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Intergenerational Mobility in Mexico: An Analysis of Education by Offspring Cohorts and Gender* **

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Abstract

Using the ESRU-EMOVI 2011 survey, this paper documents trends in intergenerational mobility of education in Mexico. The main findings are: (1) a reduction in the difference between male (father-son) and female (mother-daughter) transition matrices among the younger cohorts; and (2) a monotonic increase in the three meanings of intergenerational mobility identified by van de Gaer et al. (2001) (i.e. mobility as movement, as equality of opportunity, and as equality of life chances), common to both male and female matrices, when moving from older to younger cohorts.

JEL codes: J62, O15

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1. Introduction

Recent studies of social mobility in several dimensions of wellbeing (income, education, occupation, etc.) reveal that Mexican society remains still "highly stratified", notwithstanding absolute increases in the wellbeing indicators (Vélez *et al.*, 2012, p. 57). That is to say, socioeconomic origin is still a major determinant of individual welfare, and for people whose socioeconomic origin is disadvantageous, "the possibilities of upward mobility are limited" (Vélez *et al.*, 2012, p. 60).

This paper focuses on the intergenerational mobility of education in Mexico. Despite its relevance as one of the largest countries in the region, Mexico could not be included in the group of Latin American countries considered for the worldwide survey of intergenerational educational mobility by Hertz *et al.* (2007). That study computed correlations of years of education between parents (average of father and mother) and sons for more than fifty countries. By then, it is presumed, the 2006 ESRU Survey on Social Mobility in Mexico (EMOVI-2006) was not available. Using different statistical methods, two studies of educational mobility using the EMOVI-2006, de Hoyos *et al.* (2010) and Torche (2010), concluded that this mobility had increase among the younger cohorts of Mexican men, but that the youngest cohort partially offset that pro-mobility trend. Previous studies such as Binder and Woodruff (2002), based on different datasets, reached a similar conclusion, even though the definition of cohorts did not coincide perfectly between the three studies.

Now, with the second survey (EMOVI-2011) of The Espinosa Yglesias Research Centre(CEEY) it is possible to monitor and analyse the determinants of intergenerational mobility in Mexico with a wealth of data possibly not available in most of the countries originally included in Hertz *et al.* (2007). Moreover, there is now new evidence to test the existence of the mentioned trend in educational mobility previously documented for Mexico.

The first purpose of this paper is to analyse whether there are differences in the intergenerational mobility regimes of education between the genders, *i.e.* father-son versus mother-daughter, and how these have changed across different offspring cohorts, using the EMOVI-2011. Likewise, the paper explores, for each gender separately, the possible presence of structural breaks in the transition matrices throughout the cohorts. This analysis is based on the computation of transition matrices and seeks to quantify how different are the different probabilities of attaining each educational level, conditioned by different parental educational levels, across certain groups (*e.g.* men versus women). The motivation behind this analysis departs from the fact that two transition matrices can yield the same value for a mobility index, even when their elements (that is, their conditioned probabilities) may be significantly different. Thus, heterogeneity analysis enables, for instance, assessing whether a pair of intergenerational mobility regimes resembles more each other, or not, across time. The identification of differences between matrices is performed using the heterogeneity tests of Anderson and Goodman (1957), while their quantification relies on the Pearson-Cramer heterogeneity index.

The second purpose of this paper is to document the changes in the indices of intergenerational mobility based on transition matrices computed for each cohort. For this purpose, six indices capturing different meanings of intergenerational mobility for ordinal variables are computed. Interestingly, many of the most recent studies of educational mobility in Mexico do not clarify the concrete meaning of intergenerational mobility that their statistical methods capture. However, the methodological literature identifies several meanings, whose equivalence in empirical applications cannot be taken for granted *a priori*. Specifically, Van de Gaer *et al.* (2001) identify three fundamental meanings of intergenerational mobility: mobility as movement, mobility as equality of opportunity, and mobility as equalization of life chances. The first meaning understands mobility as intergenerational persistence of educational attainment. The second one, refers to the degree of (in)equality in the offspring's *cumulative* distributions of education conditioned by different parental educational levels; that is, the differences between the "lotteries" corresponding to different groups of sons, each one defined by parental educational levels. Finally, the third meaning is similar to the second one, but it focuses on conditional probability distributions, instead of cumulative ones. That is, in the third meaning, the order of the offspring categories is not relevant (whereas, for instance, complete primary is less desirable than complete secondary). Clearly, the third meaning is more relevant in the case of unordered categorical variables, whereas the second meaning is more relevant for ordinal variables.

Hence, this paper is the first one to account for the three meanings of intergenerational mobility in Mexico, in an explicit manner. With the aim of capturing the meaning of mobility as movement, the trace index of Shorrock sand the second index of Bartholomew are computed. The meaning of mobility as equality of opportunity is measured with two indices from the class of indices proposed by Yalonetzky (2012b). Finally, the meaning of mobility as equality in life chances is measured with two indices from another class of indices proposed also by Yalonetzky (2012b).

Empirically, transition matrices are constructed for sons and daughters. Sons are connected to their fathers and daughters to their mothers. For both groups four age cohorts are defined. In the analysis of matrix heterogeneity, the main finding is a reduction in the differences between male (father-son) and female (mother-daughter) transition matrices among the younger cohorts. In the intergenerational mobility analysis, the main empirical contribution is the identification of a monotonic increase in the three meanings of mobility, common to both male and female matrices, when moving from older to younger cohorts. That is to say, among younger Mexican men and women not only the probabilities of replicating parental educational achievements have decreased, but also the offspring's educational "lotteries", that is the offspring distributions of educational levels, depend less on the education of the parents, compared to Mexicans from older cohorts. These results contrast with previous studies, in the sense that we do not find evidence of a reduction in educational mobility among the youngest cohorts.

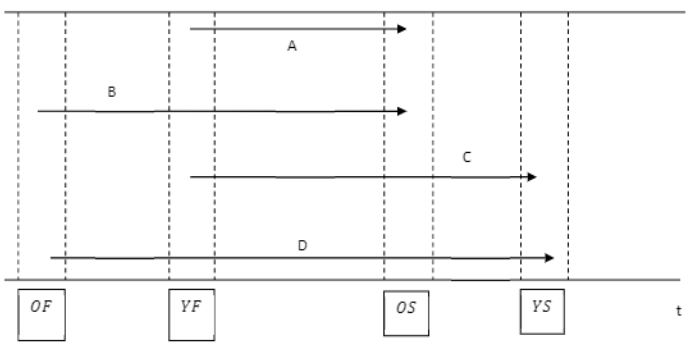
The rest of the paper continues with a section on notation and methodology in which, besides introducing the statistical tools, the conceptual differences between the different mobility indices used in the empirical section are analysed. Likewise, the section also explains the difference and complementarity between the mobility indices and the heterogeneity analysis when using transition matrices. Then comes a data section in which the transition matrices by cohort and sex are discussed. Next, the results section presents the findings from the homogeneity tests and the computation of mobility indices. The paper ends with a conclusions section in which the differences between this paper and previous studies are emphasized, in addition to suggestions for future research.

2. Notation and methodology[1]

The intergenerational transmission of wellbeing outcomes, like education, depends on several factors identified both in the theoretical and the empirical literature on intergenerational mobility (see *e.g.* Becker & Tomes, 1986; Galor & Zeira, 1993; Banerjee & Newman, 1993; Picketty, 1999). Some of these factors, like changes in the relative demand for skilled labour, or changes in the quality and/or outreach of the educational system, can affect entire cohorts while in school age (Duflo, 2001). Likewise, the effect of factors influencing household in-

1 The first part of this section, until the presentation of the Anderson and Goodman tests inclusive, are based on the fourth chapter of Yalonetzky (2008).

Figure1 Four cases of intergenerational transmission of wellbeing



Fuente: elaboración propia.

vestment in education can also operate broadly among parental cohorts. Moreover, the age gap between parents and offspring could affect investment in offspring education through a life cycle effect.

All these considerations justify controlling for both offspring and parent cohorts in intergenerational mobility analysis; like this paper's, which relies on transition matrices and its respective mobility indices. Figure 1 clarifies this point, showing four pairs of fathers and sons. Pair A is made of a young cohort of fathers (YF) and an old cohort of sons (OS); pair B comprises an old cohort of fathers (OF) and an old cohort of sons (OS); C has a young cohort of fathers (YF) and a young cohort of sons (YS); and D is made of an old cohort of fathers (OF) and a young cohort of sons (YS). Obviously, we find more cohorts of fathers and sons in a dataset. But with those of Figure 1 it suffices to introduce the notation and explain the homogeneity tests of Anderson and Goodman.

We start introducing the notation, with the variable for the wellbeing attribute (*e.g.* education), measured with ordered categories in the period or cohort *t*: $E(t) \in [1, E_{top}] \subset \mathbb{N}_{+}$. The transition probability of having a value for the son of *E*(*OS*) = *i* conditioned on a past value for the father of *E*(*OF*) = *j* is:

$$p_{i|j}^{OS,OF} \equiv \Pr[E(OS) = i | E(OF) = j] = \frac{N_{ij}^{OS,OF}}{N_{.j}^{OS,OF}} \quad (1)$$

where $N_{ij}^{OS,OF}$ is the number of father-son pairs in the population that belongs to the respective cohorts OF and OS, such that *E*(*OS*) = *i* and *E*(*OF*) = *j*. $N_{.j}^{OS,OF} \equiv \sum_{i=1}^{E_{top}} N_{ij}^{OS,OF}$ is the total number of fathers in the population who belong to cohort OF and for whom *E*(*OF*) = *j*. We also define the transition matrix, $M^{OS,OF}$:

$$M^{OS,OF} \equiv \begin{bmatrix} p_{1|1}^{OS,OF} & \cdots & p_{1|E_{top}}^{OS,OF} \\ \vdots & p_{i|j}^{OS,OF} & \vdots \cdots \\ p_{E_{top}|1}^{OS,OF} & \cdots & p_{E_{top}|E_{top}}^{OS,OF} \end{bmatrix} \quad (2)$$

Some recent mobility indices (*e.g.* those of Silber & Yalonetzky, 2011) use cumulative distribution functions. Since in this paper we use two of those indices, it is worth hereby introducing the notation for cumulative probability: $F_{i|j}^{OS,OF} \equiv \sum_{s=1}^{i} p_{s|j}^{OS,OF}$.

Anderson and Goodman (1957) homogeneity test for transition matrices

The homogeneity test of Anderson and Goodman (1957) considers the following hypotheses: $Ho: M^{OS,OF} = M^{OS,YF}$ and $Ha: M^{OS,OF} \neq M^{OS,YF}$. Anderson and Goodman use the Pearson statistic for contingency tables, but expressed in terms of the probabilities of a transition matrix:[2]

$$\chi = \sum_{g=1}^{G} \sum_{j=1}^{E_{top}} \sum_{i=1}^{E_{top}} \frac{N_{.j}^{g}\left(p_{i|j}^{g} - p_{i|j}^{*}\right)^{2}}{p_{i|j}^{*}} \quad (3)$$

where *g* denotes a population group, *e.g.* *g* = *OS, OF*, and G is the number of groups whose matrices are compared. $p_{i|j}^{*}$ is a typical element of matrix *M**, which ensues from combining all compared population groups:

$$p_{i|j}^{*} = \frac{\sum_{g=1}^{G} N_{ij}^{g}}{\sum_{g=1}^{G} N_{.j}^{g}} = \sum_{g=1}^{G} \frac{N_{.j}^{g}}{N_{.j}} p_{i|j}^{g} \quad (4)$$

where, $N_{.j} \equiv \sum_{g=1}^{G} N_{.j}^{g}$, represents the whole population of fathers from different cohorts for whom the value of the variable is j. The statistic (3) has an asymptotic sampling distribution of Chi-Square with $(G-1)E_{top}(E_{top}-1)$ degrees of freedom.[3]

2 The authors also consider a log likelihood statistic. Both are asymptotically equivalent.

3 When $p_{i|j}^{*} = 0$ the respective elements in (3) must be replaced by 0. Two inference approaches have been used in the literature when these zeroes appear: 1) To reduce the degrees of freedom for each zero present; 2) Not to alter the number of degrees of freedom. In the first approach, followed *e.g.* by Billingsley (1961), the presence of zeroes common to the matrices is not necessarily regarded as evidence of homogeneity (as perhaps with larger samples there would be values in those cells). Hence the aim is to avoid favouring the null hypothesis which is done by reducing the degrees of freedom, since the latter generates the minimum level of observed significance (p-value) for a given value of the statistic (3). In the second approach, followed *e.g.* by Collins (1974), zeroes are regarded as evidence of homogeneity, and so the degrees of freedom are not discounted. Therefore, the null hypothesis is more favoured since the maximum level of observed significance is generated for a given value of (3). This paper follows the approach of Collins (1974).

The homogeneity tests assess whether there is evidence against the null hypothesis of homogeneity between two (or more) transition matrices. However, by their very nature, its statistics are not useful to quantify the magnitude of the difference between two (or more) matrices. For instance, the statistics depend on the sample size, which is necessary in the context of statistical tests. Yet in the context of heterogeneity indices for matrices, the dependency on the sample size implies that the heterogeneity between two matrices would be affected not only by genuine differences between the respective probabilities, but also by replications, or cloning, of the population. That is, the principle of population, broadly accepted in several areas of wellbeing measurement, would be violated.

With the aim of measuring the degree of heterogeneity between the compared matrices, the homogeneity tests are complemented by computations of the Pearson-Cramer index, adapted to transition matrices. The index has the following formula:

$$PC \equiv \frac{\chi}{Nmin\{G-1, E_{top}-1\}E_{top}} \qquad (5)$$

where $N = \sum_{j=1}^{E_{top}} \sum_{g=1}^{G} N_{.j}^{g}$. The properties fulfilled by are discussed by Yalonetzky (2012a).[4]

Indices of intergenerational mobility[5]

The analysis of trends in intergenerational mobility of education requires choosing mobility indices. In this paper the selected indices are based on transition matrices; not only because the heterogeneity analysis uses such matrices, but because the variable, educational level, is ordinal. Therefore, it does not make any sense to use mobility indices that are sensitive to the distance between parental and offspring values for the variable.[6]

This paper uses six indices that capture different meanings of mobility. In this sub-section I first introduce the axioms of mobility for ordinal variables. Axioms of meaning, permutation and maximum and minimum mobility are considered. Then I mention the logical relationships between these axioms, just like they have been laid out by van de Gaer *et al.* (2001). With this information, it should be clear how and why the trends of different indices may disagree, in principle. Then I introduce the indices that are used in the empirical section, while discussing their fulfilment of the axioms.

Before starting with the axioms of meaning, it is worth introducing more relevant notation. First, we introduce the idea of a mobility index which maps from a transition matrix onto the real line, although normally we seek *normalized* indices that map onto the interval [0,1]: $\mathcal{M}: M \rightarrow [0,1] \subset \mathbb{R}$. Another important concept is that of diagonalising transformations. We say that a diagonalising transformation of matrix *M* generates a new matrix $\widetilde{M}$, *i.e.* $T_{\varepsilon}^{k,l;q,r}[M] \equiv \widetilde{M}$, if and only if:

$$\widetilde{p_{k|q}} = p_{k|q} - \varepsilon$$

$$\widetilde{p_{k|r}} = p_{k|r} + \varepsilon$$

$$\widetilde{p_{l|q}} = p_{l|q} + \varepsilon$$

$$\widetilde{p_{l|r}} = p_{l|r} - \varepsilon$$

$$\widetilde{p_{i|j}} = p_{i|j} \;\; \forall \, i,j \neq kl; qr$$

It is also assumed that, in terms of preferences over states of wellbeing (*e.g.* educational level): *q* < *r* and *k* < *l*; so that the diagonalising transformation tends to reduce the positive association between the parental and offspring distributions.

Finally, we define the matrix $M^C \equiv \Xi^C[M]$ and the matrix $M^R \equiv \Xi^R[M]$. M^C ensues from permuting two columns of *M* using the column permutation operator, Ξ^C. Analogously, M^R results from permuting the rows of *M* using the row permutation operator, Ξ^R.

Axioms of meaning:

As van de Gaer *et al.*(2001) explain, there are three meanings of mobility (when measured with transition matrices): 1) mobility as movement, that is, as a reduction in the probability that the offspring replicates the wellbeing status (education, income, etc.) of fathers; 2) mobility as equality of opportunity in which higher mobility means more proximity between the *cumulative* distributions of the wellbeing variable conditioned by paternal attributes, *i.e.* a lower intensity of the first-order stochastic dominance relationship; and 3) mobility as equalization in life chances. Unlike the second meaning, in the third the different values of the variable do not have a relative desirability, that is, the variable is categorical but not ordinal. As a consequence, higher mobility as equality of life chances is deemed to occur when the

4 Following the suggestion by Everitt (1992), this paper reports the square root of the Pearson-Cramer index since it usually takes very low values in empirical applications.

5 This sub-section is based, largely, on Yalonetzky (2012b).

6 Examples of these indices include the work of Cowell (1985), Fields and Ok (1996,1999), and Schluter and van de Gaer (2011).

conditioned probability distributions (not necessarily the cumulative ones) resemble more each other. Formally, the three axioms of meaning can be expressed the following way:

Axiom of movement (MOV): $\mathcal{M}\left[T_{\mathcal{E}}^{q,r;q,r}[M]\right] > M[M]$.

Axiom of equality of opportunity (EOP): if $k < l$, $q < r$ and $\widetilde{F_{l|q}} \geq \widetilde{F_{l|r}} \forall i \in [1, E_{top}]$; then $\mathcal{M}\left[T_{\mathcal{E}}^{k,l;q,r}[M]\right] > M[M]$.

Axiom of equalization of life chances (ELC): if $\widetilde{p_{k|q}} \geq \widetilde{p_{k|r}}$ and $\widetilde{p_{l|q}} \leq \widetilde{p_{l|r}}$; then $\mathcal{M}\left[T_{\mathcal{E}}^{k,l;q,r}[M]\right] > M[M]$.

Axioms of permutation:
Van de Gaer *et al.*(2001) introduce two axioms of permutation. The first one, anonymity, states that the mobility index should not vary when the columns of the transition matrix, *i.e.* the offspring distributions conditioned by parental values, are permuted. The second one, called focus on probabilities, states that the index should not vary when the rows of the matrix are permuted, that is when no relative appeal is attributed to the different values of the discrete variable. Formally, the two axioms of permutation are postulated the following way:

Axiom of anonymity (AN): $\mathcal{M}[M] = \mathcal{M}[M^C]$.

Axiom of focus on probabilities (FP): $\mathcal{M}[M] = \mathcal{M}[M^R]$

Axiom of maximum and minimum mobility:
Shorrocks (1978) proposes an immobility axiom whereby the mobility index must declare minimum mobility only in the case of a transition matrix shaped as an identity matrix, . An alternative version of immobility, proposed by van de Gaer *et al.* (2001), and more relevant for the notion of mobility as inequality in life chances, is the axiom of perfect predictability according to which a mobility index must declare minimum mobility in cases of matrices resulting from any permutation of columns of (including, of course, the identity matrix itself). This weak form of minimum mobility is not conceptually compatible with the notion of mobility as movement. Formally the two axioms of minimum mobility are the following:

Axiom of immobility (IM): $\mathcal{M}[M] \geq \mathcal{M}[I]$.

Axiom of perfect predictability (PP): $\mathcal{M}[I^C] = \mathcal{M}[I]$.

Finally, Shorrocks proposed two axioms of maximum (or perfect) mobility. The weak axiom of maximum mobility states that a mobility index should take a particular value when the transition matrix exhibits identical columns, that is: $p_{i|1} = p_{i|2} = \cdots = p_{i|E_{top}} \forall i \in [1, E_{top}]$. The strong axiom of maximum mobility states that a mobility index should take its *maximum* value when the transition matrix exhibits identical columns. In order to express these two axioms, we first introduce $1_{E_{top}}$, that is a column vector containing a number of ones equal to E_{top}. Then we define the matrix of identical columns: $M^M \equiv \left(p_1, p_2, \ldots, p_{E_{tope}}\right)' 1'_{E_{tope}}$.[7] Following van de Gaer *et al.*(2001), this paper focuses on the strong axiom of maximum mobility, or perfect mobility, which is defined the following way:

Axiom of perfect mobility (PM): $\mathcal{M}[M^M] > M[M]$.

It is now appropriate to point out the contradictions between the mentioned axioms. Van de Gaer *et al.* (2001, p. 524-5), prove the following contradictions:

Theorem 1: MOV and PM are incompatible. That is to say, one can obtain higher mobility as movement, beyond the situation of perfect mobility (represented by the matrix of identical columns), subtracting further probability mass from the diagonal.

Theorem 2: MOV and AN are incompatible. According to AN, a permutation of columns from the identity matrix should not affect the value of a mobility index. However, according to MOV, such permutation should yield higher mobility (by increasing the index), since the permutation subtracts probability from the diagonal.

Corollary 1: MOV and PP are incompatible; since AN implies PP.

Theorem 3: MOV and FP are incompatible. Due to a similar reasoning explaining the incompatibility between MOV and AN. In the case of MOV and FP, consider a permutation of the rows of the identity matrix.

Theorem 4: EOP and FP are incompatible. That is, a permutation of rows could reduce, or augment, the intensity of a first-order stochastic dominance relationship between

7 Note the respective transpositions of the two vectors.

two columns of the transition matrix, which would translate in a change in the value of a mobility index fulfilling EOP. However, according to FP, the index should not change its value in the face of a row permutation.

Note that the mentioned theorems imply potential incompatibilities between the three meanings of mobility. For instance, since PM indicates the maximum degree of mobility for EOP and ELC, theorem 1 implies that MOV is not, in general, compatible with the other two meanings. Likewise, since ELC is compatible with FP, theorem 4 indicates that EOP and ELC are not, in general, compatible. That is, for some mobility comparisons between matrices, the orderings produced by different indices would depend on the meaning of mobility being measured.[8]

Considering the previous discussion, I now introduce the mobility indices that are used in the empirical section. The available mobility indices based on transition matrices are numerous, but they tend not to fulfil the same axioms, including those of meaning. That is to say, they capture distinct notions of mobility. Consequently, a mobility analysis based on transition matrices should use several indices, with the aim of capturing trends corresponding to different mobility concepts.

Table 1 Selected mobility indices based exclusively on transition matrices

Index	Fulfilled axioms	Source
$ST = \frac{E_{top} - \sum_{i=1}^{E_{top}} p_{i\|i}}{E_{top} - 1}$	MOV, IM	Shorrocks (1978)
$B2 = \frac{1}{E_{top}(E_{top}-1)} \sum_{j=1}^{E_{top}} \sum_{i=1}^{E_{top}} p_{i\|j} \|i-j\|$	MOV, IM	Bartholomew (1982)
$O^1 = 1 - \frac{3}{E_{top}^2 - 1} \sum_{j=1}^{E_{top}} \sum_{i=1}^{E_{top}} \|F_{i\|j} - F_i^{av}\|$	EOP (weak), AN, PM, IM, PP	Yalonetzky (2012b)
$O^2 = 1 - \frac{6}{E_{top}^2 - 1} \sum_{j=1}^{E_{top}} \sum_{i=1}^{E_{top}} \|F_{i\|j} - F_i^{av}\|^2$	EOP, AN, PM, IM, PP	Yalonetzky (2012b)
$C^1 = 1 - \frac{1}{2(E_{top}-1)} \sum_{j=1}^{E_{top}} \sum_{i=1}^{E_{top}} \|p_{i\|j} - p_i^{av}\|$	ELC (weak), AN, FP, PM, IM, PP	Yalonetzky (2012b)
$C^2 = 1 - \frac{1}{(E_{top}-1)} \sum_{j=1}^{E_{top}} \sum_{i=1}^{E_{top}} \|p_{i\|j} - p_i^{av}\|^2$	ELC, AN, FP, PM, IM, PP	Yalonetzky (2012b)

Table 1 features the chosen indices. The first one, *ST*, is Shorrock's trace index. As van de Gaer *et al.* (2001) explain, the index satisfies MOV. Therefore, due to theorems 1 to 3, and corollary 1, it does not satisfy AN, PM and PP. Neither does it satisfy FP, but it does satisfy IM. Likewise, being insensitive to changes outside the diagonal, it satisfies neither EOP nor ELC. However, it can satisfy PM (Shorrocks, 1978) and PP in the case of matrices with quasi-maximal diagonal and/or when matrices are monotone.[9]

The second index, *B2*, is a variation of one of the indices proposed by Bartholomew (1982). In the original index, Bartholomew weighs the expression $\sum_{i=1}^{E_{top}} p_{i|j}|i-j|$ using, $\overline{p_j}$, which is the ergodic probability of obtaining . The problem with weighting that way is that, then, the index does not satisfy MOV (Shorrocks, 1978). However, when weighing with $\frac{1}{E_{tope}}$, as appears on Table 1, *B2* does satisfy MOV. The index also fulfils IM. None of the other axioms is satisfied by this index. However, if the restrictions of quasi-maximal diagonal and/or monotonicity are imposed, then the index also satisfies PM. This index also only captures mobility as movement.

The indices O^1 and O^2 are members of a family of indices proposed by Yalonetzky (2012b).[10]Both compare each cumulative conditional probability, $F_{i|j}$, against the non-weighted average for its respective offspring value, that is: $F_i^{av} \equiv \frac{1}{E_{top}} \sum_{j=1}^{E_{top}} F_{i|j}$. O^2 satisfies EOP but it does not satisfy ELC or MOV. Regarding permutation axioms, it satisfies AN, but not FP. It also satisfies PM, IM and PP. If the monotonicity restriction is imposed, then the index also satisfies MOV. Hence, as a minimum, the index captures a notion of mobility as equality of opportunity and, under certain circumstances, also mobility as movement, when both meanings coincide. O^1 satisfies the same axioms, although it only fulfils a weak version of EOP whereby: if $k < l$, $q < r$ and $\widetilde{F_{i|q}} \geq \widetilde{F_{i|r}} \forall i \in [1, E_{tope}]$; then $\mathcal{M}\left[T_{\varepsilon}^{k,l;q,r}[M]\right] \geq \mathcal{M}[M]$.

Finally, the indices C^1 and C^2 are two members of a family of indices proposed by Yalonetzky (2012).[11]

8 For an analysis of the situations in which the three meanings are reconcilable see Yalonetzky (2012b).

9 Quasi-maximal diagonal matrices always have positive values in their diagonal. For a rigorous definition see Shorrocks (1978). Monotone matrices are characterized by the presence of weak first-order stochastic dominance between their columns, favouring offspring distributions conditioned by higher parental values of the variable. Formally: . For an in-depth treatment of the properties of monotone matrices see Dardanoni (1993, 1995).

10 In turn these are based on the work of Silber and Yalonetzky (2011).

11 In turn based on the work of Reardon and Firebaugh (2002).

Both indices compare each conditional probability, $p_{i|j}$, against the non-weighted average for its respective offspring value, that is: $p_i^{av} \equiv \frac{1}{E_{top}} \sum_{j=1}^{E_{top}} p_{i|j}$. C^2 satisfies ELC but it does not satisfy EOP or MOV. Regarding permutation axioms, it satisfies both AN and FP. They also satisfy PM, IM and PP. If the monotonicity restriction is imposed, then the index also fulfils MOV. Hence, as a minimum, the index captures a notion of mobility as equalization of life chances and, under certain circumstances, also mobility as movement, when both meanings coincide. C^1 satisfies the same axioms, although it only satisfies a weak version of ELC whereby: if $\widetilde{p_{k|q}} \geq \widetilde{p_{k|r}}$ and $\widetilde{p_{l|q}} \leq \widetilde{p_{l|r}}$; then $\mathcal{M}\left[T_{\mathcal{E}}^{k,l;q,r}[M]\right] \geq \mathcal{M}[M]$.

Table 2 Hypothetical evolution of transition matrices from two populations

	A			B		
	0.8	0.2	0	0.5	0.1	0.1
Period 1	0.2	0.5	0.4	0.5	0.6	0.1
	0	0.3	0.6	0	0.3	0.8
	0.5	0.2	0	0.5	0.1	0.1
Period 2	0.5	0.5	0.4	0.5	0.6	0.1
	0	0.3	0.6	0	0.3	0.8
	0.5	0.1	0	0.5	0.1	0.1
Period 3	0.5	0.6	0.4	0.5	0.6	0.1
	0	0.3	0.6	0	0.3	0.8

Heterogeneity analysis versus intergenerational mobility indices

As it was mentioned in the introduction, the heterogeneity analysis can be motivated by realizing that two transition matrices may yield the same value for a mobility index even when their elements (that is, their conditional probabilities) are significantly different. That is, unlike the mobility analysis based on indices that measure some of its meanings, heterogeneity analysis is helpful, for instance, to assess whether a pair of intergenerational mobility regimes resemble each other more, or not, across time; *i.e.* whether the values of each of the transition matrices' probabilities become closer to each other, or not. On the extreme of perfect equality between two matrices the analyses of mobility and heterogeneity must coincide. However, in other situations, it is possible to find that changes in the degree of heterogeneity of two matrices do not always come along with changes in their mobility differences going in the same direction. For instance, consider the case of the transition matrices in Table 2.

Table 2 shows the evolution in time (from period 1 to 3) of the transition matrices belonging to two populations: A and B. The columns of each matrix represent offspring distributions of certain wellbeing indicator conditioned by the parental value. If *ST* is computed, then it can be ascertained that in period 1 both A and B have a value of 0.55. Likewise, it is easy to confirm that population B gets the same value throughout the three periods. Now, when moving from period 1 to 2 the only observed change, in population A, is the transfer of a probability "mass" of 0.3 from the top left position to the middle left position. Thus the left column of A is now identical to B's. Since the other probabilities did not change, heterogeneity between the two matrices should decrease in period 2, *i.e.* the "lotteries" resemble more each other. However, at the same time, mobility according to *ST* increased in A, from 0.55 to 0.7, while it remained the same in B. Thereby we confirmed a discrepancy between the two analyses with regards to trends: a divergence in mobility can take place while heterogeneity decreases.

Finally, when moving from period 2 to 3, the only observed change, again in A, is the transfer of probability "mass" of 0.1 from the superior central position to the middle central position. Consequently, the central column of A is now also identical to that of B. Since the other probabilities did not change, then heterogeneity should decrease further in period 3. However, at the same time, mobility according to *ST* now decreases in A, from 0.7 to 0.65, while it does not change in B. We confirm, then, that a decreasing trend in heterogeneity (during three periods) can be accompanied by fluctuations in the divergence between the mobility indices of a pair of matrices. Thence the two types of analysis, mobility and heterogeneity, offer different and complementary information concerning the comparative evolution of social mobility regimes.

3. Data

This section presents descriptive statistics of the EMOVI 2011 sample, and then the transition matrices by cohorts are presented and discussed. The mobility and heterogeneity analysis proceeds in the next section.

Table 3 shows the sample sizes of adult offspring, men and women interviewed, divided by four age cohorts *in*

2011: 25-34, 35-44, 45-54, 55-64. De Hoyos *et al.* (2010) use exactly the same age cut-offs but *starting from 2006*, hence their cohorts imperfectly overlap with this paper's. Torche (2010) uses different cohorts, considering only people older than 30 years and also with reference to 2006 (since she uses that year's EMOVI). These details should be taken into account when comparing the results of different studies, and this paper's. In any case, the ideal aim would be to have more cohorts of a shorter duration, like the year of birth, but limited sample size prevents such refinement. Also ideally, the analysis would control for parental cohorts (paternal and maternal). This possibility was discarded in this paper because, even though there are questions on parental age in the survey, the proportion of non-response for these questions is very high.

The mobility analysis is performed for both men and women. In the case of men their educational level is connected to their fathers'; while for women their educational level is connected to their mothers'. The educational level is measured using the four categories of the interviewee's *general international recoding*: less than complete primary, complete primary, complete secondary, complete university (see Data Dictionary of the EMOVI-2011, p. 7). Note that other studies use different variables for the measurement of educational level. For instance, Binder and Woodruff (2002), together with De Hoyos *et al.* (2010), use years of schooling, whereas Torche (2010) uses a variable of educational attainment which is divided into five categories. These differences should be accounted for when comparing results.

Now the transition matrices of educational levels by cohorts for father-son combinations are discussed. Table 4 features the transition matrix for the youngest male cohort (25-34). It is a monotone matrix with interesting contrasts. On one hand, a high probability of replicating paternal results among the highest educational levels (for instance, 78% of sons of fathers with complete secondary replicate the same educational level, and 54% of sons of fathers with complete university replicate the same level); and on the other hand, a low probability of replicating paternal results among low educational levels (less than 11% and less than 15% for those with less than complete primary, and complete primary, respectively).

Table 5 shows the transition matrix for the cohort of sons between 35 and 44 years. The sons' marginal distribution is dominated by that of the youngest cohort (cohort 1, on Table 4), which represents a general progress in the distribution of educational attainment. In fact, each young cohort first-order dominates the older cohorts for the male sample: the younger the cohort, the more desirable its educational distribution is, from a social welfare perspective in which more education is considered better from an individual point of view. However, interestingly, the conditional distributions of the younger cohorts do not necessarily dominate their respective column counterparts in the transition matrices of the older cohorts. For instance, the distribution conditioned on paternal complete university of cohort 1 (25-34) is dominated by the respective conditional distribution of cohort 2 (35-44). The matrix of cohort 2 is also monotone.

Table 3 Samples

Cohorts	Interviewed men	Interviewed women
1: 25-34	3,131	2,072
2: 35-44	1,160	1,152
3: 45-54	850	953
4: 55-64	870	813
Total	6,011	4,990

The transition matrix for the son cohort between 45 and 54 years is in Table 6. Unlike the two previous matrices, this one is not monotone because the distribution conditioned on complete secondary (the third column) does not dominate the distribution conditioned on complete primary (the second column), since there is a higher probability of having less than complete primary in the third column than in the second column, for this cohort.

Finally, Table 7 shows the transition matrix for the oldest cohort of the male simple, with ages between 55 and 64 years. Like the matrices of younger cohorts, this matrix is also monotone. Interestingly, even though the offspring marginal distribution of cohort 4 is dominated by the respective distribution of cohort 3, the same result does not apply to each pair of conditional distributions (the matrix's columns). In particular, the distribution conditioned on complete secondary of cohort 3 does not dominate the respective column of cohort 4, since the probability of having the lowest educational level is higher in cohort 3 than in 4. All male transition matrices exhibit quasi-maximal diagonal.

Table 4 Father-Son Cohort 1: 25-34

Sons' educational level	Fathers' educational level				Sons' marginal distribution
	Less than complete primary	Complete primary	Complete secondary	Complete university	
Less than complete primary	10.51	2.68	1.22	0.0	5.75
Complete primary	25.64	15.15	4.90	0.76	16.86
Complete secondary	57.74	75.87	78.07	45.04	66.94
Complete university	6.11	6.29	15.80	54.20	10.44
Sample size	1,408	858	734	131	3,131

Table 5 Father-Son Cohort 2: 35-44

Sons' educational level	Fathers' educational level				Sons' marginal distribution
	Less than complete primary	Complete primary	Complete secondary	Complete university	
Less than complete primary	19.09	4.35	2.74	0.0	13.53
Complete primary	28.36	17.39	6.85	0.0	22.84
Complete secondary	46.91	69.96	62.33	35.29	53.71
Complete university	5.65	8.30	28.08	64.71	9.91
Sample size	744	253	146	17	1,160

Table 6 Father-Son Cohort 3: 45-54

Sons' educational level	Fathers' educational level				Sons' marginal distribution
	Less than complete primary	Complete primary	Complete secondary	Complete university	
Less than complete primary	22.24	1.52	5.41	0.0	17.29
Complete primary	35.17	22.73	9.46	0.0	30.59
Complete secondary	38.49	68.94	55.41	30.0	44.59
Complete university	4.10	6.82	29.73	70.0	7.13
Sample size	634	132	74	10	850

Table 7 Father-Son Cohort 4: 55-64

Sons' educational level	Fathers' educational level				Sons' marginal distribution
	Less than complete primary	Complete primary	Complete secondary	Complete university	
Less than complete primary	50.67	11.24	4.17	0.0	44.71
Complete primary	27.88	37.08	4.17	0.0	27.82
Complete secondary	16.76	41.57	50.0	27.27	20.34
Complete university	4.69	10.11	41.67	72.73	7.13
Sample size	746	89	24	11	870

It is now time to comment the transition matrices of women connected to their mothers. Table 8 contains the transition matrix of the youngest female cohort. The matrix is monotone and, as in the case of the younger male cohorts, exhibits a higher probability of reproducing parental experiences at higher levels of education.

Table 9 shows the transition matrix for the female offspring cohort with ages between 35 and 44 years. It is also a monotone matrix. The daughters' marginal distribution of cohort 2 is dominated by the respective marginal distribution of cohort 1. However, not all columns of cohort 2 are dominated by those of cohort 1. For instance, the third column of cohort 2 dominates that of cohort 1.

Table 10 shows the transition matrix for cohort 3, with ages between 45 and 54 years. The matrix is monotone, like the previous ones. Interestingly, the marginal distribution of cohort 3 is not dominated by that of cohort 2. Likewise, a stochastic dominance relationship between some columns of the two cohorts cannot be established; for instance, regarding the first column (conditioned by the lowest educational level), since for cohort 3 the offspring probability of attaining the highest and lowest educational levels is higher than in cohort 2 (2.52% and 33.02% versus 1.97% and 17.32%).

Finally, Table 11 contains the transition matrix for the oldest offspring female cohort. Unlike the previous matrices, this matrix is not monotone, for the third column does not dominate the first one. The marginal distribution of cohort 4 is dominated by that of cohort 3. The same is true with respect to the column-by-column comparisons. All the female transition matrices exhibit quasi-maximal diagonals.

Table 8 Mother-Daughter Cohort 1: 25-34

Daughters' educational level	Mothers' educational level				Daughters' marginal distribution
	Less than complete primary	Complete primary	Complete secondary	Complete university	
Less than complete primary	13.16	2.23	1.10	0.0	7.48
Complete primary	28.22	13.97	3.96	0.0	18.77
Complete secondary	56.63	76.91	77.09	59.38	66.41
Complete university	2.00	6.89	17.84	40.63	7.34
Sample size	1,049	537	454	32	2,072

Table 9 Mother-Daughter Cohort 2: 35-44

Daughters' educational level	Mothers' educational level				Daughters' marginal distribution
	Less than complete primary	Complete primary	Complete secondary	Complete university	
Less than complete primary	17.06	4.72	1.08	0.0	12.93
Complete primary	29.99	17.32	5.38	0.0	25.00
Complete secondary	50.94	70.47	69.89	50.00	56.77
Complete university	2.01	7.48	23.66	50.00	5.30
Sample size	797	254	93	8	1,152

Table 10 Mother-Daughter Cohort 3: 45-54

Daughters' educational level	Mothers' educational level				Daughters' marginal distribution
	Less than complete primary	Complete primary	Complete secondary	Complete university	
Less than complete primary	32.75	10.61	4.11	0.0	27.28
Complete primary	30.72	21.97	8.22	0.0	27.60
Complete secondary	34.10	54.55	67.12	50.00	39.56
Complete university	2.43	12.88	20.55	50.00	5.56
Sample size	742	132	73	6	953

Table 11 Mother-Daughter Cohort 4: 55-64

Daughters' educational level	Mothers' educational level				Daughters' marginal distribution
	Less than complete primary	Complete primary	Complete secondary	Complete university	
Less than complete primary	56.36	4.76	12.50	0.0	51.29
Complete primary	30.10	34.92	25.00	0.0	30.26
Complete secondary	12.18	55.56	50.00	66.67	16.48
Complete university	1.37	4.76	12.50	33.33	1.97
Sample size	731	63	16	3	813

Table 12 Homogeneity tests: Sons' matrices versus daughters' matrices by cohort

Cohort	Pearson statistic	P-value	"Homogeneous" columns at 1% level of significance	Pearson-Cramer index of heterogeneity
1: 25-34	32.89883	0.001004***	2, 3, 4	0.08247
2: 35-44	18.53818	0.1003	2, 3, 4	0.097633
3: 45-54	36.99746	0.000224***	3, 4	0.174643
4: 55-64	34.84769	0.000495***	2, 3, 4	0.288556

* Null hypothesis rejected at 10% significance level.
** Null hypothesis rejected at 5% significance level.
*** Null hypothesis rejected at 1% significance level.

4. Results

In this section the results for the homogeneity tests are first presented. Then the computations of mobility indices for the transition matrices of men and women by cohort are shown.

Table 12 shows the results of the tests for homogeneity between the sons' and daughters' matrices, by cohort. With a 10% level of significance the null hypothesis of homogeneity between the sons' and daughters' matrices is rejected for all cohorts. However, in the case of cohort 2 the p-value is slightly higher than 10%. For all the other cases, the null hypothesis is rejected with a 1% level of significance. Yet in three out of the four comparisons, the first column is the only one for which the null hypothesis is rejected at the 1% level. In the comparison for cohort 3 the null hypothesis of homogeneity is also rejected for the second column, with the same level of significance. That is to say, the main source of differences between male and female matrices lies in the distributions conditioned by the lowest parental levels of education.[12] According to the Pearson-Cramer indices, which control for sample size, the degree of heterogeneity between sons' and daughters' matrices has decreased among the youngest cohorts; from almost 0.29 for cohort 4 until little more than 0.08 for cohort 1.

Table 13 hosts the results for the homogeneity tests between male transition matrices of different cohorts. The purpose of these tests is to detect significant structural breaks in the intergenerational mobility regimes between different sons' cohorts. According to the results, the hypothesis of homogeneity between the matrices of cohorts 1 and 2 is rejected, the same way as that between the matrices of cohorts 3 and 4. By contrast, the test of homogeneity between the matrices of cohorts 2 and 3 yields a p-value higher than 7%. In this same comparison the first column is the only one for which the null hypothesis of homogeneity is rejected. Reflecting these results, the lowest value of the Pearson-Cramer index for these three comparisons goes to the comparison between the matrices of cohorts 2 and 3. In summary, while we obtain evidence of breaks when moving from cohort 4 to 3, and from 2 to 1, we cannot discard the hypothesis of homogeneity between the matrices of cohorts 2 and 3, with a very low level of significance.

Table 14 hosts the results for the homogeneity tests between female transition matrices of different cohorts. According to the results, the hypothesis of homogeneity between the matrices of cohorts 2 and 3, just like between the matrices of cohorts 3 and 4, is rejected. By contrast, the homogeneity test between the matrices of cohorts 1 and 2 yields a p-value above 18%. Likewise, in this same comparison, the null hypothesis of homogeneity is not rejected for any of the columns. The Pearson-Cramer index reveals a lower degree of heterogeneity between adjacent matrices corresponding to younger cohorts. In summary, while we obtain evidence of breaks when moving from cohort 4 to 3, and from 3 to 2, we cannot rule out the hypothesis of homogeneity for the transition matrices of cohorts 1 and 2.

12 On the other hand, sample sizes tend to be lower for distributions conditioned on the highest values, especially the fourth column. That could also explain the difficulty in rejecting the null hypothesis at 1% significance level for these columns.

Table 13 Homogeneity tests: Sons' matrices by cohort

Null hypothesis	Pearson statistic	P-value	"Homogeneous" columns at 1% significance level	Pearson-Cramer index of heterogeneity
$M^1 = M^2$	60.963728	1.51E-08***	2, 4	0.107804
$M^2 = M^3$	19.515051	0.076834*	2, 3, 4	0.087731
$M^3 = M^4$	162.54403	1.59E-28***	3, 4	0.230262

* Null hypothesis rejected at 10% significance level.
** Null hypothesis rejected at 5% significance level.
*** Null hypothesis rejected at 1% significance level.

Table 14 Homogeneity tests: Daughters' matrices by cohort

Null hypothesis	Pearson statistic	P-value	"Homogeneous" columns at 1% significance level	Pearson-Cramer index of heterogeneity
$M^1 = M^2$	16.215934	0.181545	1, 2, 3, 4	0.073444
$M^2 = M^3$	78.063469	9.65E-12***	3, 4	0.146141
$M^3 = M^4$	137.95866	1.55E-23***	2, 3, 4	0.231007

* Null hypothesis rejected at 10% significance level.
** Null hypothesis rejected at 5% significance level.
*** Null hypothesis rejected at 1% significance level.

Table 15 Indices of mobility as movement by cohort and gender

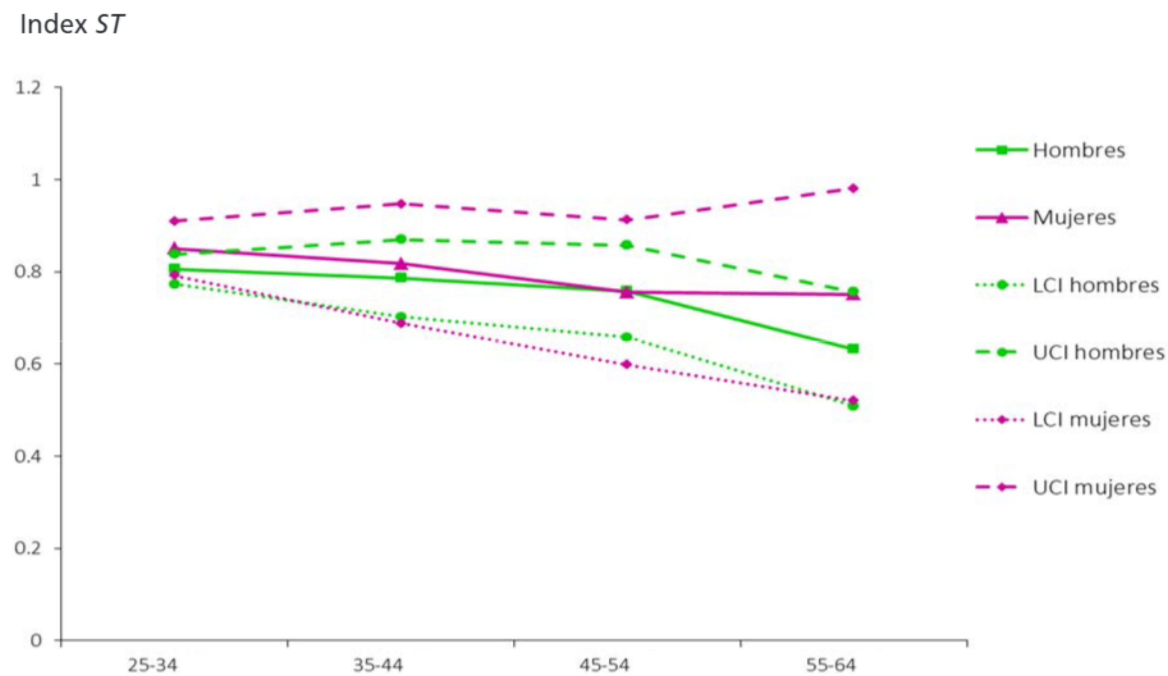
Index	*ST*		*B2*	
Cohort	Sons	Daughters	Sons	Daughters
1: 25-34	0.80691	0.85054	0.26693	0.26982
2: 35-44	0.78829	0.81907	0.25477	0.25769
3: 45-54	0.76543	0.76053	0.24045	0.23675
4: 55-64	0.63175	0.75128	0.19162	0.21463

Now the computations of mobility indices for male and female matrices by cohorts are presented and discussed.

The left half of Table 15, together with Figure 2, shows the results by cohort and gender for mobility index *ST*. For both men and women, an increase in mobility as movement, from older to younger cohorts, is manifest. Among older cohorts, this increase is more pronounced for men, but then the trend has a higher slope among women of the younger cohorts. However, according to the confidence intervals (Figure 2), the differences between men's and women's indices are not statistically significant. Likewise, the increase in female mobility is not statistically significant, which is due mainly to the lack of precision in the estimates for the oldest female cohorts. By contrast, in the male case, the comparison between extreme cohorts is statistically significant.

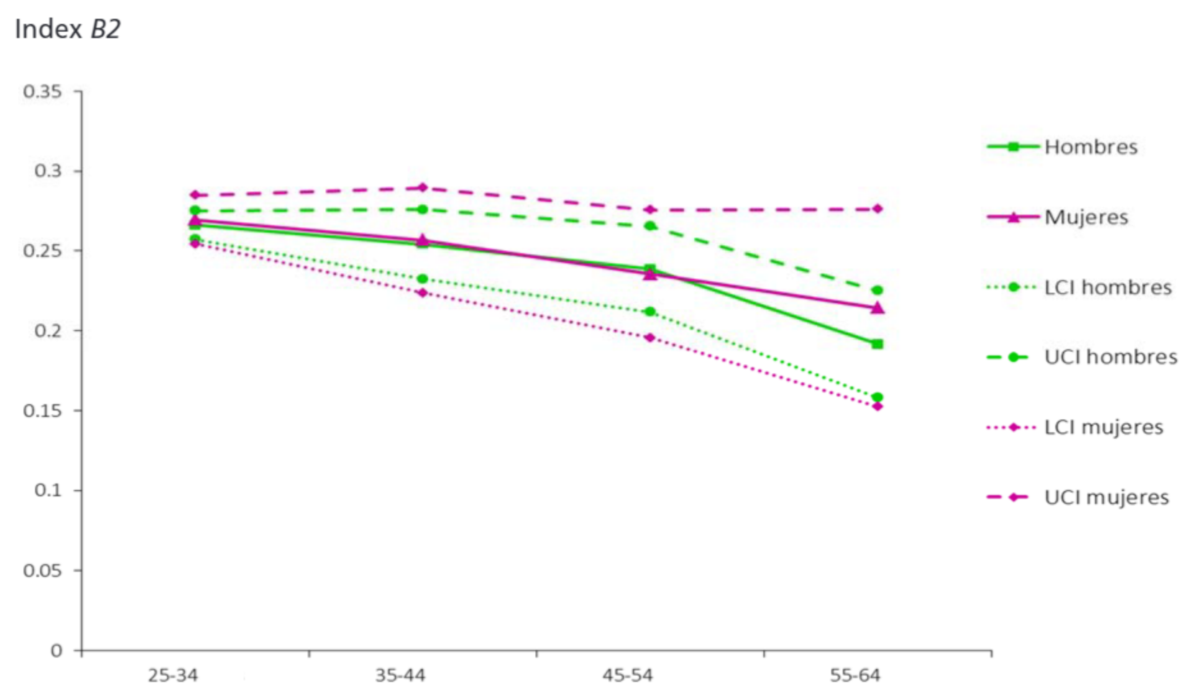
The right half of Table 15, together with Figure 3, shows the results by cohort and sex for mobility index *B2*.

Figure 2 index *ST* by cohort and gender *



*LCI and UCI: Lower and Upper confidence intervals, respectively, at 95% of confidence. Estimated with 1000 resamplings.
Source: Author's estimations from EMOVI-2011.

Figure 3 *B2* index by cohort and sex *



*LCI and UCI: Lower and Upper confidence intervals, respectively, at 95% of confidence. Estimated with 1000 resamplings.
Source: Author's estimations from EMOVI-2011.

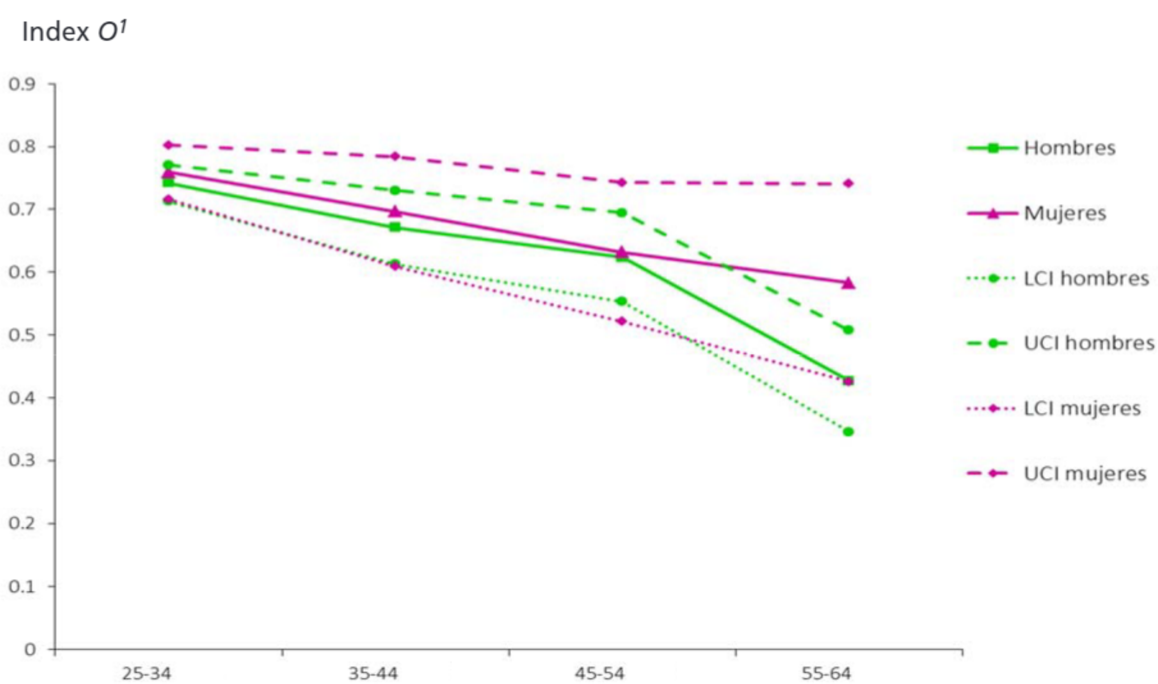
These results confirm those for *ST*: an increase in mobility as movement for men and women. Likewise, the higher increase in mobility among older male cohorts is verified. The results for both genders are remarkably similar between cohorts 1 and 3. Hence it is not surprising that the mobility difference between sexes is not statistically significant (Figure 3). The higher mobility as movement among younger men is statistically significant, whereas that is not the case for women, despite the similarity between the indices of both sexes. Again the lack of precision of the index estimates for older cohorts of women is responsible.

The left half of Table 16, together with Figure 4 shows the results by cohort and sex for mobility index O^1. Surprisingly the results resemble those already observed for the previous indices which measure mobility as movement. That is, an increase in mobility as equality of opportunity is observed, both for men and women, with an

Table 16 Indices of mobility as equality of opportunity by cohort and sex

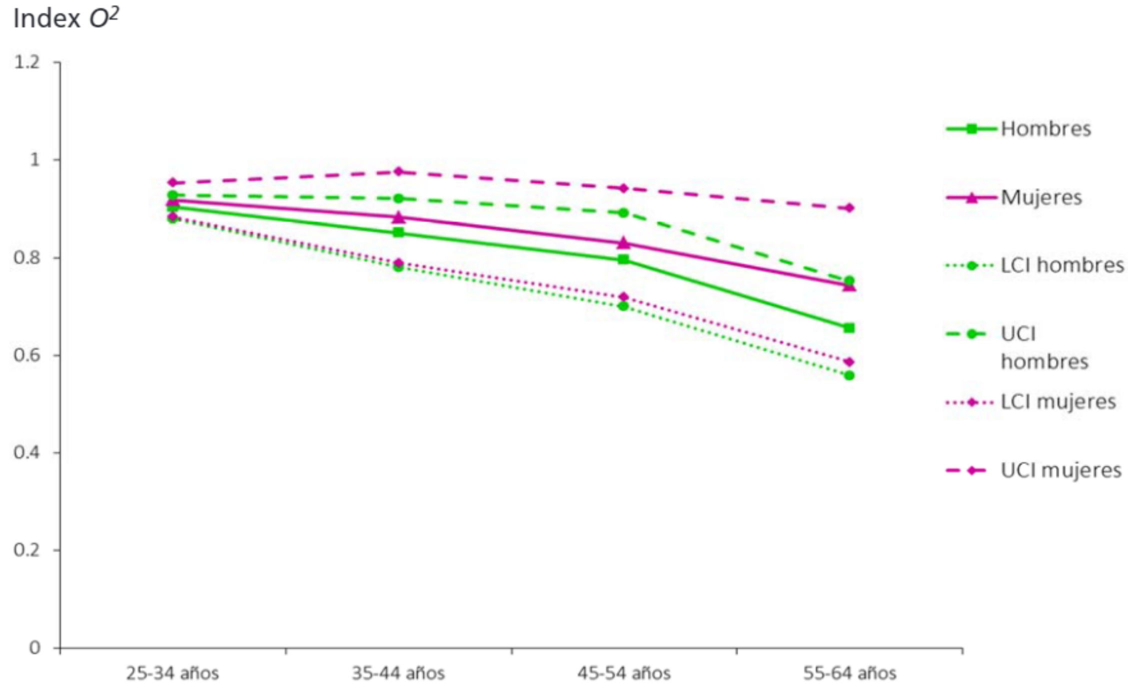
Index	O^1		O^2	
Cohort	**Sons**	**Daughters**	**Sons**	**Daughters**
1: 25-34	0.743806	0.759706	0.90519	0.91936
2: 35-44	0.672952	0.700977	0.85152	0.8844
3: 45-54	0.628999	0.634872	0.80497	0.83217
4: 55-64	0.427145	0.58462	0.65597	0.74486

Figure 4 O^1 index by cohort and sex*



*LCI and UCI: Lower and Upper confidence intervals, respectively, at 95% of confidence. Estimated with 1000 resamplings.
Source: Author's estimations from EMOVI-2011.

Figure 5 O^2 index by cohort and sex*



*LCI and UCI: Lower and Upper confidence intervals, respectively, at 95% of confidence. Estimated with 1000 resamplings.
Source: Author's estimations from EMOVI-2011.

Table 17 Indices of mobility as equality of opportunity by cohort and sex

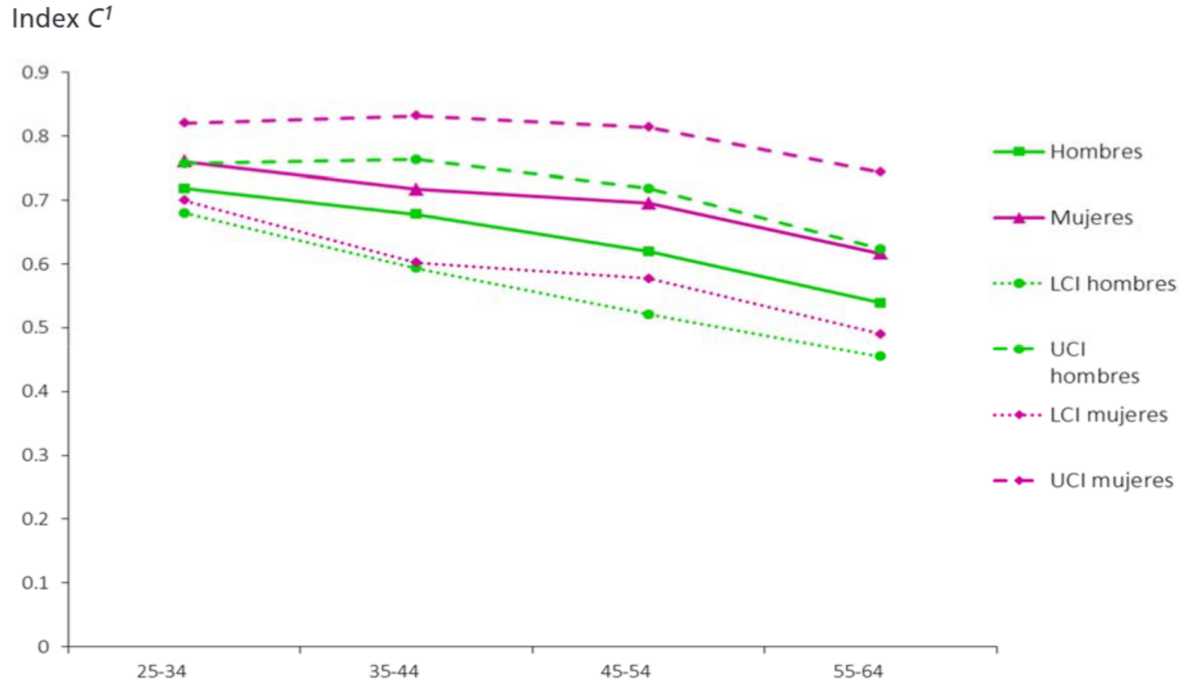
Index	C^1		C^2	
Cohort	Sons	Daughters	Sons	Daughters
1: 25-34	0.72118	0.76023	0.90856	0.93878
2: 35-44	0.67847	0.71963	0.87889	0.91671
3: 45-54	0.62832	0.69852	0.84279	0.8995
4: 55-64	0.53961	0.61758	0.79243	0.83266

important initial increase for the older cohorts of men (from baseline lower than the female one). Female values are higher than males'; that is, they reflect higher mobility, as in previous cases, although the differences are not statistically significant. By contrast, the individual trends of increase in mobility between the extreme cohorts are statistically significant.

The right half of Table 16, together with Figure 5, shows the results by cohort and sex for mobility index O^2. The indices confirm the rising trend (that is, from older to younger cohorts) in mobility as equality of opportunity. Again, gender differences are not statistically significant.

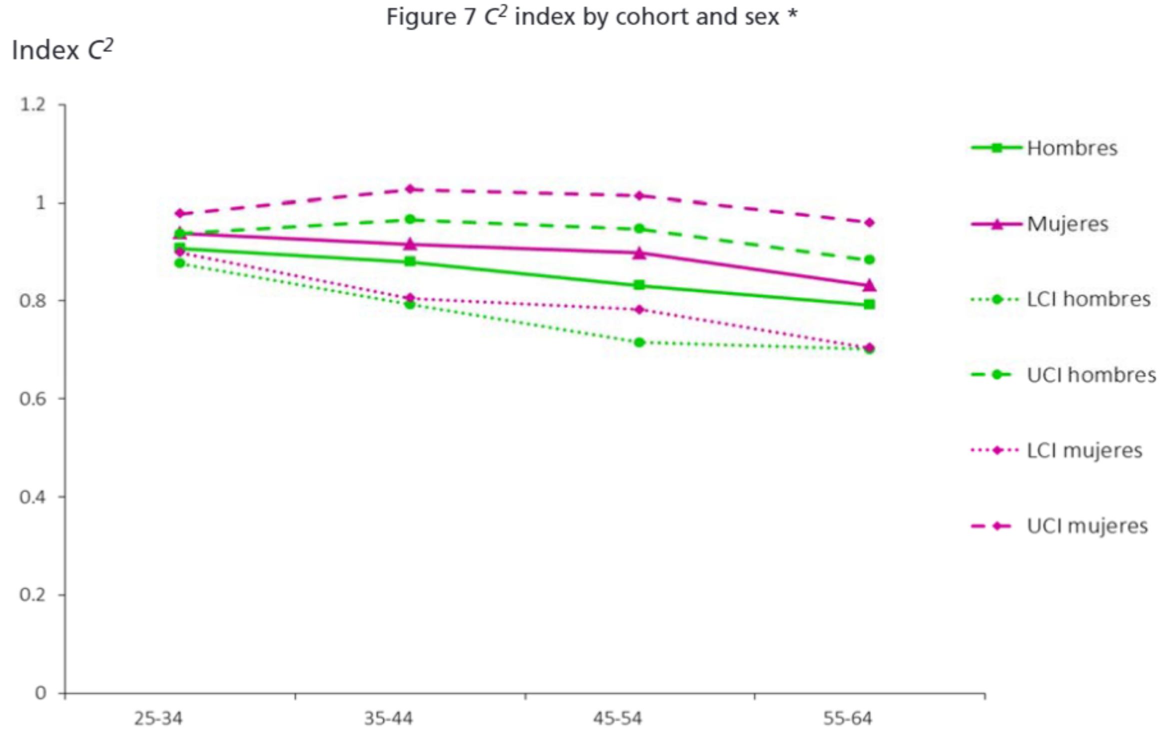
The left half of Table 17, together with Figure 6, shows the results by cohort and sex for index C^1. Again, the results are similar to those observed for other indices, but measuring mobility as equalization in life chances. An increase in mobility for both men and women is apparent, but the significant initial increase for the older male cohorts, found for other indices, is now absent. On the other hand, the gap between male and female values is

Figure 6 C^1 index by cohort and sex *



*LCI and UCI: Lower and Upper confidence intervals, respectively, at 95% of confidence. Estimated with 1000 resamplings.
Source: Author's estimations from EMOVI-2011.

Figure 7 C^2 index by cohort and sex *



*LCI and UCI: Lower and Upper confidence intervals, respectively, at 95% of confidence. Estimated with 1000 resamplings.
Source: Author's estimations from EMOVI-2011.

higher, although with substantial overlap between the respective confidence intervals. Among men, the difference between the mobility of extreme cohorts is statistically significant.

Finally, the right half of Table 17, together with Figure 7, shows the results by cohort and sex for index C^2. The results confirm the trends found for C^1, as well as with previous indices measuring other meanings of mobility. Again, the mobility differences between men and women are not statistically significant.

5. Conclusions

This paper sought to document trends in intergenerational mobility of education in Mexico, using the EMOVI2011 dataset. In previous work, like Binder and Woodruff (2002), De Hoyos *et al.* (2010) and Torche (2010), an increase in mobility from older to younger cohorts was observed, although with a reduction in mobility by the youngest cohort, which would not completely offset the continuous increase in mobility experienced previously. Binder and Woodruff (2002, p. 261-2) were the first to claim that this interruption in the trend of increase in mobility could be due both to limitations in the growth of the education supply (mainly secondary schools) and to the economic crisis which featured the debt moratorium in 1982.

However, the mentioned studies differ in key methodological aspects like definitions of age cohorts, selection of educational variables, and statistical measurement methods. Moreover, unlike the most recent studies, Binder and Woodruff (2002) use a different and older dataset. Even though it is remarkable that their conclusions are all very similar notwithstanding their methodological differences, none of the previous studies clarifies the *axiomatic* meaning of mobility that they are capturing.

By contrast, this paper finds a monotonic increase in educational mobility *in its three meanings*, which is not interrupted in any of the cohorts, and which is common to both genders. The results are corroborated by several indices. Moreover, generally, the mobility indices yield very similar values for men and women, to the point that their differences are not statistically significant. This paper also detects, among the younger cohorts, a higher similarity between the father-son and the mother-daughter transition matrices.

Surely there are methodological differences between this paper and previous ones (just like among the previous ones) regarding age cohort definitions, choices of variables and methods. However, the robustness of the results found in this paper, and their contrast with the robustness of previous studies begs a conciliatory explanation, which may require further evidence. A possible explanation would be that this paper's youngest cohort was born between 1977 and 1986 whereas, for instance, the youngest cohort, and the closest to this paper's, *i.e.* that of De Hoyos *et al.* (2010), was born between 1972 and 1981. Is it possible that the five years of difference include already young Mexicans of disadvantaged background whose educational opportunities improved again as the Mexican economy was recovering? In other words: Is it possible that the different coverage and cohort cut-offs, added to the additional evidence provided by EMOVI2011, may have softened, and even disappeared, a possible interruption in the increase in mobility which would have occurred only temporarily, affecting people born during the seventies?

It is clear then that there is a pending task of generating further evidence for the future in order to confirm whether the intergenerational mobility of education in Mexico is increasing steadily and permanently. In particular, it is important to understand whether the differences among some studies are due fundamentally to the selection of variables (*e.g.* educational level versus years of education), to the choice of statistical methods (*e.g.* parametric versus non-parametric), to the definition of age cohorts, or to other possible differences in the samples.

Considering the valuable diagnostic information that can be obtained from an analysis of trends, this paper also seeks to emphasize the importance of following the example of the EMOVI2011 toward collecting datasets with significant sample sizes that may enable a more refined cohort analysis. Likewise, with more information on the age difference between parents and offspring it would be possible also to study intergenerational mobility controlling both for offspring age and parental age. Thereby it would be possible to detect the presence of life-cycle effects which, potentially, interact with cohort effects.