in 1990. ‡ Father's and mother's earnings are predicted independently in the auxiliary dataset. However, parental resources are measure in the main dataset, as the sum of father's earnings and mother's earnings.

As I highlighted in the methodology section, to reduce the sample selection error the auxiliary dataset needs to be as similar as possible as the sample of parents in the main dataset. With this in mind and taking into consideration some data restrictions, I select pseudo-parents aged 30 to 60, who had at least one child younger than 16 years old; who were employed or self-employed; and who reported their education, occupation and earnings in the ENEU household survey. I extend this selection criteria to the period 1987-1991 to reduce the attenuation bias presented on the estimates when only one year is considered (Solon, 1992; Zimmerman, 1992; Björklund and Jäntti, 1997). A measure of pseudo-parent's permanent earnings is created for each profile by averaging across all available data during these five years. Earnings are adjusted to PPP 2011 prices, presented on Pound Sterling and its log is taken as the measure of permanent parental income (Table 2).

Among the two datasets the distribution of the parents and pseudo-parents by age, education and occupation are rather similar with the exception of the groups of parents working in an agriculture-related occupation. This is clearly explained by the fact that the ENEU survey is representative only for the urban area, and it might introduce some veil into the parents' earnings prediction of this particular group of individuals (See Table A.2 in Appendix A). Notwithstanding this possible issue, I predict parents' earnings at the national level using this urban representative survey to not impose another restriction to the sample size of the main dataset. I provide an assessment of the possible bias brought by this measurement error issue.

To predict earnings I use the parent's age, nineteen occupational classes and four levels of education (variables included in the vector Z). Due to differences in the information sources and the lag of time that exists between the ESRU-EMOVI 2011 and the ENEU surveys, the occupation has been recorder using distinct CMO codes.[15] To harmonize the occupational classes among the surveys I use the correspondence between CMO-80, CMO-90 and CMO-96 provided by INEGI (INEGI, 1998). After this process, nineteen occupations are defined using two digits CMO's classification, which allows me to compare the occupation reported by the parent's generation and that reported by offspring in the main dataset (See Table A.2 in Appendix A).

Education is recorded using the highest educational grade approved, which I use to form four different categories of education attainment: less than primary education completed, primary education completed, secondary education completed and university education completed. The same classification is used for sons in 2011. To measure parental resources, father's and mother's predicted earnings are aggregated to the main dataset.

[15]The Mexican Classification of Occupations (CMO, Spanish acronym) is a classification defined by INEGI, which organizes jobs into a defined set of groups according to the tasks and duties undertaken in the job. For international comparisons, this classification keeps the same structure as the ILO International Standard Classification of Occupations (ISCO). However, some changes are done to capture as best as possible the Mexican labour market dynamics.

4 Results

Since mexican surveys do not collect information on both sons' and their parents' earnings, I use the TSTSLS method to estimate intergenerational social mobility measures for the case of Mexico. In the first stage, the pseudo-parent's log earnings equation (2) is estimated using the auxiliary dataset. After that, the estimated coefficients are used to predict father's/mother's earnings using the retrospective father's/mother's characteristics reported by "his/her son" in the main dataset to then estimate the intergenerational earnings mobility coefficient (IGE and rank-rank coefficient).

First stage

Taking into account the considerations mentioned in the methodology section and following key previous literature (Björklund and Jäntti, 1997; Lefranc and Trannoy, 2005; Nicoletti and Ermisch, 2008; Jerrim et al., 2016), the explanatory variables used to estimate the earnings equation (2) are: the interaction between six dummies for five-years age bands, with four dummies for education and with nineteen dummies for occupations.[16]

It is important to emphasise that, since the auxiliary variables (father's education and occupation) are likely to be positively correlated with the son's earnings, even after controlling by father's earnings, the TSTSLS estimator could be overestimated due to endogeneity problems. Specifically, the upward bias of the estimator is proportional to the first stage factor $(1 - R^2)$.[17] For the particular specification of equation (2) for the case of Mexico, the auxiliary variables explain on average about 32.5% of the variance of the five year average of father's log earnings, which implies a reduction of the potential upward inconsistency of the TSTSLS estimators of at least this magnitude.[18] Even though the R^2 seems to be low, it is in line with previous empirical studies on intergenerational mobility applying TSTSLS estimators (see, Jerrim et al. (2016).).

The empirical analysis of the intergenerational earnings mobility starts by characterising the relationship between father's and son's earnings at the national level. In the first part I present baseline estimates of the relative intergenerational elasticity of earnings and the rank-rank coefficient. Then I evaluate the consistency of the estimators to alternative specifications. Finally, I analyse the relationship between father's and son's earnings in the four Mexican regions. I also contrast the consistency of the estimations using a measure of parents' earnings.

[16] To predict parents' earnings (i.e. the sum of father's and mother's earnings) in the main dataset the earnings equation is estimated in levels, for fathers and mothers separately. Results for the first stage are available on request.

[17] See footnote 7.

[18] The equation was estimated by year and the figure corresponds to the average R^2 of the five years (See Appendix B Table B.1).

Baseline estimates

After predicting fathers' earnings, I characterize the relationship between father's and son's earnings. In the baseline analysis, for a sample of sons with ages between 25 and 50 years old, I estimate the relationship between the log of son's earnings at 2011 and the log of the predicted father's earnings five-year average when their sons were 14 years old, using an approach similar to the one suggested by Lee and Solon (2009) to account for potential life-cycle bias arising from measuring son's earnings at different ages. More precisely, I include as controls the quadratic in the father's age at the time the son is 14 years old, the quadratic in the son's normalized age ($age - 40$) at the time earnings are observed, and the interactions of the quadratic in the son's normalized age with predicted father's earnings.[19] The normalized age simplifies the interpretation of β, which measures how the intergenerational earnings elasticity at son's age 40 moves forward as successive cohorts pass through that age. A high β implies that people born in disadvantaged families have a smaller chance of placing themselves on higher socio-economic positions than people born in privileged families. While a β closer to zero indicates instead a high degree of mobility and more equal opportunities.

The first column of Table 3 presents the baseline estimations of the IGE and the rank-rank coefficient for the case of Mexico, using the father's earnings as the measure of parental income. The value of the estimated IGE is 0.709, which implies that, on average, 70.9% of the relative difference in father's earnings is transmitted to their children. In other words, if a father used to earn £100 less than the average fathers' earnings, his child will earn £70.9 less than the average sons' earnings. On the other hand, the value of 0.315 for the estimated rank-rank coefficient implies that, on average, a 10 percentile point increase in the father's earnings rank within the total fathers' distribution of earnings will be associated to just a 3.15 percentile point increase in the son's earnings rank within the corresponding distribution of earnings.[20]

When total parents' earnings are used as the measure of parental income, the second column of Table 3 shows a significantly lower value for the estimated IGE. In other words, the relationship between parents' earnings and the son's earnings is weaker than the relationship between the father's and the son's earnings. Aside from the possible measurement error issue coming from the first stage, where parents' earnings are predicted, it is likely that in Mexico the presence of mothers in the labour market, whom perceive positive earnings, helps to increase the equality of opportunities and the intergenerational earnings mobility of sons, even regardless of these mothers having a male partner.[21] In the

[19] I also considered the quartic in the father's and the son's age, and in the interaction of the son's age with the father's earnings, but the additional terms were not significantly different from zero.

[20] Another way to interpret this estimated value of the rank-rank coefficient, is that the expected difference between the rank of earnings of sons of fathers at the top and the bottom of the distribution of earnings is 31.6 ($\hat{Rank}_{100}^{y^{son}} - \hat{Rank}_{0}^{y^{son}} = 100 * \rho$).

[21] Parents' earnings include single mothers who are employed and perceive earnings.

TABLE 3
Estimations of Intergenerational Elasticity of Earnings and Rank-Rank Coefficient - National

	Father	*Parents*
Parents' earnings 1987-1991 - Son's age 25-50		
$\hat{\beta}$	0.709	0.638
	(0.130)	(0.107)
Rank-rank Coefficient	0.315	0.296
	(0.048)	(0.046)
SD Son earns	0.697	0.693
SD Father/Parents earns	0.331	0.390
N	2,371	2,445

Note: Standard errors in parentheses have been obtained using bootstrap sampling.

same line of reasoning, the estimated rank-rank coefficient for parents' earnings is lower than the estimated coefficient based on father's earnings. However, this change in the value of the estimate is not substantial, since the rank-rank estimator attempts to remove scale measurement issues and is less sensitive to income fluctuations in the extremes of the distribution.

Both the baseline estimates and the ones depending on the total parents' earnings are strong evidence of a weak intergenerational earnings mobility in Mexico. Furthermore, when compared to other estimates for developing countries using similar methodologies, Mexico's intergenerational persistence is in line to that of highly unequal countries in the same region, such as Colombia (0.76; Ramírez, 2016), Ecuador, Peru (1.13 and 0.67; Grawe, 2004), Chile (0.57; Nunez and Miranda, 2010) and Brazil (0.69; Dunn, 2007). Regarding the rank-rank coefficient of earnings, estimated for the first time in the case of Mexico, it seems to be significantly higher than the one estimated for Italy (0.236; Barbieri et al., 2019) which is, to the best of my knowledge, the only study that has estimated the rank-rank coefficient by using the TSTSLS approach to predict father's earnings.

Attenuation bias and life-cycle bias

I analyse now the consistency of the estimators of intergenerational earnings mobility in Mexico, focusing the analysis on the most cited potential sources of bias: the attenuation bias and the life-cycle bias.

Attenuation bias. As Solon (1992) and Zimmerman (1992) argue, the use of point-in-time measures of father's earnings as an approximation of parental resources during childhood generates a downward bias of the estimator of intergenerational earnings mobility since it is not a direct measure of permanent income. I consider the impact of potential attenuation bias on the estimates of intergenerational mobility in Mexico, by estimating the IGE and the rank-rank coefficient using as parental income both a multiyear average, and a point-in-time father's earnings measure. *Panel A* in Table 4 presents the estimates using father's earnings in 1991, to measure the impact of attenuation bias driven by measurement error and transitory shocks.[22]

A comparison with the baseline estimates (Table 3), shows that the estimated IGE based on the five years earnings average is 11.5% larger than the estimated IGE based on one year of father's earnings. There seems to be a significant attenuation bias coming from measurement error of the permanent income of both fathers and sons. On the other hand, the rank-rank coefficient based on one year is similar to its baseline counterpart indicating that any issue of measurement error and transitory shocks present in the measure of father's earnings in 1991 does not affect positional accuracy within the earnings' distribution, but causes scale mis-measurement issues.

When parents' earnings are used as the measure of parental resources, the conclusions about attenuation bias do not change. The baseline estimated IGE is 10.6% larger than the IGE using a single year measure and the rank-rank coefficient does not present a significant change when using parents' earnings instead.

TABLE 4
Consistency of the Estimations of Intergenerational Elasticity of Earnings and Rank-Rank Coefficient

	Father	*Parents*
Panel A: ***Parents' earnings 1991 - Son's age 25-50***		
$\hat{\beta}$	0.636	0.577
	(0.137)	(0.114)
Rank-rank Coefficient	0.299	0.273
	(0.056)	(0.053)
SD Son earns	0.696	0.693
SD Father/Parents earns	0.336	0.390
N	2,364	2,439
Panel B: ***Parents' earnings 1987-1991 - Son's age 35-45***		
$\hat{\beta}$	0.532	0.474
	(0.190)	(0.159)
Rank-rank Coefficient	0.269	0.273
	(0.074)	(0.070)
SD Son earns	0.627	0.623
SD Father/Parents earns	0.312	0.351
N	686	704

Note: Standard errors in parentheses have been obtained using bootstrap sampling.

The effect of attenuation bias in the estimates of intergenerational persistence of earn-

[22]Table C.1 in Appendix C presents the estimates for different combinations of years used to measure average fathers' earnings.

ings could affect the way intergenerational mobility and inequality of opportunities are analysed. To estimate a lower intergenerational persistence of earnings entails an understatement of the intergenerational mobility problem from those responsible for the design and implementation of public policies. Therefore, it is important to improve the measurement of intergenerational persistence for a better understanding of the social mobility problem.

For Mexico, there is no previous evidence of the magnitude of the attenuation bias from measurement error and transitory shocks on the intergenerational persistence of earnings, this is the first study to measure this source of bias. The only study that estimates the IGE of earnings (Rojas, 2012), uses data from the ESRU-EMOVI 2006 and one-year father's earnings as an approximation to permanent parental resources. Therefore, it is likely that the intergenerational persistence (0.312) reported in that study is understated due to, at least, the presence of potential attenuation bias.

Life-cycle bias. The literature has shown that measuring son's earnings at early ages of the life-cycle can lead to a understatement of intergenerational persistence in lifetime earnings since children from more wealthy families have a steeper earnings profile when they are young, compared to those coming from more deprived families, because of differences in human capital investment (Haider and Solon, 2006; Chetty et al., 2014a). To evaluate whether the baseline estimate suffers from life-cycle bias, despite the fact that I already use the quadratic in the son's normalized age at age 40, I compare the intergenerational persistence of earnings between the baseline (sons aged 25-50) and that estimated from a subsample of sons aged 35-45.

When comparing the estimates from *Panel B* in Table 4 and the baseline, it is possible to see that the estimated IGE of sons based on earnings at 25-50 is 33.2% higher than the estimated IGE based on earnings at ages 35-45. This result suggests that the point at which children's earnings are measured affects considerably the intergenerational persistence of earnings due to a potential life-cycle bias. The rank-rank coefficient, which deals with measurement issues, shows a similar but less pronounced pattern between sons aged 25-50 and those aged 35-45, as expected. This indicates that the life-cycle bias is mainly determined by scale instead of positional accuracy issues. When total parents' earnings are used as the measure of parental income, the comparison shows a similar result, and gives support to the likely presence of life-cycle bias in the estimation of the intergenerational earnings mobility in Mexico.

Children with high lifetime earnings tend to be those with high earnings growth rates due to differences in human capital investment. Consequently, the current earnings gap between children from wealthy families and those from more disadvantaged families at early ages (older ages) tends to understate (overstate) their gap in lifetime earnings and therefore the IGE (Haider and Solon, 2006).

Urban vs national estimations

For Mexico, the ENEU provides annual information on the auxiliary variables and is the only survey with information available for more than one period in the early 1990's, period that coincides with the time when, on average, the children were 14 years old. However, this survey is only representative of the urban population, which makes difficult the estimation of parents' earnings, specially for those who work on agriculture activities due to the few number of individuals working in this sector in the urban area. To measure the impact of using the ENEU as the auxiliary dataset on the estimation of the intergenerational earnings mobility in Mexico at the national level, I compare the estimates using the national sample (baseline) and the urban sample for sons aged 25-50.

The comparison of national (Table 3) and urban estimates (Table 5), shows that the baseline estimated IGE is 7.3% higher than the intergenerational persistence of sons estimated for the urban area. Although the rank-rank coefficient follows a similar pattern to that seen for the estimated IGE, its estimated value is just attenuated by 0.025 in the urban sample. When parents' earnings are used, the decrease in the estimated value of the IGE is much more modest (6.1%), whilst the rank-rank coefficient is slightly attenuated when using only the urban sample.

TABLE 5
Estimations of Intergenerational Elasticity of Earnings and Rank-Rank Coefficient - Urban

	Father	*Parents*
Parents' earnings 1987-1991 - Son's age 25-50		
$\hat{\beta}$	0.661	0.602
	(0.136)	(0.110)
Rank-rank Coefficient	0.291	0.271
	(0.052)	(0.049)
SD Son earns	0.693	0.689
SD Father/Parents earns	0.343	0.405
N	1,844	1,904

Note: Standard errors in parentheses have been obtained using bootstrap sampling.

Regarding the attenuation and life-cycle biases, a similar pattern to that described at the national level is observed when only the urban sample is used to generate the estimated values. In the first case, the size of the downward attenuation bias is just slightly stronger, whilst in the case of the life-cycle bias the effect is significantly stronger. For instance, the IGE estimated for sons aged 25-50 is approximately 60% higher than the one estimated for sons aged 35-45, regardless of the measure of parental earnings used (See Table C.2 in Appendix C).

It is important to highlight two different considerations. First, in a developing country like Mexico a higher IGE in the national level is expected regardless of the possible issue of measurement error of earnings. By including individuals from the non-urban area, whom are more likely to be at the bottom of any distribution of income or earnings, the intergenerational persistence tends to be stronger. Second, the fact that parents' earnings in the non-urban area are predicted using information from parents in the urban area introduces a potential bias in the estimation of the intergenerational mobility of earnings, an issue that could reduce the reliability of the estimates. Nevertheless, the intergenerational persistence of earnings in Mexico is highly strong regardless of which sample I use to compute the estimates, making the high inequality of opportunities visible both in the urban and in the national context.

Regional analysis

In this section, I characterize intergenerational earnings mobility across regions in Mexico, by disaggregating the main sample at the national level into four subsamples associated with the four regions defined by Banco de México (2016), which are aggregations of the federate states where the sons used to live in at age 14.[23] Table 6 presents the estimated values of the relative (IGE and rank-rank coefficient) and the absolute (upward mobility) intergenerational mobility using the baseline specification disaggregated by region.

The North, North-Centre and Centre regions present the lowest IGE of earnings. In contrast, the South region presents the highest IGE of earnings, and its estimated value is the only one above the IGE estimated for the national level. On average, the fraction of the relative difference in fathers' earnings that is transmitted to their sons vary between 37.1% and 97.4% and it depends on the region where the children grew up. The heterogeneity of this estimate across regions is largely explained by the fact that the IGE is a measure that captures both re-ordering among generations and inequality within generations. Consequently, the cross-regional comparison is affected by differences in the regional distribution of earnings.

The rank-rank coefficient ensures a better cross-regional analysis given that this measure is based on ranks of both parents' and sons' earnings within the national distribution of earnings. The baseline estimated values of the rank-rank coefficient show that the North region presents the lowest degree of intergenerational persistence of earnings, followed by the North-Centre region. On the other hand, the South region presents the highest degree of persistence, whilst the Centre region evidences a similar intergenerational mobility as the one estimated for the national level. In other words, the difference between the expected rank of sons' earnings, whose fathers are at the top and the bottom of the distribution of earnings ranges between 13.0 and 40.3 positions across regions in Mexico. Note that both the IGE and the rank-rank coefficient, measures of relative mobility, con-

[23] In order to not impose more restrictions to the sample size, I do not consider the urban-only subsample for the regional analysis.

TABLE 6

Regional Estimates of Intergenerational Elasticity of Earnings and Rank-Rank Coefficient

	North		**North-Centre**		**Centre**		**South**	
	Father	*Parents*	*Father*	*Parents*	*Father*	*Parents*	*Father*	*Parents*
$\hat{\beta}$	0.371	0.239	0.377	0.541	0.627	0.553	0.974	0.802
	(0.255)	(0.196)	(0.328)	(0.244)	(0.173)	(0.130)	(0.303)	(0.196)
Rank-rank Coefficient	0.130	0.118	0.163	0.189	0.308	0.289	0.403	0.355
	(0.089)	(0.091)	(0.125)	(0.118)	(0.056)	(0.054)	(0.100)	(0.096)
Upward Mobility	55.848	55.465	44.542	43.697	40.223	41.133	31.233	32.063
SD Son earns	0.666	0.668	0.645	0.644	0.608	0.604	0.776	0.773
SD Father/Parents earns	0.325	0.377	0.298	0.359	0.315	0.380	0.361	0.419
N	432	447	498	507	819	849	620	641

Note: Standard errors in parentheses have been obtained using bootstrap sampling.

firm the North region as the one with the highest intergenerational earnings mobility in Mexico, and the South region as the one where intergenerational mobility and equality of opportunities seem to be highly limited.

It could be possible to argue that in Mexico, high levels of economic inequality seem to be associated with low levels of social mobility, which might be evidence of the existence of a *Great Gatsby Curve* (Krueger, 2012). Figure 1 shows a strong and statistically significant correlation between income inequality and intergenerational persistence among regions.[24] These results are much in line with those found in Delajara and Graña (2017), where intergenerational mobility in wealth and economic inequality were negatively associated across regions.

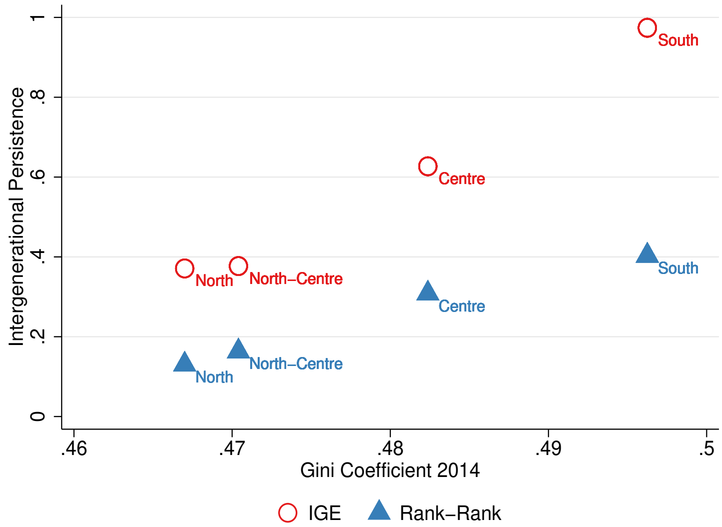
Since the rank-rank relationship is nearly linear, the "absolute upward mobility" could be measured as the expected rank of the earnings of a child who grew up in region r with a father who has a national earnings rank of 25. In Mexico, children who grew up with disadvantaged fathers are on average at the 40.2 percentile rank in their distribution of earnings, which means that these children experienced an upward mobility of 15.2 percentiles compared to their fathers' position. At the cross-regional level, children from a poor background who grew up in the North region switched 30.9 rungs on the ladder, whilst in the South region, children from the same background switched just 6.2 rungs. Progress is similar to the national level in the Centre region (15.2 rungs) and greater than the national average in the North-Centre region (19.5 rungs). That is, among fathers earning $\pounds 2,782.69$, the limit value of the 25th percentile of the national father's distribution of earnings, children who grew up in the North region are, on average, 24.6, 15.6 and 11.3 rungs above the earnings of children who grew up in the South, Centre and North-Centre regions within their respective distribution of earnings.

Absolute mobility of earnings is higher in the North region, not just for son of below-median fathers, but for all sons of fathers within the fathers' distribution of earnings. The

[24]See the economic inequality by federative state in Table D.1 in Appendix D.

FIGURE 1

Great Gatsby Curve Across Regions: Relationship Between Intergenerational Earnings Persistence and Gini



Source: ESRU-EMOVI 2011 and INEGI 2014, author's calculations.

expected rank of children with disadvantaged fathers varies more across regions than the expected rank of children with wealthy fathers, which means that the region where children grow up is more important for those with disadvantaged fathers. In addition, regions with lower rank-rank coefficient tend to have better outcomes for children from disadvantaged fathers. This is, "absolute upward mobility" is highly correlated with relative mobility.

When the total earnings of parents are used as the measure of parental income, the North, North-Centre and Centre regions present once more the lowest intergenerational persistence, whilst, the South region presents the highest level of intergenerational persistence. The rank-rank coefficient and "absolute upward mobility" estimates do not present substantial changes and keep the same cross-regional pattern shown in the analysis based on father's earnings.[25]

5 Conclusions

Intergenerational earnings mobility is a topic of considerable academic and policy concern. In spite of its theoretical and pragmatic relevance, it is not an issue that has been explored enough in developing countries due to the fact that earnings data cannot be directly linked across generations. In the particular case of Mexico, most of the studies have been focused on the analysis of intergenerational mobility in education, occupation status and wealth

[25]Early research for Mexico found a similar pattern for the intergenerational mobility of wealth (Vélez-Grajales et al., 2017; Delajara and Graña, 2017), education and occupational status (Delajara and Graña, 2017) across regions: South - Centre - North-Centre - North (from lowest to highest mobility).

and few have been focused on earnings. However, the multidimensionality of the inequality requires the study of intergenerational mobility in earnings for a better understanding of the intergenerational transmission of the socioeconomic status. To fill the gap I present compiling evidence on earnings mobility for Mexico using the ESRU-EMOVI 2011 survey.

Four significant contributions to the current literature on intergenerational economic mobility for Mexico are presented. First, I combine information from the ESRU-EMOVI and the ENEU surveys using the TSTSLS estimation procedure to measure intergenerational earnings mobility at the national, urban and regional levels. Second, I estimate rank-rank coefficients to measure mobility in earnings among generations. Third, I illustrate the sensitivity of the IGE and the rank-rank coefficient to attenuation bias, life-cycle bias and alternative earnings definitions. Finally, I perform a detailed analysis of intergenerational earnings mobility across regions in Mexico.

The results show that intergenerational earnings mobility in Mexico is 0.709, as measured by the estimated IGE, and 0.315 according to the rank-rank coefficient. On the other hand, the estimated IGE for the urban area is 0.661, whilst the value of rank-rank coefficient is 0.291. Attenuation bias, due to measurement error and transitory shocks, leads to an understatement of the IGE when permanent parental earnings are measured by point-in-time earnings, rather than by a five-years average of parental earnings. Given the baseline specification, the life-cycle bias seems to be also important as evidenced by a significant decrease of the IGE estimator when a subsample of sons aged 35-45 is considered.

Although the estimates are not completely comparable, these results suggest that previous estimates of intergenerational earnings mobility in Mexico have understated the true magnitude of the Mexican's earnings mobility problem. The exclusion of women from the analysis is also a valid reason to believe that the estimates presented here are still understating the true levels of intergenerational persistence in earnings for Mexico. Nevertheless, this is an outstanding start to understand the persistence in earnings inequalities across generations in developing countries.

The rank-rank coefficient presents the same pattern than the IGE, although it is less susceptible to measurement problems. The results suggest that attenuation bias and life-cycle bias affect substantially the scale measurement, rather than the positional accuracy within the earnings distribution. The rank-rank coefficient could be a reliable indicator for time and cross-country comparisons due to data limitations. However, this would imply missing the degree of inequality across generations accounted in the scale measurement, which is an essential part of the analysis of intergenerational mobility. When parents' earnings are considered, the IGE and the rank-rank coefficient present changes in magnitude, but keep the same pattern when compared to the case of using father's earnings as the measure of parental earnings, which implies that mothers that actively participate in the labour market increase the chances of their sons moving upward on the socio-economic ladder.

A cross-regional analysis of earnings mobility indicates that the South region presents the highest degree of inequality of opportunities, while the North region evidences the highest intergenerational earnings mobility. Independent of the dimension used to measure intergenerational mobility, the South region is the one where children's social destination is more affected by their social origin. Consequently, children who grew up in this region have less chance to climb the social ladder and improve their conditions.

It is essential to incorporate women to the analysis of social mobility, to determinate the effects of the progressive increase in female labour market participation and the changes in family dynamics (e.g. assortative matting, distribution of responsibilities inside the household) over the last twenty years. Furthermore, to identify the impact of family structures (e.g. single mothers, number of siblings), access to the credit market and migration on intergenerational earnings mobility will allow to improve the mechanisms of redistribution to generate more equality of opportunities.

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Appendix A Sample characteristics

TABLE A.1
Main Sample Characterization

	In the sample		*Out of the sample*		*Total*	
	Individuals	*%*	*Individuals*	*%*	*Individuals*	*%*
Child						
Age						
25-29 years old	405	16.50	469	19.31	874	17.90
30-34 years old	626	25.49	540	22.20	1,165	23.85
35-39 years old	575	23.44	477	19.63	1,052	21.54
40-44 years old	435	17.73	491	20.22	927	18.97
45-50 years old	414	16.85	453	18.65	867	17.74
Education						
Less than primary completed	179	7.31	305	12.54	484	9.91
Primary completed	469	19.12	596	24.53	1,066	21.81
Secondary completed	1,393	56.76	1,170	48.15	2,564	52.47
University completed	413	16.82	359	14.79	772	15.81
Economic activity						
Employed	2,412	98.24	1,976	81.30	4,388	89.81
Unemployed	7	0.27	146	6.01	153	3.12
Other activity	37	1.49	291	11.96	327	6.71
Don't Know/Don't Answer			18	0.73	18	0.36
Income						
Missing			909	37.38	909	18.6
Greater than zero	2,455	100	1,522	62.62	3,977	81.4
Parents						
Father's age						
Younger than 30 years			53	2.19	53	1.09
30-60 years old	2,455	100	1,217	50.05	3,672	75.15
Older than 60 years			109	4.46	109	2.22
Missing			1,052	43.29	1,052	21.54
Mother's age						
Younger than 30 years			187	7.71	187	3.83
30-60 years old	2,455	100	1,481	60.92	3,855	78.91
Older than 60 years			32	1.32	32	0.66
Missing			843	34.70	843	17.26
Father's education						
Less than primary completed	1,176	47.92	1,563	64.28	2,739	56.06
Primary completed	663	27.01	438	18.03	1,101	22.54
Secondary completed	536	21.82	350	14.40	886	18.13
University completed	80	3.25	80	3.30	160	3.27
Mother's education						
Less than primary completed	1,213	49.42	1,468	60.39	2,681	54.88
Primary completed	724	29.47	544	22.38	1,268	25.94
Secondary completed	492	20.03	361	14.84	853	17.45
University completed	26	1.07	58	2.38	84	1.72
Parents work						
Both parents work	306	12.45	272	11.20	578	11.82
One parent works	2,149	87.55	1,472	60.56	3,622	74.12
No-one works			475	19.55	475	9.73
Don't Know/Don't Answer			211	8.70	211	4.33
Observations	2,455	100	2,431	100	4,886	100

Source: ESRU-EMOVI 2011.

TABLE A.2: *Descriptive Statistics for Mexican Samples of Parents and Synthetic Parent - 2011 and 1987-1991*

	Main Dataset		*Auxiliary Dataset*									
			1987		*1988*		*1989*		*1990*		*1991*	
	Father	*Mother*	*Father*	*Mother*	*Father*	*Mother*	*Father*	*Mother*	*Father*	*Mother*	*Father*	*Mother*
Age												
30-34 years old	18.01	25.96	25.28	31.16	27.13	31.14	27.63	32.27	27.17	31.77	27.63	31.71
35-39 years old	29.16	26.63	25.40	29.22	25.38	29.23	24.55	28.14	25.81	30.28	25.97	30.83
40-44 years old	20.48	28.18	20.17	19.49	20.37	20.32	20.66	20.57	20.57	20.53	21.14	21.31
45-49 years old	16.92	11.36	14.29	12.45	13.89	12.03	13.98	12.00	13.83	10.77	13.60	10.51
50-54 years old	9.61	7.16	9.97	5.99	8.25	5.69	7.82	5.09	8.05	4.93	7.62	3.76
55-60 years old	5.82	0.72	4.88	1.69	4.99	1.59	5.37	1.93	4.56	1.72	4.05	1.88
Education												
Less than primary completed	47.97	34.75	27.54	31.11	24.94	27.76	24.24	26.83	21.58	24.80	19.52	24.03
Primary completed	26.89	31.67	35.40	32.55	34.49	32.06	32.98	32.48	32.77	31.06	32.81	30.18
Secondary completed	21.85	29.67	23.88	28.69	26.37	31.37	27.05	30.17	29.04	33.20	31.19	34.18
University completed	3.29	3.91	13.18	7.65	14.20	8.81	15.74	10.52	16.61	10.93	16.48	11.61
Occupation												
Professionals	2.11	2.71	4.75	2.37	4.97	2.87	5.57	3.44	5.88	3.68	6.14	3.47
Technicians	1.09	0.50	4.90	15.33	4.45	14.44	4.22	13.93	4.13	14.68	3.94	15.22
Working on Education	1.14	3.51	2.33	9.37	2.72	10.28	2.64	10.12	2.67	10.18	2.71	10.52
Working on Art, Shows and Sports	0.51		1.17	0.48	1.10	0.43	1.05	0.55	1.09	0.33	1.22	0.76
Officers and Directors on a Public, Private and Social Sectors	0.68	0.81	5.21	2.99	5.84	2.91	5.90	2.48	6.40	2.71	5.65	2.10
Working on Agriculture, Ranching, Foresting, and Hunting and Fishing Activities	29.77	5.93	1.83	0.30	1.60	0.28	1.33	0.36	1.33	0.14	1.16	0.10
Chiefs, Supervisors and other Control Workers in Artisan Manufacturing and Industrial Activities	1.00	0.56	2.89	0.83	3.26	0.89	3.15	0.84	3.22	0.70	2.79	0.83
Artisans and Workers on Transformation Industry and Repair and Maintenance Activities	26.38	9.42	23.03	8.39	22.77	8.51	23.05	6.98	22.68	6.35	21.51	5.39
Operators of Continuous Movement Fixed Machinery and Industrial Fabrication	1.01	0.24	6.84	3.18	6.69	3.30	7.01	3.61	6.24	3.92	6.93	4.66
Assistants and Labourers in the Artisanal and Industrial Fabrication Process	4.20	0.42	4.04	0.31	3.51	0.21	3.72	0.32	3.71	0.23	3.86	0.32
Drivers and Drivers assistants (Mobile Machinery and Transport)	9.64	0.03	9.71	0.21	10.51	0.06	9.43	0.06	9.65	0.05	10.78	0.06
Chiefs of Department, Coordinators and Supervisors in Administrative Activities	0.15	0.06	3.71	1.95	3.56	1.91	3.57	1.88	3.54	1.83	3.51	2.06
Administrative Activities Assistants	2.23	6.7	5.38	5.03	5.56	5.76	5.37	5.93	5.24	6.26	5.36	7.13
Shopkeepers, Shop employees and Sales Agents	12.16	23.13	11.01	15.53	11.18	16.33	11.52	16.92	11.61	15.83	11.21	13.63
Street Vendors	0.79	5.66	3.16	6.72	2.33	3.60	2.64	4.16	2.61	2.97	2.91	4.41
Personal Services Workers	3.71	14.31	5.70	14.99	6.05	16.35	5.79	16.69	5.96	18.57	6.18	16.33
Domestic Services Workers	0.44	12.73	0.52	11.90	0.50	11.74	0.46	11.63	0.51	11.41	0.42	12.72
Security Workers and Armed forces	2.51	0.26	3.84	0.10	3.37	0.12	3.57	0.09	3.50	0.17	3.70	0.26
Other Workers	0.46	13.02	0.01	0.01	0.01		0.02		0.01		0.03	0.01
Area												
Urban	81.03	86.89	100	100	100	100	100	100	100	100	100	100
Observations	2,373	421	50,677	15,223	55,535	16,742	55,956	16,639	55,537	16,931	54,313	17,462

Source: ESRU-EMOVI 2011 and ENEU 1987-1991.

Appendix B First stage parameter estimates

TABLE B.1
Log Earnings Equation (First Stage) R^2

	1987	*1988*	*1989*	*1990*	*1991*
Fathers	0.275	0.314	0.323	0.358	0.356
Mothers	0.339	0.321	0.340	0.348	0.360

Note: For comparative purposes the R^2 reported here is from the log specification, despite the coefficients used to predict the father's and mother's earnings are in level.

Appendix C Robustness of intergenerational earnings mobility estimates

C.1 Attenuation bias - National

TABLE C.1
Intergenerational Elasticity and Rank-Rank Coefficient by Number of Years Used to Measure Father's Earnings

	Years Used to Compute Mean Father's Earnings				
	1991	*1990-1991*	*1989-1991*	*1987-1991*	*1987-1991*
$\hat{\beta}$	0.636	0.584	0.653	0.668	0.709
	(0.137)	(0.101)	(0.179)	(0.127)	(0.130)
Rank-rank Coefficient	0.299	0.305	0.310	0.304	0.316
	(0.056)	(0.059)	(0.034)	(0.064)	(0.048)
N	2,364	2,369	2,370	2,371	2,371

Note: Standard errors in parentheses have been obtained using bootstrap sampling.

C.2 Attenuation and life-cycle biases - Urban area

TABLE C.2

Consistency of the Estimations of Intergenerational Elasticity of Earnings and Rank-Rank Coefficient - Urban Area

	Father	*Parents*
Panel A:		
Parents' earnings 1987-1991 - Son's age 25-50		
$\hat{\beta}$	0.661	0.602
	(0.136)	(0.110)
Rank-rank Coefficient	0.291	0.271
	(0.052)	(0.049)
SD Son earns	0.693	0.689
SD Father/Parents earns	0.343	0.405
N	1,844	1,904
Panel B:		
Parents' earnings 1991 - Son's age 25-50		
$\hat{\beta}$	0.570	0.514
	(0.131)	(0.111)
Rank-rank Coefficient	0.265	0.238
	(0.054)	(0.052)
SD Son earns	0.693	0.689
SD Father/Parents earns	0.348	0.406
N	1,838	1,898
Panel C:		
Parents' earnings 1987-1991 - Son's age 35-45		
$\hat{\beta}$	0.408	0.374
	(0.207)	(0.169)
Rank-rank Coefficient	0.220	0.231
	(0.084)	(0.081)
SD Son earns	0.619	0.616
SD Father/Parents earns	0.325	0.365
N	539	553

Note: Standard errors in parentheses have been obtained using bootstrap sampling. Parents' average earnings for the period 1987-1991.

Appendix D Economic inequality in Mexico

TABLE D.1
Poverty Measure by Federate State

Federative States	*Region*	*Gini Coefficient*	
		1990	*2014*
Baja California	North	0.476	0.434
Chihuahua	North	0.509	0.458
Coahuila	North	0.510	0.503
Nuevo León	North	0.499	0.453
Sonora	North	0.497	0.476
Tamaulipas	North	0.522	0.478
Aguascalientes	North-Centre	0.488	0.486
Baja California Sur	North-Centre	0.458	0.454
Colima	North-Centre	0.500	0.457
Durango	North-Centre	0.486	0.446
Jalisco	North-Centre	0.560	0.468
Michoacán	North-Centre	0.543	0.452
Nayarit	North-Centre	0.501	0.471
San Luis Potosí	North-Centre	0.551	0.477
Sinaloa	North-Centre	0.515	0.486
Zacatecas	North-Centre	0.492	0.507
Ciudad de México	Centre	0.536	0.507
Guanajuato	Centre	0.519	0.449
Hidalgo	Centre	0.528	0.504
México	Centre	0.520	0.461
Morelos	Centre	0.532	0.467
Puebla	Centre	0.563	0.572
Querétaro	Centre	0.583	0.488
Tlaxcala	Centre	0.485	0.411
Campeche	South	0.504	0.500
Chiapas	South	0.543	0.517
Guerrero	South	0.542	0.489
Oaxaca	South	0.517	0.513
Quintana Roo	South	0.538	0.494
Tabasco	South	0.540	0.456
Veracruz	South	0.538	0.490
Yucatán	South	0.526	0.511

Source: Calculated by the National Council for the Evaluation of Social Development Policy (CONEVAL) from the INEGI. *Note:* The Gini coefficient has been sorted by year; the Lowest levels of economic inequity appear in blue and highest levels in red.