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Long run economic mobility

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Université Paris 1 - Panthéon Sorbonne - Paris School of Economics

Long run economic mobility

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« Qui dit étudiant dit parisien ; étudier
à Paris, c'est naître à Paris. »

“Les Misérables - Fantine”
Victor Hugo (1862)¹

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The idea of movement motivates this work. Hence, I want to dedicate this work to Elsa who has invariably ‘moved’ with me in this roller coaster. To my parents and siblings: their thoughts and prayers travel with me wherever I go.

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¹ Tome I – Fantine, Chapitre II : Double quatuor »

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Introduction in English

Long run economic mobility

The road was rising and falling. A man I saw told me, "It rises or falls, depending on whether you're coming or going. For someone who is going, it rises; for someone who is coming, it falls."

Juan Rulfo, "Pedro Páramo"

Economic mobility constitutes a social aspiration in many modern societies.² This complex notion of prosperity implies that progress is open for everyone regardless of the fortuitous circumstances of birth or social position. It also evokes the aspiration for children to be better off than their parents did. A justified concern then emerges when mobility is determined by individual, *intra*-generational or *inter*-generational, origins. Not only that. This pattern leads to vivid academic and political discussions with direct implications in terms of public policies. For instance, downward mobility was recently considered as *the defining challenge of our time*, by to the former President of the United States whilst the quest for upward mobility originated the recent creation of *The Social Mobility Commission* in the UK.³

² Social mobility has already paired social inequality recently at least according to Google trends. See <https://trends.google.com.mx/trends/explore?q=social%20inequality,social%20mobility>

³ See Obama, Barak (2013) and SMC (2016) respectively.

Do these reactions correspond to the actual evolution of social mobility? In other words: 1) how can we measure economic mobility with the data available or with the technology at hand? 2) What are the trends of economic mobility experienced by the current generation? Moreover 3) how mobile is a society relative to previous generations? These questions motivate this dissertation. The complexity of these issues may derive in some sort of paralysis but it is claimed here that it may be possible to learn something about its evolution by restricting analysis to a couple of key dimensions within the economic discipline: income and education. This is the scope followed by this research.

The first part of this research addresses the initial of the above-referred interrogations. The first paper in this dissertation, co-authored with François Bourguignon, is devoted to deal with the lack of the required data to examine the income dynamics within one generation. It is well known that longitudinal data is often scarce and is seldom available in many countries. This is the case even in well-developed countries! This conundrum has been partially addressed through recent methodological approaches by the so-called synthetic panels.

The second part of this dissertation is entirely devoted to applied research. More specifically, the second and third papers describe long run trends of economic mobility in income and education respectively. The former is devoted to *intra*-generational mobility while the later is devoted to *inter*-generational mobility. Each of them address the second and third interrogations referred above. In a way this dissertation attempts to improve the addition of the time dimension in the analysis of economic wellbeing. It attempts to produce the effect of a motion picture by the use multiple snapshots. The trends contained herein are far from being perfect and complete but they are based on the use of extensive data and multiple methods covering three decades and the same number of generations in each case.

This research expects to expand our knowledge on the empirics of economic mobility as most of the studies refer to few years of intra-generational mobility or to a couple of generations only. Furthermore, most of the empirical evidence available refers to Nordic and highly industrialized countries. Mexico is the canvas of this work but the approaches and principles followed here could be easily mimicked elsewhere.

Finally, this introduction is not mere to describe technicalities of this work. Instead it aims at providing a brief and an integrated version of the research with some perspective. The chapters of this dissertation corresponds actually to self-contained research articles with detailed methodological descriptions. Readers interested in the technicalities of this research are therefore referred to the actual chapters or the corresponding papers following this introduction.

From snapshots to a motion picture: On synthetic income panels

*« C'est de la physionomie des années
que se compose la figure des siècles. »*

« Les Misérables -Fantine »

Victor Hugo (1862)⁴

The first paper examines the current technology to construct artificial panels and provides a discussion on its potential uses and implications. The study is motivated by the fact that longitudinal data, that allows examining the dynamics of individual incomes, are seldom available in many developing countries. The idea then is to construct synthetic panel data based on *snapshots* of the distribution of income that are more and more accessible under the form of repeated cross-sectional household surveys. A principle that resembles the one used by the cinematograph to produce the effect of motion.

We examined most of the recent knowledge to construct artificial longitudinal data and propose a method that uses of multiple methods, i. e. matching techniques, pseudo-panel estimation and calibration algorithms. To contribute to this branch of the literature we generalized the original methodology in Dang et al. (2014) and Dang and Lanjouw (2013) to avoid the most arbitrary assumptions often used. The study also expanded the scope of analysis by exploring the 'confidence set' of mobility matrices based on key parameters - in particular the autocorrelation coefficient of first order.

⁴ Tome I, Chapitre II : Double quatuor »

The procedure delivered very satisfactory outcomes and was confirmed by multiple tests in several potential applications. We learned that the current methodologies are strongly dependent on their underlying assumptions and, very importantly, the way key parameters are estimated. In particular the AR(1) coefficient is a key parameter that requires extremely caution when studying income mobility based on synthetic panel techniques.

Synthetic panels might still be imperfect machinery. Their notion of motion is still in early stages of its development and so the empirical evidence emerging from this device is to be improved. Even the Lumière brothers, who were credited the development of Cinematograph, were skeptical about their creation in early stages.⁵ However it is unmistakable that their moving images have had a significant influence on modern societies. Similarly, what it is to be acknowledged here is the emergence of larger, and better equipped, 'audience' interested on the dynamics of income inequality.

Income mobility over a generation: a 'long run' motion picture

« Si quelque chose est effroyable, s'il existe une réalité qui dépasse le rêve, c'est ceci : vivre, voir le soleil,... avoir la lumière, et tout à coup, le temps d'un cri, en moins d'une minute, s'effondrer dans un abîme, tomber,... être là-dessous, et se dire : tout à l'heure j'étais un vivant ! »

« Les Misérables -Cosette »

Victor Hugo (1862)⁶

⁵ "Le cinéma est une invention sans avenir" (The cinema is an invention without any future)" -they claimed. See: https://en.wikipedia.org/wiki/Auguste_and_Louis_Lumi%C3%A8re

⁶ Tome II, Chapitre XIX : Le champ de bataille la nuit

The above-referred anxiety of social in-mobility (at the beginning of this introduction) might be well rooted in the fear that changes in the macroeconomic environment exacerbate this risk of stagnation over the life span. The 2008 global economic crises is a worldwide recent example. A common concern is that no matter how hard people work, the floor of individual progress might have been stickier than previously known.⁷ Societal debates about income mobility are sometimes based on preconceived opinions, political preferences, limited information or defective methodologies. It appears useful to fill this gap with empirical evidence using the data and machinery at hand.

Unfortunately, only a handful of countries can challenge these concerns with empirical evidence from genuine longitudinal surveys. In most cases, these panel surveys cover only short periods. Other countries simply have to resort to the evidence from artificial data by the construction of synthetic panels. Studies following this approach, however, construct a unique panel with data from very distant points in time, which compromises the panel's quality and, very importantly, disregard the macroeconomic environment. Conversely, the vast majority of countries rely on the comparison of two, or multiple, snapshots based on independent cross-sectional data from household income surveys. This last approach is not satisfactory as it neglects an essential part of the analysis: the dynamics of wellbeing.

The second paper of this dissertation then examines the patterns of income mobility over three decades in Mexico -from 1989 to 2012. The recent economic history of this developing country allowed examining multiple episodes of the economic cycle. The analysis focused on the outbreak of two strong economic downturns, one internal in 1995 and the other external in 2008. In both cases the Mexican economy sharply fell by around 7%.

Naturally, the definition and measurement of income mobility is complex, however the analysis followed three notions of mobility, described in Fields (2010) and Jäntti & Jenkins (2015), each of which were examined through multiple indicators. These notions are: positional movement, directional movement and mobility as an equalizer of longer-term incomes. The strategy then consisted in constructing eleven short-term synthetic panels using the methodology referred on the previous section.

⁷ This was in fact one of the motivations in the President Obama's speech referred before.

It is claimed here that the paper contributed to this emerging branch of income mobility literature by delivering empirical evidence on the long run trends of intra-generational mobility from a developing country. The paper documents low levels of mobility with downward mobility during both episodes of economic slump. It follows that that the mobility patterns experienced during these periods of economic downturn produced an equalization process.

Mexico emerges as a country characterized by low levels of mobility. This situation changes in periods of economic crisis where the country is better characterized by an analogy of *glass ceilings* with *sticky floors*. We learn that the patterns obtained by the construction of synthetic panels are already useful to form societal judgements on the structure of growth experiences and have already a descriptive value on the distributional impact of growth.

Mobility across three generations

« La patrie périra si les pères sont foulés
aux pieds. Cela est clair. La société, le
monde roulent sur la paternité. »

« Le père Goriot »

Honoré de Balzac

The idea of mobility also vindicate an *inter-generational* expectation: children are expected to attain the fullest stature of what they are capable regardless of their incidental origins. In other words, children are expected to be better off than their parents and more distant ancestors. This lead us to the last inquiry stated at the beginning of this introduction: how mobile is a society relative to previous generations?

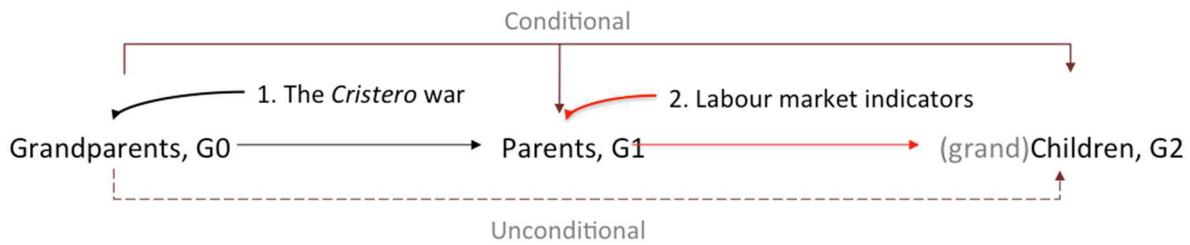
The answer to this question required coping with two sensitive issues: 1) having access to longstanding data that neatly distinguishes parent-children links on a relevant economic variable-not a simple task, I may say- and, 2) dealing with endogeneity issues. The first one refers to a problem of data availability and was addressed by the use of a unique Mexican survey that gathered retrospective information on three generations. The second lead us to the use of a demanding statistical method: a two fold instrumental variable approach.

Educated at Lyon's largest technical high school, *La Martiniere*, the Lumière brothers worked for their father, an artist and businessman, who specialised in photographic equipment. Their story exemplifies the fact that parents not only invest monetary (financial) and non-monetary (time) resources on their offspring but also transmit part of their unobserved ability to their children. This transfer is likely to produce biased estimates of intergenerational mobility using OLS - the most widely statistical technique used in a large body of this branch of the literature.

The endogeneity of paternal schooling was addressed by the use of a two-fold instrumental variable approach described in **Diagram 1**. A natural experimental set up from a regional war that occurred at the beginning of the 20th century was exploited to instrument years of schooling of the "grand-father" generation whereas labour market indicators, a well-known instrument in the labour economics literature, served as an instrument for the education of the "parents" generation.⁸ This unified framework allowed examining the intergenerational transmission of human capital across three generations and, very importantly allowed comparing the conditional and the unconditional effect of grand-parental education on their grandchildren. The following diagram illustrates this approach.

⁸ La Cristiada was a massive armed conflict that lasted three years from 1926-1929. This religious conflict can be briefly summarized by a massive rural rebellion in the western and central states of Mexico after the enforcement of anticlerical laws that emerged from the Mexican Constitution of 1917.

Diagram 1: identification strategy



The paper shows that parental education has a significant effect on their children's education. It also shows that the IV estimate is larger than the OLS estimate, which implies that accounting for endogeneity unveils a larger importance of familiar background (less educational mobility than traditionally considered) than ignoring it. This holds true for both the grandparent-parent link as well as for the parent-child link.

We learned that parental education is the most important family background in the children's years of education though it seems to play a lesser role in successive generations (implying more mobility with every new pair of generations). Very importantly, we also learned that beyond the findings of two contiguous generations, results also suggest that the influence of the grandparents' educative legacy, conditional on parental education, did not seem to reach the second generation -in Mexico. The origins of inequality are long rooted but they could be tackled from one generation to the following one.

Final remarks

The roads of our lives are constantly moving: *rising and falling* –as the initial epigraph implied. In a democratic context, it is useful to know, whether our society provides the chance to get ahead regardless of our origins, or whether this chance is ruled or doomed by them.

If good fortune is only determined to a group that is constantly “*going and rising*” whereas the lack of upward mobility is predetermined to those who are systematically “*coming and falling*” by their individual backgrounds, then it may well be the case that we may actually be facing a *defining challenge of our time* -like recently stated in the USA. We may also want to know, from a policy perspective, whether the long run mobility trends justifies the creation of a *Social Mobility Commission* or other public policies -like the one created in the UK.

Empirical evidence is needed to foster these deliberations -which are often absent in many modern societies. This dissertation may well be an invitation to sustain this kind conversation.

Paris, January 2018

Résumé Substantiel en Français

La mobilité économique à long terme

« Le chemin allait par monts et par vaux.

Il monte ou descend selon que l'on va ou que l'on vient.

Pour qui va, il monte ; pour qui vient, il descend. »

Juan Rulfo,

« Pedro Páramo »

La mobilité économique est une des aspirations de toute société moderne. Cette notion assez complexe de la prospérité implique que le progrès économique est une possibilité pour chacun, peu importe les circonstances fortuites de sa naissance ou de sa position sociale. Cette notion évoque également l'aspiration de la part des enfants, de s'en sortir mieux que leurs parents. Ces suppositions qui sembleraient des évidences soulèvent pourtant une préoccupation, tout-à-fait justifiée, où moment où la mobilité se voit déterminée par les origines de chaque personne, soient celles individuelles ou familiales.

Ce le sujet de la mobilité amène ainsi à des discussions politiques ou universitaires qui ont un impact direct sur les politiques publiques. Par exemple, la mobilité vers le bas a été récemment considérée « le défi définissant de notre temps » par l'ancien président des États-Unis, tandis que la quête de la mobilité vers le haut a été l'idée à l'origine de la création de la Commission pour la mobilité sociale au Royaume Uni.

Comment peut-on savoir si ces réactions politiques correspondent à la véritable évolution de la mobilité sociale ? C'est-à-dire : 1) peut-on mesurer la mobilité sociale avec les données ou la technologie disponibles aujourd'hui ? 2) Quelles sont les tendances de la mobilité sociale qui a traversées la génération actuelle ? Ou encore 3) à quel point la société actuelle est-elle mobile par rapport aux anciennes générations ?

Ce sont les trois questions à la base de cette thèse. Certes, la complexité de ces problématiques pourrait nous amener vers une sorte de paralysie, mais nous soutenons ici que c'est possible de connaître encore plus sur l'évolution de la mobilité sociale en restreignant son analyse à quelques dimensions dans le champ de l'économie : le revenu et l'éducation. Ce parcours est donc l'objectif de notre recherche.

La première grande partie de la thèse, composée par le premier des trois articles, s'occupe de la première des questions posées plus haut. Co-écrit avec François Bourguignon, cet article s'attaque au problème du manque des données nécessaires pour l'analyse des dynamiques du revenu à l'intérieur d'une génération. Il est avéré que les données longitudinales sont rares et très peu disponibles dans la plupart des pays, ce qui est vrai même pour les pays développés ! Nous avons essayé d'assembler ce casse-tête par des approches méthodologiques récentes, telles que les « panels synthétiques », une méthodologie normalement utilisée pour l'analyse des dynamiques de la pauvreté.

La seconde grande partie de la thèse est dédiée à la recherche appliquée. Les articles deux et trois décrivent, plus spécifiquement, les tendances à long terme de la mobilité économique pour le revenu et pour l'éducation, respectivement. Le deuxième papier s'occupe de la mobilité intra-générationnelle, tandis que le troisième est dédié à la mobilité intergénérationnelle. Tous les deux répondent aux questions deux et trois posées plus en haut, en cherchant d'améliorer la façon dont la dimension temporelle est incluse dans l'analyse du bien-être économique, ceci avec pour but de reproduire l'effet d'un film fait avec plusieurs clichés. Bien que les tendances présentées ici soient loin d'être parfaites ou même complètes, elles se basent dans l'utilisation de larges quantités de données et de différentes méthodes pour couvrir trois décades et trois générations dans chaque cas.

Cette thèse cherche à élargir le savoir expérimental sur la mobilité économique, vu que la plupart des études ne prennent en compte que quelques années de mobilité intra-générationnelle ou à peine quelque génération. En outre, la plupart des résultats des expériences existantes font référence aux pays scandinaves ou à des pays fortement industrialisés. Pour cette thèse nous avons donc pris l'exemple du Mexique, mais les approches et les principes méthodologiques utilisés pourront être appliqués à n'importe quel autre pays.

Enfin, ce n'est pas le but de cette introduction de décrire les aspects techniques du travail présenté. L'objectif est plutôt de faire une mise en perspective à travers une explication succincte. Chaque chapitre de la thèse est un article indépendant avec des descriptions méthodologiques détaillées. Les lecteurs intéressés aux aspects techniques pourront donc s'adresser directement à chaque chapitre.

1. De la succession de clichés au film en mouvement : les panels synthétiques du revenu

*« C'est de la physionomie des années
que se compose la figure des siècles. »*

« Les Misérables -Fantine »

Victor Hugo (1862)⁹

Le premier article étudie les techniques actuelles pour la construction de panels artificiels, en apportant des éléments pour mieux comprendre leur utilisation et leurs implications. Cette analyse est motivée par le fait que les données longitudinales qui normalement permettent l'étude de la dynamique du revenu individuel sont rares dans les pays en développement. L'idée est donc de construire des données de panel synthétiques basées sur des « clichés » de la distribution du revenu, qui sont en revanche de plus en plus disponibles grâce à l'accessibilité des enquêtes de coupe transversale sur le revenu du ménage. Ce principe ressemble celui utilisé par le cinématographe pour la reproduction de l'effet de mouvement.

On a analysé ici la plupart de la littérature scientifique sur la construction de données longitudinales artificielles par différentes méthodes, y compris les techniques de matching, les estimations par pseudo-panel et la calibration d'algorithmes. Dans le but de contribuer à cette branche des études économiques, nous avons généralisé la méthodologie originale trouvée en Dang et al. (2014) et en Dang and Lanjouw (2013) pour éviter leurs suppositions les plus arbitraires. Notre approche a été aussi d'élargir la portée de l'analyse en explorant la 'région de confiance' des matrices de mobilité basées dans des paramètres clés, notamment dans le coefficient d'autocorrélation de première ordre.

⁹ Tome I, Chapitre II : Double quatuor »

Vérifiée à partir de plusieurs tests pour de différentes applications potentielles, cette procédure a donné des résultats satisfaisants. L'exercice nous a permis d'observer la façon dont les paramètres clé sont estimés –les AR(1), ainsi que d'apprendre que les méthodologies actuelles dépendent fortement de leurs suppositions sous-jacentes. Nous conseillons donc d'agir avec précaution au moment d'utiliser cette technique pour examiner la mobilité du revenu.

Le présent article améliore la méthodologie d'étalonnage de ces panneaux synthétiques dans plusieurs directions. Nous exploitons la dimension transversale d'une enquête par panel mexicaine représentative au niveau national pour évaluer la validité de cette approche. La matrice de mobilité du revenu dans le panel synthétique sur deux régimes utilisées se révèle être très proche de la matrice observée dans l'authentique panel (voir table 1). Le chapitre comprend un résumé pratique menant à la construction d'un panel synthétique pour faciliter sa mise en œuvre par les praticiens intéressés.

C'est fort possible que la méthodologie des panels synthétiques soit encore imparfaite. Même les frères Lumière, connus pour l'invention du cinématographe, étaient sceptiques de leur propre création, mais leurs images motrices ont eu sans doute une influence significative dans les sociétés modernes : ce qu'il faut retenir au-delà de la machine, est l'émergence d'un public avide. Similairement, l'importance de la construction des panels synthétiques peut être mesurée en fonction de la demande d'analyses longitudinales du bien-être humain.

Table 1. Matrice de mobilité du revenu, 2002-2005.

- Porcentaje -

		2005 groups (Destination)					
		1	2	3	4	5	Total
Régime 1							
2002 Quintiles (Origine)	1	7.3 (6.7-7.9)	6.3 (5.7-6.9)*	3.6 (3.1-4.2)*	2.2 (1.8-2.6)	0.6 (0.4-0.9)	20
	2	3.3 (2.8-3.8)	6.0 (5.3-6.6)*	5.0 (4.4-5.6)*	4.0 (3.4-4.6)*	1.6 (1.2-2)*	20
	3	1.7 (1.3-2.1)	4.5 (3.9-5.1)*	5.2 (4.5-5.8)*	5.5 (4.9-6.2)*	3.2 (2.6-3.7)	20
	4	0.8 (0.5-1.1)	3.1 (2.6-3.6)	4.6 (4-5.2)	6.3 (5.7-7)	5.3 (4.7-5.9)*	20
	5	0.2 (0.1-0.4)	1.3 (1-1.7)	2.8 (2.3-3.3)*	5.7 (4.9-6.5)	9.9 (9.1-10.7)*	20
Authentique							
2002 Quintiles (Origine)	1	6.6	6.0	3.5	2.9	1.1	20
	2	3.9	5.7	5.0	4.0	1.4	20
	3	2.7	4.0	5.8	5.5	2.0	20
	4	1.8	2.5	3.5	7.4	4.8	20
	5	0.6	2.0	2.5	4.7	10.1	20
Régime 2							
2002 Quintiles (Origine)	1	7.1 (6.1-8.1)*	6.3 (5.6-7)*	3.7 (3.1-4.2)*	2.2 (1.5-2.8)	0.7 (0.3-1.1)*	20
	2	3.3 (2.9-3.8)	6.0 (5.1-6.8)*	5.1 (4.5-5.8)*	4.0 (3.4-4.6)*	1.6 (1-2.2)*	20
	3	1.7 (1.2-2.1)	4.6 (4-5.1)	5.2 (4.5-6)*	5.4 (4.8-6.2)*	3.1 (2.4-3.7)	20
	4	0.8 (0.4-1.2)	3.1 (2.5-3.7)	4.7 (4.1-5.3)	6.4 (5.5-7.3)	5.1 (4.4-5.8)*	20
	5	0.3 (0.1-0.5)	1.4 (0.9-1.9)	2.8 (2.2-3.4)*	5.7 (5-6.4)	9.8 (8.7-10.8)*	20

Notes: 95% C.I. in parenthèses. Voir table 3, chapitre 1.

2. Mobilité économique tout au long d'une génération : un film 'à long terme'

« Si quelque chose est effroyable, s'il existe une réalité qui dépasse le rêve, c'est ceci : vivre, voir le soleil,... avoir la lumière, et tout à coup, le temps d'un cri, en moins d'une minute, s'effondrer dans un abîme, tomber,... être là-dessous, et se dire : tout à l'heure j'étais un vivant ! »

« Les Misérables -Cosette »

Victor Hugo (1862)¹⁰

La crainte de l'immobilité sociale dont on parlait plus en haut, pourrait très bien avoir ses racines dans la peur que les fluctuations dans le climat macro-économique puissent aggraver le risque de stagnation tout au long de la vie des individus. Les crises économiques globales de 2008 n'en sont qu'un exemple récent de ceci. En effet, une préoccupation fréquente est le fait que malgré le travail dur des gens, les planchers du progrès individuel s'avèrent en fait plus gluants de ce qu'on pensait . En tout cas, les débats sur la mobilité du revenu sont très souvent basés sur des idées reçues, des références politiques ainsi que sur des méthodologies défectives ou de l'information limitée. Il semble donc utile de remplir ce besoin avec des résultats empiriques en se servant des données et des techniques à notre portée.

¹⁰ Tome II, Chapitre XIX : Le champ de bataille la nuit

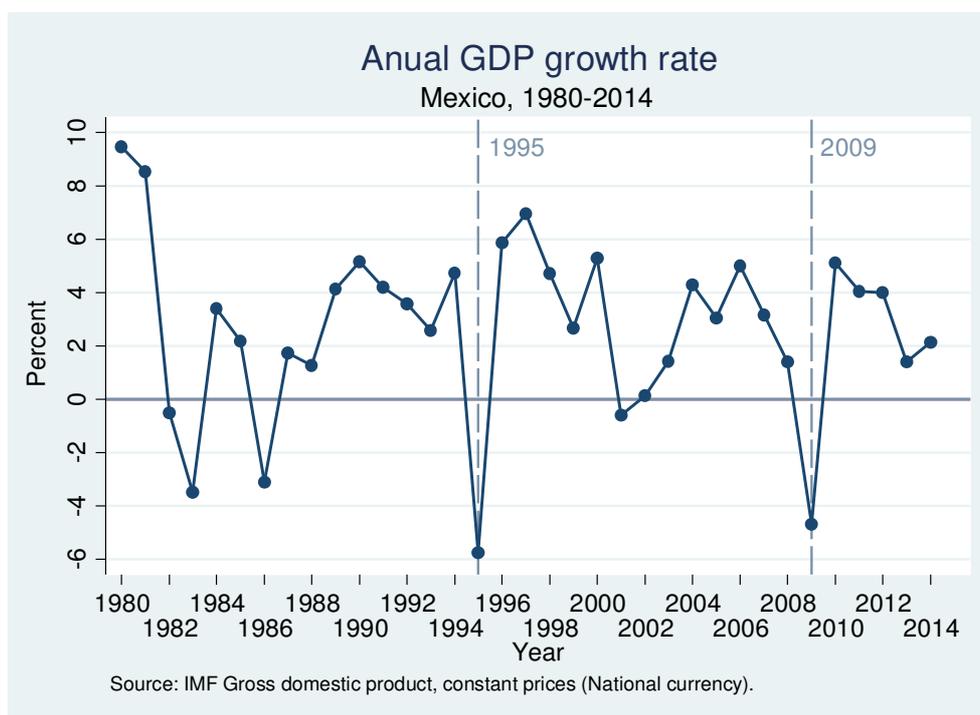
Malheureusement à peine quelques pays peuvent utiliser des données provenant d'enquêtes longitudinales pour prendre en charge ces préoccupations, tandis que d'autres nations se résolvent avec des données artificielles créées avec des panels synthétiques. En construisant très souvent un panel unique avec des données provenant des points éloignés dans le temps, ces études tendent à compromettre leur qualité et ne prennent pas en considération l'environnement macroéconomique.

Mais la vaste majorité des pays de la planète s'appuie sur la comparaison de deux ou plusieurs 'clichés' (snapshots) provenant des coupes transversales indépendantes de données d'enquêtes du revenu des ménages. Cette approche est loin d'être satisfaisant, car elle néglige une partie essentielle de l'analyse : les dynamiques du bien-être.

Le deuxième article composant cette thèse étudie les patrons de la mobilité du revenu au Mexique tout au long de trois décennies –de 1989 à 2012. L'histoire économique récente de ce pays en développement nous a permis d'examiner différents épisodes du cycle économique (voir graphique 1). Notre analyse se concentre ainsi dans l'explosion de deux baisses économiques, une interne en 1995 et l'autre externe en 2008. Dans les deux cas, l'économie mexicaine a subi une baisse d'environ 7%.

Bien que la définition et la mesure de la mobilité du revenu soient complexes, notre analyse est basée sur trois notions de mobilité, telles qu'elles ont été établies par Fields (2010) et par Jäntii & Jenkins (2015) en faisant des examens à partir de différents indicateurs. Il s'agit des notions suivantes : mouvement positionnel, mouvement directionnel et mobilité en tant qu'équaliseur de revenus de long terme. La stratégie a donc consisté en la construction d'onze panels synthétiques à court terme réalisés avec la méthodologie décrite dans la section précédente.

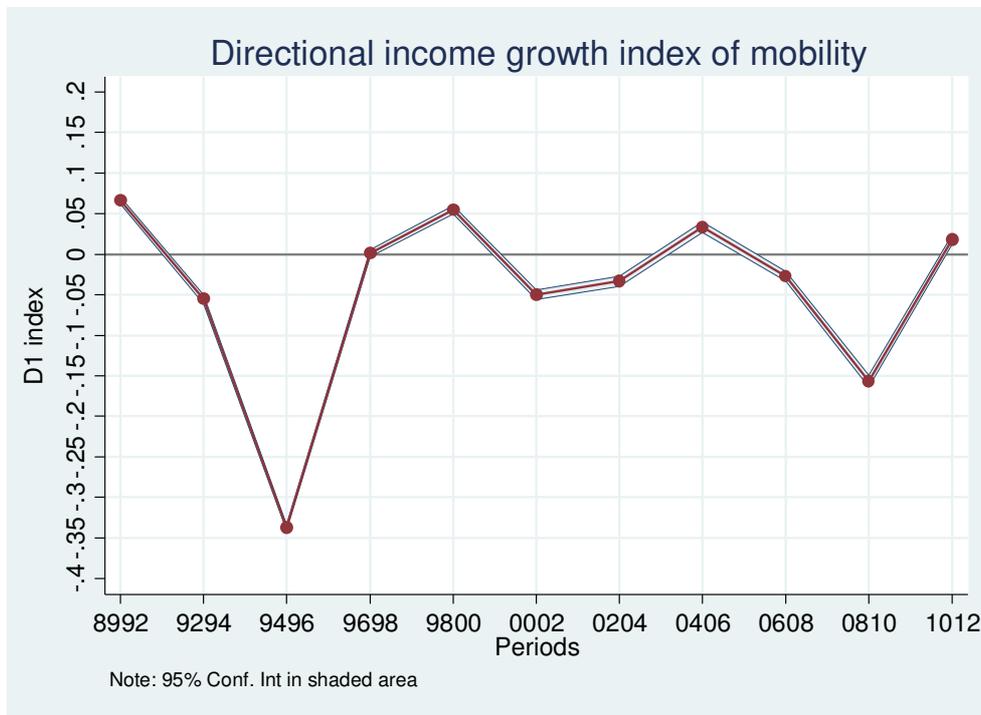
Graphique 1



Nous soutenons que cet article contribue à cette branche émergente de la littérature sur le revenu économique dans la mesure où il rend des résultats empiriques sur les tendances de la mobilité intra-générationnelle à long terme dans un pays en développement. L'article rend compte des bas niveaux de mobilité et de la mobilité vers le bas pendant les deux périodes de récession économique. On peut conclure ainsi que les patrons de mobilité économique observés pendant ces périodes produisent un processus d'égalisation.

Le Mexique se dessine ainsi comme un pays avec des bas niveaux de mobilité. Cette situation bouge dans des périodes de crise économique, où le pays est bien représenté par l'analogie des planchers gluants et les plafonds de verre (voir graphique 2). Ceci nous permet d'observer que les patrons sortis de la construction des panels synthétiques sont utiles pour informer les opinions sur la structure de la croissance et pour l'obtention de valeurs descriptives sur son impact distributif.

Graphique 2



3. Mobilité éducative à travers trois générations

« La patrie périra si les pères sont foulés
aux pieds. Cela est clair. La société, le
monde roulent sur la paternité. »

« Le père Goriot »

Honoré de Balzac

L'idée de la mobilité revendique une expectative intergénérationnelle positive : les enfants sont censés atteindre le maximum de leur capacités malgré l'incertitude de leurs origines. C'est-à-dire, ils sont censés s'en sortir mieux que leurs parents et leurs ancêtres lointains. Ce principe nous amène à la dernière des questions posées au début de cette introduction : à quel point une société est-elle mobile par rapport aux générations précédentes ?

La réponse à cette interrogation a voulu l'attention à deux problèmes : 1) l'accès à des données de longue date qui permettent l'observation des liens entre parents et enfants sur une variable économique importante –ce qui n'est pas évident- et 2) le traitement des problèmes d'endogénéité. Le premier point répond au problème de la disponibilité des données auquel on s'attaque avec l'utilisation d'une enquête mexicaine recueillant de l'information rétrospective de trois générations. Pour le second nous avons dû utiliser une méthode statistique : l'approche de la variable instrumentale.

Éduqués à la Martinière, le plus grand lycée de Lyon, les frères Lumière ont travaillé pour leur père, artiste et homme d'affaires spécialisé en équipe photographique. Leur histoire donne un exemple du fait que les parents ne font pas uniquement un investissement financière ou temporaire dans leurs enfants, mais ils leur transfèrent aussi leur habilité inobservée. Ce transfert tend à produire des estimations biaisées de la mobilité intergénérationnelle avec l'utilisation d'OLS –la technique statistique la plus utilisée dans la plupart de la littérature de ce domaine. L'endogénéité de la scolarité des parents a été adressée par l'utilisation d'une variable instrumentale double, telle qu'elle est décrite dans la figure n°1. Une expérience naturelle à partir d'une guerre régionale ayant lieu au début du XXe siècle (voir carte 1) a été utilisée pour instrumenter les années de scolarité de la génération des « grands-parents » tandis que les indicateurs du marché du travail, un instrument assez connu dans la littérature de l'économie du travail, ont été utilisés pour instrumenter l'éducation de la génération des « parents

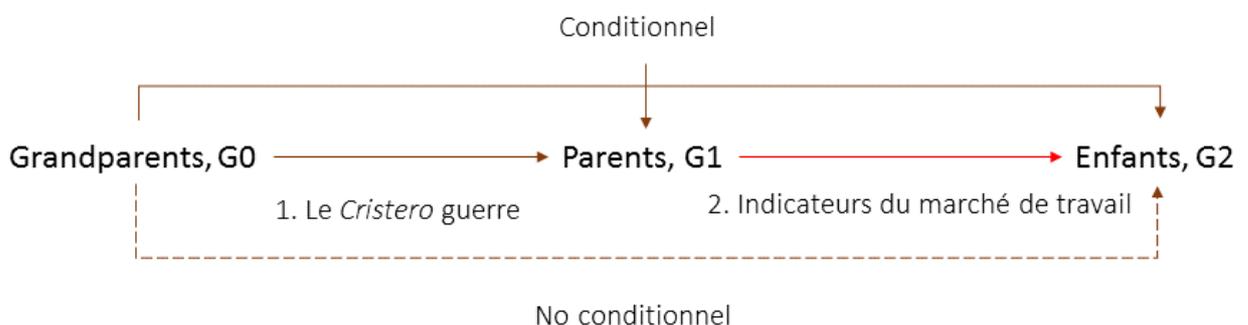


Meyer (1973a)

». Cet encadrement unifié nous a permis d'analyser la transmission intergénérationnel du capital humain à travers trois générations, et notamment de comparer les effets conditionnel et non-conditionnel de l'éducation des grands-parents envers celle de leurs petits enfants. Une fois équipé d'un ensemble de stratégies d'identification pour chacune des deux premières générations, l'article examine la transmission intergénérationnelle du capital humain sur trois générations.

Plus spécifiquement, le papier étudie l'effet de l'éducation grand-parentale sur l'éducation de leurs petits-enfants, conditionnel à l'éducation des parents dans le cadre d'une approche variable instrumentale. L'analyse montre d'abord que l'éducation parentale est le milieu familial le plus important dans les années d'éducation des enfants, bien qu'elle semble jouer un rôle moindre dans les générations successives.

Diagramme 1: stratégie d'identification



L'article permet aussi d'observer que l'éducation des parents a un effet significatif sur l'éducation de leurs enfants. Il montre également que l'estimation IV est plus grande que l'estimation OLS, ce qui implique que le fait de prendre en compte l'endogénéité dévoile une importance majeure du milieu familial (moins de mobilité éducative de ce qui était traditionnellement considéré). Ceci est vrai soit pour le lien entre les grands-parents et les parents que pour celui d'entre les parents et les enfants (voir table 2).

Mobilité éducative à travers trois générations, Mexico

Dep. Var.:	Education petits-enfants	
	OLS	IV 1
Reduced form		
Education parentale	0.353***	0.418***
	-0.0369	-0.0512
Education grand-parentale	0.0239	-0.015
	-0.0357	-0.159
Sex, G2, G1	Yes	Yes
Birthyear, G1, G2	Yes	Yes
Wealth, G0, G1	Yes	Yes
Number of children, G0, G1	Yes	Yes
State fixed eff.	Yes	Yes

Note: Voir Table 5. Chapitre III

Nous avons ainsi découvert que l'éducation parentale est le trait le plus important pendant les années d'éducation des enfants, mais pas autant dans les générations successives (ce qui implique plus de mobilité toutes les deux générations). Si l'héritage éducatif des grands-parents est conditionnel de l'éducation parentale, les résultats permettent aussi de d'observer qu'il ne l'est plus pour la seconde génération.

Remarques finales

Les chemins de nos vies sont dans un mouvement perpétuel : par monts et par vaux comme dans l'épigramme au début de cette introduction. Dans une société démocratique, il semble utile de savoir si notre appartenance sociale nous permet de nous en sortir malgré nos origines, ou si au contraire, notre destin est voué à l'échec à cause d'elles.

Si la bonne chance est prérogative d'un seul groupe qui peut constamment « monter et s'élever » tandis que le manque de mobilité vers le haut appartient uniquement à ceux qui sont systématiquement en train de tomber à cause de leur entourage familial ou leur histoire individuelle, alors on se trouve bien devant « le défi définissant de notre temps » comme il a été déclaré aux États-Unis. Nous pourrions également essayer de comprendre comment, à partir d'une perspective de politiques publiques, les tendances de mobilité à long terme justifient la création d'une commission pour la mobilité sociale ou d'autres politiques publiques comme celle créée au Royaume Uni. Il nous faut en effet, des résultats empiriques pour répondre à ces délibérations, très souvent absentes des sociétés modernes. Cette thèse est peut-être une invitation osée à mettre en marche cette conversation.

À Paris, janvier 2018.

Chapter 1: On synthetic income panels¹¹

*« C'est de la physionomie des années
que se compose la figure des siècles. »*

« Les Misérables »
Victor Hugo (1862)¹²

¹¹ Based on a co-authored paper with François Bourguignon.

¹² Tome I – Fantine , Chapitre II : Double quatuor »

Abstract ¹³

In many developing countries, the increasing public interest for economic inequality and mobility runs into the scarce availability of longitudinal data. Synthetic panels based on matching individuals with the same time-invariant characteristics in consecutive cross-sections have been proposed as a substitute to such data - see Dang and Lanjouw (2014). The present paper improves on the calibration methodology of such synthetic panels in several directions: a) it abstracts from (log) normality assumptions; b) it improves on the estimation of auto-correlation of unobserved determinants of (log) earnings; c) it considers the whole mobility matrix rather than mobility in and out of poverty. We exploit the cross-sectional dimension of a national-representative Mexican panel survey to evaluate the validity of this approach. The income mobility matrix in the synthetic panel calibrated on the former turns out to be very close to the observed matrix in the latter. The chapter includes a practical summary leading to the construction of a synthetic panel to facilitate its implementation by interested practitioners.

¹³ We gratefully acknowledge comments on previous versions from Andrew Clark (PSE-LSE), Hai Ann Dang (World Bank), Rodolfo de la Torre (CEEY), Dean Jolliffe (World Bank), Marc Gurgand (PSE), Thierry Magnac (TSE), Jaime Montaña (PSE), Christophe Muller (AMSE), Umar Serajuddin (World Bank), Elena Stancanelli (PSE- CNRS) and attendants to internal seminars at the Paris School of Economics (WIP and SIMA) and NEUDC 2015 at Brown University (USA).

1. Introduction

The issue of income mobility is inextricably linked to the measurement of inequality and poverty. Incomes of persons A and B may be very different at both times t and t' . But can this difference be truly considered as inequality if persons A and B switch income level between t and t' ? Likewise, should a person above the poverty line in period 1 be considered as non-poor if it is below the line in period 2? Clearly, this depends on how much above the line she was in the first period and how much below in the second. Measuring inequality and poverty in a society may thus be misleading if one uses only a snapshot of income disparities at a point of time instead of individual income sequences.

Longitudinal or panel data that would permit analysing the dynamics of individual incomes are seldom available in developing countries. Yet, snapshots of the distribution of income are increasingly available under the form of repeated cross-sectional household surveys. The idea thus came out to construct *synthetic* panel data based on these data by appropriately matching individuals in the two cross-sections with the same time invariant characteristics but with the appropriate age difference in two consecutive cross-sections. Such synthetic panels potentially offer advantages over real ones. They may cover a larger number of periods and they suffer much less from typical panel data problems like attrition, non-response and measurement errors (Verbeek, 2007). But, of course, their reliability depends on the quality of the matching method.

This type of approach has received much attention recently (Dang et al., 2014; Cruces et al., 2011, Ferreira et al., 2011,). These papers are based on the methodology designed in Dang et al. (2014) - which was circulated as a working paper in 2011.¹⁴ This methodology permits to obtain an upper and a lower bound of mobility, in and out of poverty, by matching individuals with identical time invariant characteristics and assuming that that part of their (log) income that is independent of these characteristics is normally distributed across the two periods with a correlation coefficient equal respectively to 0 or 1. In an unpublished paper, Dang and Lanjouw (2013) refined this method by providing a point estimate of income mobility based on a correlation coefficient estimated through pseudo-panel techniques applied to the two cross-sections.

¹⁴ Bourguignon et al. (2004) was an earlier attempt in the same direction.

Unsurprisingly, the properties of such synthetic panels are strongly dependent on the assumptions being made and the way key parameters are estimated. In the methodology designed by Dang and Lanjouw (op. cit.), for instance, the bi-normality assumption made on the joint distribution of initial and final incomes – conditionally on time invariant characteristics - and the way the associated coefficient of correlation is estimated strongly influence the synthetic income mobility matrix. As this coefficient is bound to have a strong impact on the extent of estimated mobility, the estimation method and its precision clearly are of first importance.

The purpose of the present paper is to analyze in some depth the properties of synthetic panels and their precision in reproducing income dynamics. This is done first by generalizing the original estimation and simulation methodology in Dang et al. (2014) and Dang and Lanjouw (2013) so as to avoid the most arbitrary assumptions found there and then by exploring the 'confidence set' of mobility matrices generated by the confidence intervals on key parameters as the correlation coefficient mentioned above.

Departure from previous work includes explicitly involving the calibration of synthetic panels within the realm of AR(1) processes, conditional on time invariant, a more robust estimation of the associated auto-regressive coefficient, and going beyond the normality assumption. Also, the focus of the exercise is the whole income mobility matrix, rather than the share of population moving in and out of poverty.

The validity and the precision of the synthetic panels constructed with that method are tested by comparing the synthetic mobility matrix obtained on the basis of the initial and terminal cross-sections of a Mexican panel household survey between 2002 and 2005 and the observed actual matrix in that survey. Although no formal test is possible on a single observation, the results are encouraging as the synthetic joint distribution of initial and final incomes is rather close to the joint distribution in the authentic panel. However, simulations performed by allowing the AR(1) coefficient to vary within its estimation confidence interval show a rather high variability of the synthetic mobility matrix and associated income mobility measures. This should plead in favour of extreme caution in analyzing income mobility based on synthetic panel techniques.

There is also a connection with the growing literature of partial identification literature.¹⁵ This paper addresses a problem similar to the “classic” ecological inference (EI) problem where individual-level and aggregate data are combined to predict an individual-level outcome of interest (the outcomes of interests are observed only at aggregated level, while the conditional covariates are observed at the individual level). However, EI literature explicitly frames this lack

¹⁵ We thank Thierry Magnac for raising this point.

of longitudinal data in the program evaluation framework - the problem then becomes one of identifying the mean counterfactual outcome in a treatment effect model (Cross & Maski, 2002). Another association with this literature arises by the aim of obtaining bounds on these counterfactual outcomes. Fan, Sherman & Shum (2016) for instance obtained these bounds as functionals of quintile functions of generated variables. In our approach, these bounds are generated by the confidence set of an autoregressive parameter of first order. A closer connection with this literature is still to be made but it is reassuring that the copula literature, like in Fan, Sherman & Shum (2016) and Foster and Rothbaum (2015), would be an avenue of future research.

The paper is structured as follows. Section two and three describe methodology used in this paper to construct synthetic panels based on AR(1) conditional income processes, comparing it to previous work in this area. Section four present the data used to test this methodology. Section five presents the central results of the whole procedure and compare the central estimate of the synthetic income mobility matrix and various mobility measures to those obtained from the authentic panel. In section six, some sensitivity analysis is performed on various aspects of the methodology so as to test its robustness. The last section concludes.

2. The construction of a synthetic panel

2.1 Matching techniques and the synthetic panel approach

Consider two rounds of independent cross-section data at time t and t' . If $y_{i(\tau)\tau}$ denotes the (log) income in period τ of an individual i observed in period τ ¹⁶, what is actually observed is $y_{i(t)t}$ and $y_{i(t')t'}$. Constructing a synthetic panel is somehow 'inventing' a plausible value for $y_{i(t)t'}$.

A first step is to account for the way in which time invariant individual attributes, z , may be remunerated in a different way in periods τ and τ' . To do so, an income model defined exclusively on time invariant attributes observed in the two cross-sections is estimated with OLS:

$$y_{i(\tau)\tau} = z_{i(\tau)}\beta_{\tau} + \varepsilon_{i(\tau)\tau} \quad \tau = t, t' \quad (1)$$

where β_{τ} represents the vector of 'returns' to fixed individual attributes, z , and $\varepsilon_{i(\tau)}$ denotes a 'residual' that stands for the effect of time variant individual characteristics and other unobserved time invariant attributes. Fixed attributes may include year of birth, region of birth, education, parent's education, etc. More on this in a subsequent section. For now it is just enough to stress

¹⁶ This notation is borrowed from Moffit (1993).

that it would not make sense to introduce time-varying characteristics in the income model (1), even though some of them may be observed as their value in the terminal (or initial) year are essentially unknown.

Denote $\hat{\beta}_\tau$ and $\hat{\varepsilon}_{i(\tau)\tau}$ and $\hat{\sigma}_\tau^2$ at time $\tau = t, t'$ respectively the vector of estimated returns, the corresponding residuals and their variance as obtained from OLS:

$$y_{i(\tau)\tau} = z_{i(\tau)}\hat{\beta}_\tau + \hat{\varepsilon}_{i(\tau)\tau} \quad \tau = t, t' \quad (2)$$

Consider now an individual i observed in the first period, t . Part of the dynamics of her income between t and t' stems from the change in the returns of fixed attributes, or $z_{i(t)}(\hat{\beta}_{t'} - \hat{\beta}_t)$ and can be inferred from OLS estimates. The remaining is the change in the residual term: $\hat{\varepsilon}_{i(t)t'} - \hat{\varepsilon}_{i(t)t}$. The problem is that the first term in this difference is not observed. The issue in constructing a synthetic panel thus is the way of finding a plausible value for it. Let $\tilde{\varepsilon}_{i(t)t'}$ be that 'virtual' residual. At this stage, the only information available about it is that it has zero mean and variance $\hat{\sigma}_{t'}^2$ across the whole population.

2.2 Previous approaches

In their first attempt at constructing synthetic panels, Dang et al. (2011, 2014) simply assumes the virtual residual at time t' to be normally distributed conditional on the residual $\hat{\varepsilon}_{i(t)t}$ at time t with an arbitrary correlation coefficient, ρ . Assuming that the initial residual is also normally distributed, then the synthetic income mobility process can be described by the joint cdf:

$$\Pr(y_{i(t)t} \leq Y; y_{i(t)t'} \leq Y') = N \left[\frac{Y - z_{i(t)}\hat{\beta}_t}{\hat{\sigma}_t}, \frac{Y' - z_{i(t)}\hat{\beta}_{t'}}{\hat{\sigma}_{t'}}; \rho \right]$$

where $N(\cdot)$ is the cumulative probability function of a bi-normal distribution with correlation coefficient ρ .

In their initial paper, Dang et al. (2011,2014) considered the two extreme cases of $\rho = 0$ and $\rho = 1$, so as to obtain an upper and a lower limit on mobility. Applying this approach to the probability of getting in or out of poverty in Peru and in Chile, the corresponding ranges proved to be rather broad. In other words, the change $(\hat{\beta}_{t'} - \hat{\beta}_t)$ in the returns to fixed attributes was playing a limited role in explaining income mobility.

In a later, unpublished paper, Dang & Lanjouw (2013) generalized the preceding approach by considering a point estimate rather than a range for the correlation between the initial and

terminal residuals. Their method consists of approximating the correlation between the (log) individual incomes in the two periods t and t' , ρ^y , by the correlation between the mean incomes of birth cohorts in the two samples, ρ^{yc} , as in pseudo-panel analysis. Then, the covariance between (log) incomes is approximated by $cov_y = \rho^{yc} \cdot \sigma_{y_t}^2 \sigma_{y_{t'}}^2$, where $\sigma_{y_\tau}^2$ is the variance of (log) income at time τ . Then it comes from the two equations in (2), if both applied to the same sample of individuals, that:

$$cov_y = \beta_t' Var(z) \beta_{t'} + cov_\varepsilon \quad (3)$$

where $Var(z)$ is the variance-covariance matrix of the fixed characteristics, z , and cov_ε the covariance between the residual terms. With an approximation of cov_y , and estimates of β_t and $\beta_{t'}$, as well as of the variance of the residual terms, it is then possible to get an approximation of the correlation coefficient between these residuals.

This appears as a handy way of getting an estimate of the correlation coefficients between initial and terminal cross-sections by relying on their pseudo-panel dimension. Yet, it will be seen below that this method is not fully correct.

2.3. Synthetic panels with AR(1) residuals

The methodology proposed in this paper assumes explicitly that the residual in the income model (2) for a given individual $i(t)$ follows an first order auto-regressive process, AR(1), between the initial and the final period. If it were observed at the two time periods t and t' the income of an individual would thus obey the following dynamics:

$$y_{i(t)t'} = z_{i(t)} \beta_{t'} + \varepsilon_{i(t)t'} \quad \text{with} \quad \varepsilon_{i(t)t'} = \rho \varepsilon_{i(t)t} + u_{i(t)t'} \quad (4)$$

where the 'innovation terms', $u_{i(t)t}$, are assumed to be orthogonal to $\varepsilon_{i(t)t}$ and i.i.d. with zero mean and variance σ_u^2 .

The autoregressive nature of the residual of the basic income model can be justified in different ways. The time varying income determinants may be AR(1), the returns to the unobserved time invariant characteristics may themselves follow an autoregressive process of first order or, finally, stochastic income shocks may be characterized by this kind of linear decay. It is reasonably assumed that the auto-regressive coefficient, ρ , is such that: $0 < \rho < 1$.

Consider now the construction of the synthetic panel when the parameters of the AR(1) model in equation (4) are all known. The issue of how to estimate these parameters will be tackled in the

next section. As described in the previous section, income is regressed on time invariant attributes in the two periods as in (2). Equation (4) can then be used to figure out what the residual of the income model, $\tilde{\varepsilon}_{i(t)t'}$, could be in time t' for observation $i(t)$:

$$\tilde{\varepsilon}_{i(t)t'} = \rho \hat{\varepsilon}_{i(t)t} + \tilde{u}_{i(t)t'}$$

where $\tilde{u}_{i(t)t'}$ has to be drawn randomly within the distribution of the innovation term, of which cdf will be denoted $G_{t'}^u$. If estimations or approximations of ρ and the distribution $G_{t'}^u$ are available, the virtual income of individual $i(t)$ in period t' can be simulated as:

$$\tilde{y}_{i(t)t'} = z_{i(t)} \hat{\beta}_{t'} + \rho \hat{\varepsilon}_{i(t)t} + G_{t'}^{u^{-1}}(p_{i(t)}) \quad (5)$$

where $p_{i(t)}$ are independent draws within a (0,1) uniform distribution. After replacing $\hat{\varepsilon}_{i(t)t}$ by its expression in (2), this is equivalent to:

$$\tilde{y}_{i(t)t'} = \rho y_{i(t)t} + z_{i(t)} (\hat{\beta}_{t'} - \rho \hat{\beta}_t) + G_{t'}^{u^{-1}}(p_{i(t)}) \quad (6)$$

Thus the virtual income in period t' of individual $i(t)$ observed in period t depends on his/her observed income in period t , $y_{i(t)t}$, his/her observed fixed attributes, $z_{i(t)}$, and a random term drawn in the distribution $G_{t'}^u$. Because those virtual incomes are drawn randomly for each individual observed in period t , the income mobility measures derived from this exercises necessarily depends on the set of drawings. Various simulations will have to be performed to compute the expected value of these measures - and, actually, their distribution.

The two unknowns, ρ and $G_{t'}^u(\cdot)$ must be approximated or 'calibrated' in such a way that the distribution of the virtual period t' income, $\tilde{y}_{i(t)t'}$, coincides with the distribution of $y_{i(t)t'}$ observed in the period t' cross-section. We first focus on the estimation of the auto-regressive coefficient, ρ , through pseudo-panel techniques.

2.3.1 Estimating the autocorrelation coefficients

The estimation of pseudo-panel models using repeated cross-sections has been analysed in detail since the pioneering papers by Deaton (1985) and Browning et al. (1985) - see in particular Moffit (1993), McKenzie (2004) and Verbeek (2007). We very much follow the methodology proposed by the latter when estimating dynamic linear models on repeated cross-sections. Note, however, that in comparison with this literature, a specificity of the present methodology is to rely on only two rather a substantial number of cross-sections.

With repeated cross-sections, the estimation of an AR(1) process at the individual level can be done by aggregating individual observations into *groups* defined by some common time invariant characteristic: year of birth - as in Dang and Lanjouw - but possibly regions of birth, school achievement, gender, etc... The important assumption in defining these groups of observations is that the AR(1) coefficient should reasonably be identical for all of them.

If G groups g have been defined overall, one could think of estimating the auto-regressive correlation coefficient ρ by running OLS on the group means of residuals:

$$\bar{\varepsilon}_{gt'} = \rho \bar{\varepsilon}_{gt} + \eta_{gt'} \quad (7)$$

where $\bar{\varepsilon}_{g\tau}$ is the mean OLS residual of (log) income for individuals belonging to group g at time τ , and $\eta_{gt'}$ is an error term orthogonal to $\bar{\varepsilon}_{gt}$ with variance σ_u^2/n_{gt} where n_{gt} is the number of observations in group g . The estimation of (7) raises a major difficulty, however. It is that the group means of residuals of OLS regressions are asymptotically equal to zero at both dates t and t' so that (6) is essentially indeterminate.

There are two solutions to this indeterminacy. The first one is to work with second rather than first moments. Taking variances on both sides of the AR(1) equation:

$$\varepsilon_{i(t)t'} = \rho \varepsilon_{i(t)t} + u_{i(t)t'}$$

for each group g leads to:

$$\sigma_{\varepsilon_{gt'}}^2 = \rho^2 \cdot \sigma_{\varepsilon_{gt}}^2 + \sigma_{u_{gt'}}^2$$

where $\sigma_{\varepsilon_{g\tau}}^2$ is the variance of the OLS residuals within group g in the cross-section τ and $\sigma_{u_{gt'}}^2$ the unknown variance of the innovation term in group g . As mentioned above, the expected value of that variance within a group g mean is σ_u^2/n_{gt} . ρ can thus be estimated through non-linear GLS across groups g according to:

$$\sigma_{\varepsilon_{gt'}}^2 = \rho^2 \cdot \sigma_{\varepsilon_{gt}}^2 + \sigma_u^2/n_{gt} + \omega_{ut'} \quad (8)$$

where $\omega_{ut'}$ stands for the deviation between the group variance of the innovation term and its expected value and can thus be assumed to be zero mean, independently distributed and with a variance inversely proportional to n_{gt} .

The second approach to the estimation of ρ is to estimate the full dynamic equation in (log income) given by (3) across groups g . Using the same steps as those that led to (5), this equation can be written as:

$$\bar{y}_{gt'} = \rho \bar{y}_{gt} + \bar{z}_{gt} \gamma + \bar{u}_{gt'} \quad (9)$$

where it has been reasonably assumed that \bar{z}_{gt} and $\bar{z}_{gt'}$ were close to each other so that the coefficient γ actually stands for $\beta_{t'} - \rho \beta_t$. In any case, ρ can be consistently estimated through GLS applied to (8), keeping in mind that the residual term $\bar{u}_{gt'}$ is heteroskedastic with variance σ_u^2/n_{gt} .

Note that this approach departs from Dang and Lanjouw (2013). As seen above they derive the covariance of residuals from the covariance of (log) incomes through (3). The latter is estimated through OLS applied to:

$$\bar{y}_{gt'} = \delta \bar{y}_{gt} + a + \theta_{gt'} \quad (10)$$

and $cov_y = \hat{\delta} \sigma_{yt} \sigma_{yt'}$. As can be seen from (9), however, a term in \bar{z}_{gt} is missing on the RHS of (10), which means that the residual term $\theta_{gt'}$ is not independent of the regressor \bar{y}_{gt} . It follows that $\hat{\delta}$ is biased, the same being true of the covariance of (log) incomes.

The two approaches proposed above to get an unbiased estimate of the auto-regressive coefficient ρ can be combined by estimating (8) and (9) simultaneously. As this is essentially adding information, moving from G to 2G observations, this joint estimation should yield more robust estimators.

Note finally, that it is possible to obtain additional degrees of freedom in the construction of the synthetic panel by assuming that the auto-regressive coefficient differs across several g-groupings. For instance, there may be good reasons to expect that ρ declines with age. Of course, this would require that individuals are described by enough fixed attributes and that there are enough observations in the whole sample so that a large number of 'groups' with a minimum number of observations can be defined.

2.3.2. Calibrating the distribution of the innovation terms

It turns out that once an estimate of the autoregressive coefficient ρ is available, the distribution $G_{t'}^U(\cdot)$ of the innovation terms, $u_{i(t)t'}$, can be recovered from the data.

The AR(1) specification implies :

$$\tilde{\varepsilon}_{i(t)t'} = \hat{\rho}\hat{\varepsilon}_{i(t)t} + \tilde{u}_{i(t)t}$$

where $\hat{\rho}$ is the pseudo-panel estimator obtained in (8) or (9), the $\tilde{\varepsilon}_{i(t)t'}$ are the virtual residuals and the $\tilde{u}_{i(t)t'}$ are the randomly generated innovation terms. The problem is to find the distribution $G_{t'}^U(\cdot)$ of the innovation terms such that the distribution of the virtual residuals be the same as the distribution, $F_{t'}$, of the observed OLS residuals $\hat{\varepsilon}_{i(t)t'}$ obtained with the income regression (1). With a continuous time formulation, this distribution must satisfy the following functional equation:

$$F_{t'}(X) = \int_{-\infty}^{+\infty} F_t[(X - u)/\hat{\rho}] \cdot g_t^u(u) du \quad (11)$$

where F_t is the cdf of the observed residuals $\hat{\varepsilon}_{i(\tau)\tau}$ and g_t^u the density of the innovation term. Hence, knowing the distribution of the residuals in the two periods and the autocorrelation coefficient it is logically possible to recover the distribution of the innovation terms that make the distribution of the synthetic panels identical to the observed distributions at the two points of time.

Yet the functional equation (11) is not simple. Known as the Fredholm equation, it can be solved through numerical algorithms, which are rather intricate. A simpler parametric method was chosen based on the assumption that the distribution g_t^u is a mixture of normal variables, whose parameters are to be determined so as to minimize the square of the difference between the two sides of (11). It turned out to give rather satisfactory results but this is only an approximation, which justifies describing that methodology as a 'calibration' rather than an 'estimation'. The detail of the calibration of the distribution $G_{t'}^u$ with a mixture of two normal distributions is given in the appendix to this paper.

2.4 Practical summary

Practically, the whole procedure leading to the construction of a synthetic panel under the assumption that the income residuals follow an AR(1) process and with the constraint that the initial and terminal distribution of income match the corresponding cross-sections may be summarized as follows.

1. Income model
 - a. Define set of time-invariant attributes, z , to be used in the (log) income model.

- b. For each period, run OLS on (log) income with z as regressors and store both vectors of residuals, $\hat{\varepsilon}_{i(t)t}$ and $\hat{\varepsilon}_{i(t)t'}$, and the returns to time invariant attributes, $\hat{\beta}_t$ and $\hat{\beta}_{t'}$.
2. Autoregressive parameter
 - a. Define a number of groups g based on time invariant attributes with enough observations for group means to be precise enough.
 - b. Average the (log) income and the time invariant characteristics for each group and compute the variance of the OLS residuals of the models estimated in 1.a).
 - c. Estimate the residual auto-correlation coefficient $\hat{\rho}$ through the joint pseudo-panel equations (8) and (9)
3. Distribution of innovation terms. Calibrate the set of parameters, θ , of the distribution of the innovation term supposed to be a mixture of two normal variables, as described in Appendix 1.
4. Synthetic panel. For each observation in the initial cross-section, t , draw randomly a value in the preceding distribution and compute the virtual income in period t' using (6). Evaluate income mobility matrices and mobility measures based on that drawing.
5. Repeat 4 to obtain the expected value and distribution of the mobility matrices and measures.

3. Construction and validation and of a synthetic panel in Mexico: 2002-2005

The procedure detailed above was applied *forwardly* to estimate the synthetic income in 2005 for the households sampled in 2002. Synthetic panel can be obtained either at household or individual level, although the former bring about access to a larger set of time-invariant attributes. We focused on households as observational units, as these tend to offer a wider perspective of family wellbeing and gave access to a larger set of time-invariant attributes. The results in terms of income mobility were then compared to the actual income mobility observed in the panel.

3.1 Data

The data corresponds to the *Mexican Family Life Survey* (MxFLS onwards). It is based on a sample of households that is representative at national, regional and urban-rural level. It was fielded by the National Institute of Statistics (INEGI by its acronym in Spanish) but was coded and critically assessed by its study directors. The MxFLS is a multi-thematic and longitudinal database, which gathers information on socioeconomic indicators, migration, demographics and health indicators on the Mexican population. This panel survey is expected to track the Mexican population throughout a period of at least ten years. ¹⁷

The first and second waves, conducted in 2002 and 2005 respectively, rely on a baseline sample size of 8,400 households and collected data on the socio-demographic characteristics of each household member, individual occupation and earnings, household income and expenditures, and assets ownership. The sample in 2005 was expanded to compensate for attrition, which amounted to 10% of the original sample in the second wave. Due confidentiality data on the simple design (primary/secondary sampling units) are not public (see MXFLS website).

3.2 Income estimates

Household income data follow the official definition for computing income poverty in Mexico. They include both monetary and non-monetary resources. The former comprise receipts from employment, own businesses, rents from assets and public and private transfers. Non-monetary income includes in-kind gifts received and the value of services provided within the household, such as the rental value of owner occupied dwelling or self-consumption.¹⁸ Total income is then divided by the household size in order to obtain per capita income and is deflated by the Consumer Price Index (August 2005=100) to make 2002 and 2005 data comparable.

In order to focus on the steadiest set of households and to facilitate the use pseudo-panel instruments, the sample was restricted to households whose head was aged between 25 and 62 years in 2002 which is the baseline (28-65 years old in 2005). Finally, to overcome possible adverse effects due to atypical observations two percent of the sample in the two ends of the income distribution and households with missing income were discarded.

3.3 Time invariant attributes and the income models

¹⁷ Two more waves were conducted in 2009 and 2012.

¹⁸ In 2008 this definition changed to introduce economies of scale and adult equivalent units for implementing a multidimensional poverty approach. See CONEVAL (2013). The official measurement of poverty uses a cross section survey (ENIGH).

This section describes the income models being estimated in the initial and terminal waves. It first introduces the criteria for the selection of time-invariant attributes. Estimation of the returns to these attributes in 2002 and 2005 are discussed in a second stage.

Time invariant attributes

Time-invariant attributes could stem from multiple criteria and sources. Individual deterministic attributes like the year of birth, sex, educational achievement and ethnicity are the most natural set of characteristics. Depending on the issue of interest, the time horizon and country studied other variables can be obtained from the household characteristics like the household size which could be introduced in terms of its demographic composition. Consider also the location, the population density in the area of residence (urban or rural localities), and the state or regional fixed effects depending on the territorial representativeness of the survey. Needless to say, all variables ought to strictly follow the same definition and construction in all periods.

It is reasonably questioning how realistic is the assumption of ‘time invariance’ of these attributes. In this respect, it helps to bear in mind that the longer the period between the cross-sections, the more severe ought to be the time invariability criterion. The long-standing feature of these attributes is perhaps more important than the number of variables when conceiving the specification of the income model. Many variables are not strictly time-invariant and should easily be discarded like current employment status and occupation but this has to be considered on the particular case of the country under analysis. Other variables could be considered time-invariant under reasonable circumstances, like marital status and highly-valuable wealth possessions (dwelling or physical assets) during periods of economic stability.

Estimating the income model and residuals

We followed a grading approach by the use of alternative model specifications to assess the sensibility of variables selection. All of them stuck to a strict degree of time invariability. The first specification uses the head’s individual characteristics like gender, formal years of schooling, birth year and the household composition by age groups. It also includes variables for the size of the locality (urban/rural), marital status and regions.¹⁹ An alternative specification includes long-lasting productive assets such as real estate and farming assets (land for to agricultural production and cattle), and household dwelling as well as the possession of other dwellings other

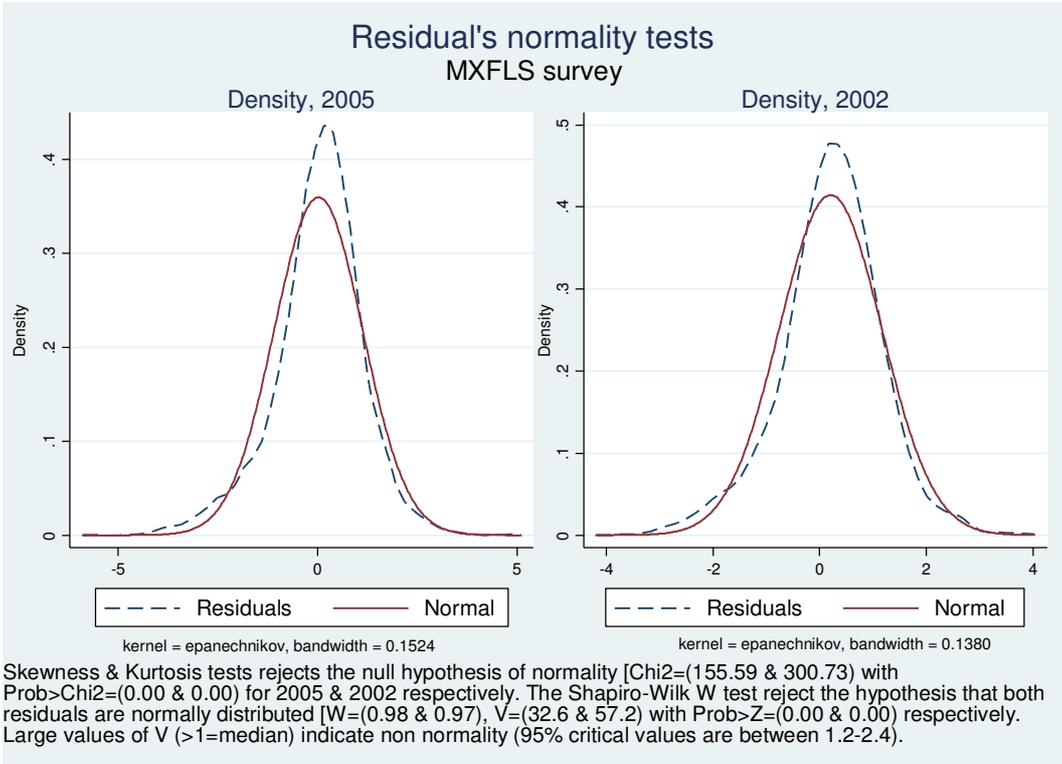
¹⁹ Of course, the problem here is how frequent migration may be but considering this short period analysis its effect is expected to be low. According to census data the internal migration rate in México, from 2000 to 2005, was around 2% (Chavez & Wanner, 2012).

than the one in use. This is our most preferred model. See **Annex 1** for descriptive statistics and OLS estimates.

It is important to mention some restrictions encountered to enrich the income model. The survey collected data on ethnicity, religious conviction and household head literacy. Also contains data on historic or retrospective data like birth city size; the year of marriage; household’s head’s parents’ education, place of birth and migration records. Those attributes, like many others, were gathered by the survey but finally not included in the income model due to: 1) high prevalence of missing data, 2) lack of statistical significance, or 3) extremely low frequency.

Although the proposed method does not assume normality for the residuals, neither for the initial nor for the final year, we tested this assumption for these models. For illustrative purposes the **Graph 1** shows the kernel distribution of (log) income residuals for the last model specification, in both years, and compares it with the normal distribution. These and other tests (Skewness and Kurtosis tests and Shapiro-Wilk normality tests -see note on the referred graph) confirm that the normality assumption in the distribution of residuals is strongly rejected.

Graph 1. Residuals’ normality test for 2002 and 2005



4. The autocorrelation coefficient and the calibration parameters

Estimating the autocorrelation coefficient is a central, and a sensitive task in this procedure. This section aims at obtaining an autocorrelation coefficient with the two waves of cross-sectional data at hand. Firstly, observations were grouped by some common characteristics. In our case, thirty-five clusters were obtained by the interaction of seven birth-year cohorts, of 6 years interval each, and five groups of education: incomplete primary education, complete primary but incomplete secondary education, complete secondary education but incomplete high school and complete high school or more.²⁰

Table 1 shows separate estimates from equations 8 and 9 using. Results have the expected signs and order of magnitude. The genuine coefficient here served as a benchmark and appears to be around 0.25. Though the genuine parameter is close to these set of estimates it is reassuring that the combined use of these two approaches, through a non-linear equation system, delivers a more accurate estimate whose confidence intervals are fully consistent with those from the actual panel.²¹

Table 1. Rho estimates by model and method, 2002-2005

Models	Pseudo panel			Genuine panel
	Equation 8	Equation 9	Eq. system (8, 9)	With microdata (residuals)
	Non linear (1)	Linear (2)	Non linear (3)	
Model 1	0.292* (-0.05-0.64)	0.132 (-0.14-0.40)	0.254** (0.04-0.47)	0.257*** (0.235 - 0.280)
Model 2	0.176 (-0.82-1.17)	0.158 (-0.1-0.42)	0.299*** (0.15-0.45)	0.226*** (0.203 - 0.249)

²⁰ Other studies working with pseudo panel methods use age interactions with alternative characteristics like manual or non-manual worker (Browning et.al 1985), regions (Propper, et. al, 2001), sex (Cuesta, et. al 2007), or education levels (Blundell et. al, 1998). Proper, Rees and Green (2001) use cells of around 80 observations whereas Alessie, Devereux and Weber (1997) use more than one thousand observations. Antman & Mackenzie (2007, 2007b) used 100 observations as a reference. In our case the vast majority of the groups possess no less than one hundred observations.

²¹ Similar results are obtained with twenty-eight clusters by the use of four, instead of five, educational groups.

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 95% Conf. Interval in parentheses. GLS estimates controlling for time invariant variables. Each estimate represents the coefficient from a different regression.

The rho estimate and its corresponding 95% confidence interval enabled us to determine the set of calibration parameters, $(\hat{\theta}|\rho) = \{\rho, (p_1, \mu_1, \sigma_1), (p_2, \mu_2, \sigma_2)\}$, from the empirical basis of two normal variables. We followed two regimes. The first regime employs the point estimate of rho. The second is based on 100 different rhos, with the corresponding set of calibration parameters for each. In this case, rho is randomly obtained from a normal distribution within its 95% confidence interval. This means that the mean of this random drawings corresponds to the point estimate, but some of them might deviate. **Table 2** shows the descriptive statistics of the resulting parameters for each model. These parameters characterize the distribution of the innovation terms to compute the expected value of mobility measures and their distribution as described next.

Table 2. Innovation terms' calibration parameters by regime and model

	Regime 1	Regime 2			
	Point estimate	Mean	Std. Dev.	Min	Max
Model 1					
ϑ_1	0.01	0.00	0.02	-0.10	0.04
ϑ_1	1.16	1.13	0.11	0.78	1.78
P_1	0.56	0.51	0.03	0.35	0.61
ϑ_2	0.01	0.00	0.01	-0.09	0.04
ϑ_2	1.08	1.10	0.10	0.80	1.26
Model 2					
ϑ_1	0.01	0.00	0.01	-0.03	0.01
ϑ_1	1.18	1.10	0.09	0.80	1.27
P_1	0.53	0.51	0.03	0.38	0.57
ϑ_2	0.01	0.00	0.01	-0.04	0.01
ϑ_2	1.03	1.08	0.09	0.91	1.33

Note: The parameters in the second regime stem from 100 optimization processes.

5. Estimation results

This section provides empirical estimates from a household level synthetic panel over a period characterized by positive economic growth in Mexico.²² We first examined the shape of a synthetic distribution for 2005 compared with the genuine income distribution. **Graph 2** shows the kernel density of one hundred simulations to provide a first visual element to assess the shape of the distribution at every income level. This preliminary inspection shows that even a basic model specification is capable of reproducing the shape of the actual income distribution.

Graph 3. Genuine and synthetic income density, 2005

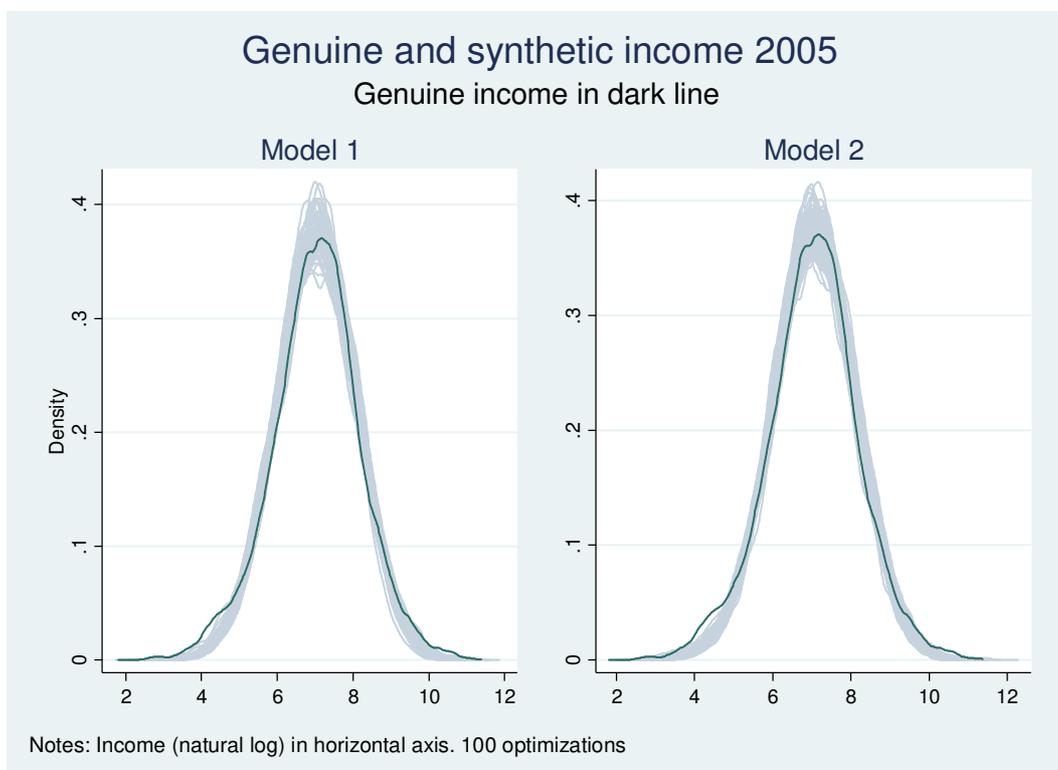


Table 3 shows the resulting synthetic panel 2002-2005 through a transition matrix defined on the income brackets from the quintiles of 2002. This means that the marginal income distribution in the base year is the same in the genuine and the synthetic panels by construction. Each line shows the movement of individuals that belonged to a specific income quantile in the baseline over the same, real income, references in the final year. The table contains three sections. Section 1 and 3 correspond to two different regimes: regime 1 computes the virtual income using the point estimate of ρ and 500 repetitions, whereas regime 2 performs it with 100 random draws of ρ

²² According to World Bank's World Development Indicators figures, the Mexican economy grew by 0.8%, 4.0% and 3.2% from 2002 - 2005 in annual basis.

and the corresponding calibration parameters for each. Section 2 contains the genuine estimates. In most cases, the synthetic figures appear close to the genuine ones and fall within their 95% confidence intervals (reported in parentheses). As expected, working with various values of rho, i.e. regime 2, deliver slightly larger confidence intervals. In general, both the genuine and the synthetic panels suggest a process of upward mobility implied by a reduction in the share of households below the income limits of the first quintile from 2002 to 2005.

Table 3. Transition matrix, 2002-2005.

Confidence intervals in parentheses

- Percentage of population -

		2005 groups (Destination)						
		1	2	3	4	5	Total	
1. Synthetic regime 1	1	7.3 (6.7-7.9)	6.3 (5.7-6.9)	3.6 (3.1-4.2)	2.2 (1.8-2.6)	0.6 (0.4-0.9)	20	
	2	3.3 (2.8-3.8)	6.0 (5.3-6.6)	5.0 (4.4-5.6)	4.0 (3.4-4.6)	1.6 (1.2-2.0)	20	
	2002 Quintiles (Origin)	3	1.7 (1.3-2.1)	4.5 (3.9-5.1)	5.2 (4.5-5.8)	5.5 (4.9-6.2)	3.2 (2.6-3.7)	20
		4	0.8 (0.5-1.1)	3.1 (2.6-3.6)	4.6 (4-5.2)	6.3 (5.7-7)	5.3 (4.7-5.9)	20
	5	0.2 (0.1-0.4)	1.3 (1.0-1.7)	2.8 (2.3-3.3)	5.7 (4.9-6.5)	9.9 (9.1-10.7)	20	
<i>Marginal distribution</i>		13.3	21.1	21.1	23.8	20.7	100	
2. Authentic	1	6.6	6.0	3.5	2.9	1.1	20	
	2	3.9	5.7	5.0	4.0	1.4	20	
	2002 Quintiles (Origin)	3	2.7	4.0	5.8	5.5	2.0	20
		4	1.8	2.5	3.5	7.4	4.8	20
	5	0.6	2.0	2.5	4.7	10.1	20	
<i>Marginal distribution</i>		15.5	20.2	20.4	24.5	19.4	100	
3. Synthetic regime 2	1	7.1 (6.1-8.1)	6.3 (5.6-7.0)	3.7 (3.1-4.2)	2.2 (1.5-2.8)	0.7 (0.3-1.1)	20	
	2	3.3 (2.9-3.8)	6.0 (5.1-6.8)	5.1 (4.5-5.8)	4.0 (3.4-4.6)	1.6 (1-2.2.0)	20	
	2002 Quintiles (Origin)	3	1.7 (1.2-2.1)	4.6 (4-5.1)	5.2 (4.5-6.0)	5.4 (4.8-6.2)	3.1 (2.4-3.7)	20

4	0.8 (0.4-1.2)	3.1 (2.5-3.7)	4.7 (4.1-5.3)	6.4 (5.5-7.3)	5.1 (4.4-5.8)	20
5	0.3 (0.1-0.5)	1.4 (0.9-1.9)	2.8 (2.2-3.4)	5.7 (5.0-6.4)	9.8 (8.7-10.8)	20
<i>Marginal distribution</i>	13.2	21.4	21.5	23.7	20.2	100

4. Ratio marginal distributions

Synthetic/genuine - regime 1	0.86	1.05	1.03	0.97	1.06	1.00
Synthetic/genuine - regime 2	0.85	1.06	1.05	0.97	1.04	1.00

Notes: 95% C.I. in parentheses. Groups in 2005 from real income quintile limits in the baseline. Regime 1 refers to 500 repetitions from a point estimate of rho. Regime 2 refers to 100 optimization processes, each rho randomly draw within its C.I., with the corresponding set of calibration parameters for each.

We also used the Mann-Whitney test to assess the synthetic rank distribution of 2005 conditioned on its rank at the origin. The test delivers a statistic based on the difference between the sum of the ranks of both distributions: the genuine and the synthetic one. To increase the sensitivity of the test we use twenty equally sized groups. 23 Results in **Table 4** shows that our synthetic estimates satisfactorily reproduce the dynamic described by the genuine panel in almost all points of the distribution, the exception being the *ventile* at the bottom of the 2002 income distribution. At least 90% of samples passed this test in most of remaining groups.

Table 4. 2005 rank test: Synthetic Vs. Genuine conditional on the baseline rank

Mann-Whitney test [H_0 : 2005 ranking (synthetic=genuine)]

2002 ventil	z	Prob.> z	Samples that pass the test (share)	2002 ventil	z	Prob.> z	Samples that pass the test (share)
1	3.63	0.000	0.15	11	1.01	0.311	0.91
2	1.70	0.089	0.61	12	0.81	0.419	0.92
3	0.93	0.352	0.88	13	0.88	0.378	0.92
4	0.74	0.459	0.99	14	1.07	0.286	0.90
5	0.71	0.476	0.99	15	0.92	0.358	0.91
6	0.53	0.597	1.00	16	1.05	0.295	0.89
7	0.57	0.571	0.99	17	1.66	0.097	0.67

23 This test utilizes information regarding the rank order and constitutes an alternative for the two-sample t-test of independent samples (Kirk, 2008).

8	0.95	0.343	0.96	18	0.90	0.369	0.92
9	0.49	0.625	1.00	19	1.20	0.229	0.84
10	0.73	0.465	0.97	20	1.12	0.262	0.84

Notes: The table shows the test of destination ranks (the rank in 2005 synthetic Vs genuine) conditioned on the real income ventile limits in the baseline (2002). H0: synthetic rank = genuine rank in 2005. The share refers to samples with $z < z_{95\%}$. Weighted sample restricted to household's heads aged 25-62 in 2002. Repetitions from one hundred optimizations.

Poverty dynamics is the most popular empirical application of this type of procedures. To illustrate the performance of this approach on this issue we computed two sets of poverty transitions, in-and-out of poverty, using the upper limits from the first two income quintiles as poverty thresholds. These thresholds constitute a direct reference to the 'shared prosperity' goal adopted by the World Bank recently. **Table 5** shows that the proposed approach delivers an encouraging approximation to actual figures in all poverty transitions. For instance, our estimate for persistent poverty for ≤ 0.20 (and 0.30), being poor in both periods, using the first poverty line is 6.5% (7.3% respectively) whereas the actual figure is 6.6%. The largest difference is found in the downward mobility group. Larger values of rho, also in **Table 5**, illustrate the sensitivity of this type of methodologies to this parameter. Interestingly substantial differences emerge when using a correlation coefficient that separates from the actual parameter.²⁴ Note that this occurs on top of the calibration procedure here implemented. These results reinforce the utter importance of this parameter with this and similar methodological approximations.

Table 5. Poverty dynamics, 2002-2005.

Alternative rho specifications						
-Percentage of households -						
	Genuine	≤ 0.20	≤ 0.30	≤ 0.40	≤ 0.50	≤ 0.60
	(1)	(3)	(4)	(5)	(6)	(7)
A. Using income limits from quintile 1 as poverty line						
Poor 02, Poor 05	6.6	6.5	7.3	8.4	9.6	10.9

²⁴ In each case, one-hundred optimization process were obtained from random values of rho being drawn within a 95% confidence interval following a normal distribution $N(\rho_i, SE_{\rho=0.29})$. Because these values $i = \{0.20, 0.30, 0.40, 0.50, 0.60\}$ for rho are hypothetical, $SE_{\rho=0.29}$ refers here to the standard errors for estimates in Table 1.

Poor 02, Non poor 05	13.5	13.5	12.8	11.6	10.4	9.1
Non poor 02, Poor 05	8.9	6.6	6.0	5.1	4.2	3.4
Non poor 02, Non poor 05	71.1	73.3	74.0	74.9	75.8	76.6
Total	100.0	100.0	100.0	100.0	100.0	100.0

B. Using income limits from quintile 2 as poverty line

Poor 02, Poor 05	22.1	21.8	23.0	24.8	26.4	28.1
Poor 02, Non poor 05	17.9	18.2	17.0	15.2	13.6	11.9
Non poor 02, Poor 05	13.5	12.7	11.6	10.1	8.6	7.0
Non poor 02, Non poor 05	46.5	47.3	48.4	49.9	51.4	53.0
Total	100.0	100.0	100.0	100.0	100.0	100.0

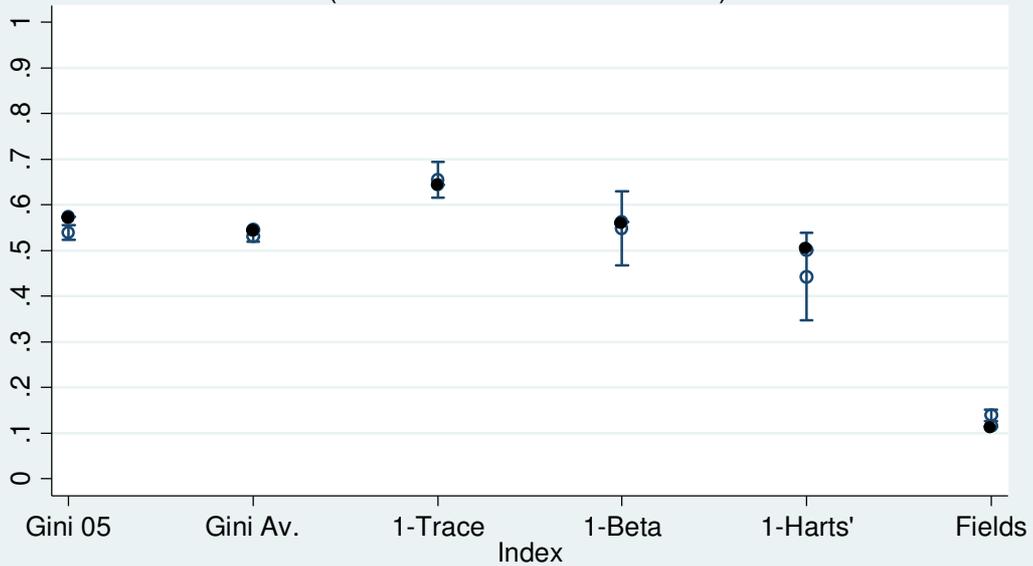
Notes: Using upper income quintile limits as observed in 2002 as poverty lines in both periods. Weighted, sample restricted to household's heads aged 25-62 in the baseline. Using 100 optimization processes.

Lastly, once equipped with a synthetic estimate for each household we also computed some measures of income inequality and income mobility. Income mobility indicators constitute natural candidates for a final robustness check. **Graph 3** plots a 95% confidence interval for these inequality measures against their true point-estimate. Results suggest no statistically significant differences between the synthetic and the authentic estimates. Similarly, the four most popular mobility indicators (the Hart's index, the 1-Beta index, the 1-Trace index, and the Fields' index of 'Mobility as an Equalizer of Longer-term Incomes') appear in line with the actual estimates. Together our synthetic results confirm some process of upward mobility in Mexico during 2002-2005.

25 See Jäntti & Jenkins (2015) for a comprehensive description of these measures.

Income inequality and income mobility indicators

Synthetic estimate and 95% confidence intervals
(Genuine values in solid circle)



Note: 100 optimizations. Av: average income 2002-2005.

6. Concluding remarks

This document proposes an alternative approach to improve the construction of synthetic panels using micro data from repeated cross-sections. We performed an empirical validation through the use of two consecutive waves of a genuine panel survey in Mexico. The procedure delivered very satisfactory results as the marginal distribution of the synthetic income accurately reproduced the genuine one and the resulting panel was consistent with its genuine panel dimension. This was confirmed by multiple tests in several potential applications. The proposed approach allowed examining the importance of the autocorrelation coefficient used in this and other synthetic panel methodologies. Indeed, this parameter constitutes a central and sensitive component in the construction of synthetic panels. Adding heterogeneity in this parameter is an avenue of future research. Our results seem of sufficient quality to envisage a systematic application of this methodology with sequences of two cross-sectional household surveys over a longer time span so as to study a possible evolution in the income mobility of the population on top of that of instantaneous inequality.

Appendix 1. Algorithm to calibrate the distribution of the innovation terms

Let $\hat{\varepsilon}_{i(t)t}$ be the residuals of the income equation in period t and $\hat{\varepsilon}_{i(t')t'}$ be the same for the observations in period t' . We first obtain a continuous Gaussian Kernel approximation of the corresponding cumulative distribution functions F_t and $F_{t'}$ as follows:

$$F_t(x) = \frac{1}{N_\tau h} \sum_{i=1}^{N_\tau} \exp \left[-\frac{(x - \hat{\varepsilon}_{i(t)\tau})^2}{h^2} \right] \quad (\text{A1})$$

where N_τ is the number of observations in the cross-section τ and h is the bandwidth of the Kernel approximation. Then define the following approximation of the integral term in (11) in the main text:

$$H_{t'}(x) = \sum_{m=1}^M F_t \left[\frac{x - \bar{u}_m}{\hat{\rho}} \right] \cdot g_{t'}^u(\bar{u}_m, \theta) \quad (\text{A2})$$

Where:

$$\bar{u}_m = (U_m + U_{m-1})/2 \quad \text{and} \quad g_{t'}^u(\bar{u}_m, \theta) = \left[\frac{G_{t'}^u(U_m; \theta) - G_{t'}^u(U_{m-1}; \theta)}{U_m - U_{m-1}} \right] \quad (\text{A3})$$

The U_m are M arbitrary real numbers spanning the range of variation of the innovation term and $G_{t'}^u(U; \theta)$ stands for the cdf of the innovation term. The calibration of the synthetic panel is based on the assumption that $G_{t'}^u(U; \theta)$ is the cdf of a mixture of two normal variables. It is formally given by:

$$G_{t'}^u(U|\theta) = p \cdot N \left(\frac{U - \mu_1}{\sigma_1} \right) + (1 - p) \cdot N \left(\frac{U - \mu_2}{\sigma_2} \right) \quad (\text{A4})$$

where $N(\cdot)$ is the cumulative of a Gaussian. The set of parameters that characterize this mixture of normal variables is thus: $(\theta|\rho) = \{p, \mu_1, \sigma_1, \mu_2, \sigma_2\}$. These parameters must satisfy the zero mean constraint on the innovation term:

$$p\mu_1 + (1 - p)\mu_2 = 0$$

Finally, (A3) shows how the density is approximated in intervals generated by the grid of real numbers U_m .

The set of parameters θ defining the distribution of the innovation term is obtained by minimizing the following distance between the actual distribution of the residual term in the cross-section t' and the theoretical distribution generated by the AR(1) defined on the residuals of the cross-section t and the distribution of the innovation term:

$$\text{Min}_{\theta} = \sum_{k=1}^K [F_{t'}(x_k) - H_{t'}(x_k)]^2 \quad (\text{A5})$$

Where the x_k 's are a set of arbitrary values spanning the range of variation of $\hat{\varepsilon}_{i(t) t'}$.

ANNEX 1

Table A1. Income model, descriptive statistics, 2002-2005

Variables	Mean		Std. Dev.		Min		Max	
	2002	2005	2002	2005	2002	2005	2002	2005
Ln real income	6.87	7.04	1.32	1.17	0.2	1.8	11.9	11.4
HH sex (female)	0.18	0.18	0.38	0.38	0.0	0.0	1.0	1.0
HH birth year	1959.56	1959.43	9.98	9.83	1940.0	1940.0	1977.0	1977.0
HH schooling (years)	7.15	7.17	4.52	4.55	0.0	0.0	18.0	18.0
HM aged<3	0.21	0.14	0.41	0.34	0.0	0.0	1.0	1.0
HM aged 3-24 (2002)	2.34	2.37	1.69	1.74	0.0	0.0	11.0	12.0
HM aged>65 (2002)	0.05	0.05	0.23	0.23	0.0	0.0	2.0	2.0
Urban area	0.76	0.78	0.43	0.42	0.0	0.0	1.0	1.0
HH married	0.71	0.72	0.45	0.45	0.0	0.0	1.0	1.0
Real estate & Fin assets	0.04	0.04	0.20	0.19	0.0	0.0	1.0	1.0
Farming assets	0.09	0.08	0.29	0.27	0.0	0.0	1.0	1.0
Dwellings property	0.24	0.19	0.43	0.39	0.0	0.0	1.0	1.0
Region south	0.25	0.25	0.43	0.43	0.0	0.0	1.0	1.0
Region occident	0.26	0.26	0.44	0.44	0.0	0.0	1.0	1.0
Region centre	0.33	0.33	0.47	0.47	0.0	0.0	1.0	1.0
Region north	0.16	0.16	0.37	0.37	0.0	0.0	1.0	1.0

Notes: HH_ household head, HM_ Household members

Table A2. Estimated Parameters of Income Model, MxFLS 2002 and 2005

Variables	2000		2005	
	lnincome	lnincome	lnincome	lnincome
	(1)	(2)	(1')	(2')
HH Sex (female)	-0.236*** (0.0505)	-0.224*** (0.0502)	-0.152*** (0.0440)	-0.139*** (0.0438)
HH birthyear	-0.0185*** (0.00195)	-0.0167*** (0.00195)	-0.0169*** (0.00169)	-0.0167*** (0.00170)
HH Schooling (years)	0.0768*** (0.00438)	0.0750*** (0.00438)	0.0757*** (0.00378)	0.0767*** (0.00380)
HM aged<3 in 2002	-0.299*** (0.0457)	-0.306*** (0.0452)	-0.380*** (0.0459)	-0.374*** (0.0456)
HM aged 3-24 in 2002	-0.140*** (0.0102)	-0.140*** (0.0101)	-0.129*** (0.00864)	-0.127*** (0.00858)
HM aged>65 in 2002	-0.153** (0.0722)	-0.186*** (0.0713)	-0.188*** (0.0639)	-0.213*** (0.0640)
Urban	0.602*** (0.0363)	0.663*** (0.0369)	0.525*** (0.0319)	0.564*** (0.0324)
HH Married	-0.00423 (0.0424)	-0.0219 (0.0421)	0.0286 (0.0370)	0.0202 (0.0369)
Real St. & Fin assets		0.354*** (0.0836)		0.387*** (0.0813)
Farming assets		0.201*** (0.0586)		0.161*** (0.0550)
Dwellings property		0.145*** (0.0413)		0.0718* (0.0393)
Constant	42.69*** (3.809)	39.12*** (3.818)	39.61*** (3.310)	39.18*** (3.312)
Region fix effects	yes	yes	yes	yes
Observations	5,030	4,940	4,848	4,768
Adjusted R-squared	0.237	0.256	0.260	0.277

Note: *p>0.1, **p>0.05, ***p>0.01. Standard errors in parentheses. Sample restricted to heads aged 25-62 as observed in the baseline. HH_ household head, HM_ household member.

Chapter 2: Three decades of income mobility with synthetic panels: empirical evidence from Mexico²⁶

*« Si quelque chose est effroyable, s'il existe une réalité qui dépasse le rêve, c'est ceci :
vivre, voir le soleil, être en pleine possession de la force virile, avoir la santé et
la joie, rire vaillamment, courir vers une gloire qu'on a devant soi,... avoir la
lumière, et tout à coup, le temps d'un cri, en moins d'une minute, s'effondrer
dans un abîme, tomber, rouler, écraser, être écrasé,... étouffer, hurler, se tordre,
être là-dessous, et se dire : tout à l'heure j'étais un vivant ! »*

« Les Misérables »

Victor Hugo (1862)²⁷

²⁶ Paris School of Economics – Université Paris 1 Panthéon-Sorbonne. Acknowledges financial support from CONACYT and CEEY. I thank for helpful comments from François Bourguignon, Rodolfo de la Torre, Thierry Magnac, Christophe Muller, Nora Lustig, and Elena Stancanelli.

²⁷ Tome II- COSETTE, Chapitre XIX : Le champ de bataille la nuit

Abstract

Long-run analyses of income mobility are constrained by the limited availability of longitudinal data. This study examines long-run income mobility trends through a continuum of eleven short-run synthetic panels in Mexico. The paper applies the method for the construction of such panels with standard cross-sectional data developed in Bourguignon & Moreno (2017). The examined period of analysis (1989-2012) is characterized by the lack of panel data and by a changing macroeconomic environment. This descriptive exercise employs several measures of income (im) mobility indicators from three complementary notions of economic mobility used in the literature: *positional* mobility, *directional* movement and *mobility as an equalizer of longer-term incomes*. This paper documents low levels of economic mobility for the whole period of analysis except for the period of economic downturn of 1995. The type of intra-generational mobility observed during this internal crisis worked to *equalize longer-term incomes* by downward income mobility both *positional* and *directional*.

1. Introduction

The increasing interest on economic mobility is often addressed with explanations from data that is static in nature. In the absence of longitudinal data, income mobility analysis relies on intertemporal comparisons over several points of the income distribution, e.g. quantiles, from independent cross-sectional surveys. This approach however neglects an important component of economic mobility, i.e. *the movers*, as it is assumed that the composition of individuals within each of these groups remains the same in time. This paper provides empirical evidence on the trends in income mobility through the construction of synthetic panels over the last three decades. Although this is essentially a descriptive exercise, the analysis employs multiple indicators that consider the whole income distribution in a period characterized by the lack of longitudinal data and in a changing macroeconomic environment.

Few countries possess the longitudinal data to perform long or even medium-run analysis on the evolution of income mobility.²⁸ Jenkins & Van Kerm (2011), for instance, examined the patterns of income growth and its progressivity in Britain over 13 years using data from the British Household Panel Survey from 1992-2005. This descriptive study, employed growth incidence curves and summary indices to show that income growth was significantly more pro-poor in the early years of the Labour government (1998-2002) than in earlier Conservative years.²⁹ Fiscal records are an alternative source of information. Zhang, et al. (2016) found that Canadian tax-fillers experienced larger income growth in the last 15 years than in the previous 15 years. However, long series of household panel data or detailed fiscal records are rather scarce in many countries.

Synthetic panels have been increasingly used to examine poverty dynamics following a method proposed by Dang et al. (2014). This methodology uses matching and simulation techniques to construct virtual panels out of cross-sectional data. The matching consists on a linear projection of income from an OLS regression of (log) income on time-invariant characteristics. Also, a synthetic residual is obtained by assuming either a perfect or a zero intertemporal correlation of residuals which delivers an upper and a lower bound of poverty transitions.³⁰ Vakis et al. (2016) used this methodology to construct a synthetic panel of around 8 years, from 2004 to 2012, for 17

²⁸ The longest panels available, as reviewed by Jantti & Jenkins (2015), are: Panel Study of Income Dynamics (USA, from 1968-onwards), German Socioeconomic Panel (Germany, 1984-onwards), British Household Panel Survey (UK, 1991-2008), Household Income and Labour Dynamics (Australia, 2001-onwards), Survey of Labor Dynamics (Canada, 1998-2011). In Mexico, the MXFLS have only three waves: 2002, 2005-06 and 2009-12.

²⁹ Bradbury (2011) used the Panel Study of Income Dynamics to examine mobility profiles from 1969-2006 for USA. Similarly, Jenkins & Van Kerm (2006) compare two decades of mobility between USA and Germany.

³⁰ In a validation exercise of of this methodology, Cruces et al (2015) also constructed synthetic panels with alternative lengths: one, three and four years for Peru, Nicaragua and Chile respectively.

Latin American countries, whereas Ferreira et al. (2013) constructed medium and long-term synthetic panels (from 6 to 20 years) on a sample of 18 Latin-American countries.

More recently, Dang & Lanjow (2013) improved that methodology to produce a point estimate of poverty and vulnerability transitions. The method also applies matching techniques and relies on a bi-normal distribution of residuals but employs a correlation coefficient, ρ , that collapse the above-referred bounds of mobility into a single point estimate. This coefficient stems from the correlation of income using age cohorts from both cross sectional surveys. This methodology has been used to examine poverty and vulnerability transitions like Dang & Lanjow (2016) who estimated a five-year length synthetic panel for India (2004-2009) or Dang & Dabalén (2017) who constructed synthetic panels of six-year length each for 21 African countries.

The rising research on welfare dynamics using synthetic panels has some common characteristics. Firstly, a strong focus on poverty transitions and vulnerability profiles and secondly, a tendency to construct a *unique* synthetic panel for short, medium, or even long-term, time periods. The macroeconomic conditions are largely taken for granted. On this regard, the current paper departs from previous empirical research on three ways: the methodology, the implemented strategy and the scope.

This paper applies the method described in Bourguignon & Moreno (2017), which generalizes Dang & Lanjow (2013) methodology. This approach abstracts from the bi-normality assumption of residuals, and applies calibration techniques to ensure that the distribution of synthetic residuals reproduces the distribution of observed residuals. Also, the method follows an autoregressive approach of first order to estimate ρ from pseudo panel techniques. The empirical validation of this methodology, using also Mexican panel data as described in the referred paper, proved useful to examine poverty transitions and income mobility indicators.

The study constructs 11 short-term synthetic panels from household income surveys to examine income mobility from 1989 to 2012. The strategy of constructing multiple short-term panels is convenient to examine medium and longer-term periods for several reasons: 1) for methodological consistency as this strategy improves the quality of the matching using a comparable set of time-invariant characteristics and, more importantly, allows using only contemporaneous *rho*'s in its construction. 2) The strategy delivers a continuum of points sensitive to a changing macroeconomic environment. Every sub period tracks an updated set of households on a two-year interval -the only exception being the first panel 1989-1992, which defines the beginning of a period of a comparable set of household surveys in Mexico. The unit of

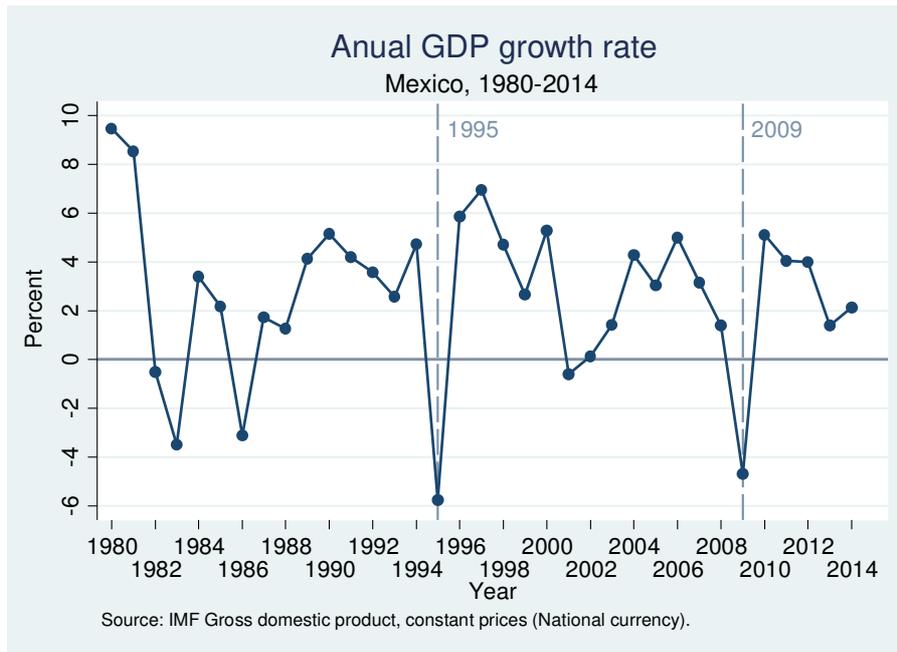
analysis are households with heads aged between 22 and 62 years old as observed in each baseline.³¹

Differently to previous studies, mainly focusing on dichotomous analysis or poverty transitions, this paper examines the whole distribution of income. The analysis uses multiple notions of mobility described in Fields (2010) and Jäntti & Jenkins (2015) to examine long run mobility through multiple indicators. These notions are *positional* movement, *directional* movement and *mobility as an equalizer of longer-term incomes*. The use of these complementary approaches with synthetic panels expects to provide a more comprehensive analysis on the dynamics of wellbeing in a society.

Mexico is an interesting case of study as its empirical evidence might prove useful for other countries. Firstly, a changing macroeconomic environment characterizes the contemporary economic history of this country as described in **Graph 1**, which highlights two episodes of strong economic downturn; an *internal* in 1995 and an *external* in 2009. The (negative) income fluctuation from these exogenous shocks is not always the most preferred source of movement and so the trends of income mobility in changing economic conditions may well enrich the scope of social policies to address these uncertainties. Secondly, Mexico, like many countries, lacks longitudinal data and hence relies uniquely on cross-sectional comparisons of wellbeing indicators. Adding the time dimension in this analysis might prove useful in the design of compensatory policies in periods of economic downturn.

Graph 1

³¹ The study discarded the first edition of this survey, 1984, due to lack of consistency, with macroeconomic indicators, and comparability with subsequent surveys in terms of survey design. Its use would lead to inconsistent trends relative to contemporaneous macroeconomic indicators as studied by Lustig (1992). The author thanks Nora Lustig for pointing it. On the other hand, the resulting 5-year length panel would suggest larger mobility trends relative to the shorter panels being used in the rest of the work. More on this below.



The paper finds low levels of intra-generational mobility in Mexico. Positional mobility indicators suggest low levels of mobility with a sharp increase around the economic downturn of 1995. *Directional mobility* indicators confirms this trend and documents downward mobility (income fall) during both episodes of economic slump –being particularly abrupt in 1995. The last notion of *mobility as equalizer of longer-term incomes* extend these results and confirms that the type of mobility that took place during the economic crisis of 1995 worked to equalize longer-term incomes. The paper is structured as follows. The second section describes the methodology and the empirical implementation. Section 3 describes mobility trends for each notion of mobility used and section four concludes.

2. Analytical framework

This paper follows the methodology described in Bourguignon and Moreno (2017) to construct synthetic panels with cross-sectional data. The following section presents a brief description of the procedure. See the referred paper for a more detailed methodological revision.

2.1 The construction of synthetic panel with AR(1) residuals

Let $y_{i\tau(\tau)}$ represent the income of an individual ‘i’ observed at time period $\tau=0,1$. Here $t=0$ denotes the base year. Then an income model, defined exclusively on a set of time invariant characteristics, z , is to be obtained through OLS as follows³²:

³² This notation, from Moffit (1993), indicate that every individual in the whole set of cross-sections is observed in (τ) at time period τ . Cross-sectional income then corresponds to y_{00} and y_{11} , for the baseline and terminal year respectively, whereas the synthetic income in period 1 for an individual observed in the baseline is y_{01} .

$$\hat{y}_{i(\tau)\tau} = z_{i(\tau)}\hat{\beta}_{\tau} + \hat{\varepsilon}_{i(\tau)\tau}$$

Where; β represents the ‘returns’ of time-invariant features and ε denotes the income residual. These estimates are some basic inputs for the construction of synthetic panels. Fixed attributes may include deterministic characteristics at the individual or household level. The synthetic income of an individual can reasonably be conceived by the following expression:

$$\tilde{y}_{i01} = z_{i0}\hat{\beta}_1 + \check{\varepsilon}_{i01}$$

Where the first term is simply the updated returns of time invariant characteristics. The problem, however, is that the synthetic residual, the second component of this expression, is not observed. To deal with this problem of lack of information the employed methodology explicitly assumes an AR(1) approach. The synthetic residual then is assumed to obey the following autoregressive process:

$$\varepsilon_{i01} = \rho\varepsilon_{i00} + u_{i01}$$

The parameter ρ is to be estimated through pseudo panel techniques. In particular, this parameter is to be estimated by the use of a non-linear equation system as described in the above-referred paper. The second term is the so-called *innovation term* whose distribution is unknown. Under this approach the synthetic income (t=1) of an individual observed or sampled in the baseline (t=0) can be obtained from the following expression:

$$\tilde{y}_{i01} = z_{i0}\hat{\beta}_1 + \hat{\rho}\varepsilon_{i00} + G_1^u(p_{i01}) \quad (1)$$

Where $G^u(\cdot)$ is a random term to be drawn from the distribution of the innovation terms, $p(\cdot)$ refer to independent draws within a uniform distribution. Because ρ can be estimated by pseudo panel techniques, then the last component to be obtained is the distribution of the innovation terms $G^u(\cdot)$. The idea is that the distribution of innovation terms, obtained by calibration and simulation methods, should be able to make that the distribution of synthetic residuals to be the same as the cross-sectional distribution of residuals in the terminal year.

2.2 Empirical implementation

Each synthetic panel tracks the same set of households: those with heads aged between 25 and 62 years old as observed in each baseline. This means that the analysis does not track the same set of households *between* these twelve panels but *within* them. For instance, in the construction of the 1992-1994 synthetic panel, the analysis follows the set of households whose heads were

between 25 and 62 years old in 1992 and between 27 and 64 in 1994. The next panel, 1994-1996, follows a different cohort that corresponds to the updated cohort: 25-62 in 1994 and 27-64 in 1996. The difference in these panels are then those households whose heads are on the age limits (25-27 and 62-64) in each period. This decision allows focusing on the steadiest households in terms of its formation and dissolution and covers most of the households in the sample.

This is a convenient strategy as it provides a more accurate measurement of mobility with the method at hand rather than other alternatives. For example, constructing a unique long-run synthetic panel, of 23 years length may compromise the quality of matching as the linear projection of income, the matching, would need to deal with migration issues and rely on a more limited number of time-invariant characteristics. This may well be the case even with three medium-run synthetic panels, of around 10 years length each. The use of multiple short-term panels adds flexibility in its construction and hence attenuates this risk. Moreover, this strategy expects to deliver a more direct association between economic performance and mobility.

2.2.1 Data and income definition

The study uses the National Survey of Household Income and Expenditures, or ENIGH henceforth by its acronym in Spanish.³³ The survey was first available in 1984 and 1989 but it was periodically conducted, in a two-year basis, since 1992. Its main objective is to provide information about the distribution, amount and structure of household income. This survey is widely used in poverty assessment by the Mexican government and includes information on socio-demographic characteristics, work status, housing characteristics and household equipment.

Income estimates follow the former official definition of income poverty in Mexico. Total current income considers monetary and non-monetary resources; monetary income comprises receipts from employment, owned businesses, lending of assets and public and private transfers. Non-monetary income considers gifts received and the value of services provided within the household, such as rental value of owner occupied dwelling or self-consumption. Total income is then divided by the household size in order to obtain per capita income and was deflated by the Consumer Price Index (August 2014) from Mexican central bank to obtain real household income.

2.2.2 Income model

This study followed a homogeneous procedure to estimate the income model specification for all panels. The objective here is to ensure its comparability in all sub periods and avoid using variables that could affect the quality of the matching (i.e. unstable variables in periods of economic slowdown like employment status or the possession of physical assets). The selection

³³ Encuesta Nacional de Ingresos y Gastos de los Hogares.

of the variables then followed a strict criterion of time invariability. The study focuses on households as observational units but the model specification uses both individual and household characteristics.

Individual attributes include deterministic characteristics of the household head (HH) like years of schooling of formal education, year of birth, sex, and marital status (married). A second set of characteristics stem from the other household members (HM) characteristics like household size and its demographic composition: individuals below 5 years old, between 6 and 24 years old and, older than 65 years. A final set of variables stems from local characteristics like the population density in the area of residence (urban or rural localities), and four regional categories (central, southeast, northeast and west). All variables follow the same definition in all periods.

Table 1 in appendix shows descriptive statistics for each pair of years in each panel. The table shows, as expected, that the mean of these characteristics appears stable in each sub period. Complementarily, **Table 2** in the appendix shows that all the estimates of the income model are strongly significant. In general, the model explains around 0.51 of the total variation of (log) income and this figure, as well as all the estimated coefficients, follow a smooth trend in time.

2.2.3 The autocorrelation coefficient

A contemporaneous autocorrelation coefficient was estimated for each sub period through pseudo panel methods.³⁴ It is convenient to obtain an estimate for each synthetic panel as it allows this parameter to vary in a changing macroeconomic environment. On the contrary, the use of rho estimates from different periods may introduce methodological inconsistencies in the construction of these synthetic panels as the dynamics captured by even the same model specification may vary along the economic cycle. We follow the procedure described in Bourguignon & Moreno (2017) to estimate this parameter through a system of non-linear equations.

We first obtained a pseudo panel by the use of thirty-five groups (g) from the interaction of seven birth-year cohorts, of 6 years interval each, and five groups of education. The educational groups are the following: incomplete primary education, complete primary but incomplete secondary education, and complete secondary but incomplete high school and complete high school or more. These groupings contain a large number of observations (n_g) to preserve the asymptotic properties of the estimated parameters. In general, the group with the least number of observations (the oldest group with higher levels for education) contains around three hundred

³⁴ Deaton (1985) suggests using cohorts to obtain consistent estimators when working with series of repeated cross-sections. Verbeek (2008), for instance, used birth-year cohorts with alternative bandwidths. Other studies use age interactions with alternative characteristics like manual or non-manual worker (Browning et.al 1985), regions (Propper, et. al, 2001), sex (Cuesta, et. al 2007), or education levels (Blundell et. al, 1998).

observations.³⁵ **Table 1** shows the results. All the estimates are highly significant, have the expected signs and order of magnitude -lying reasonably between zero and one.

Table 1. Rho estimates by number of grouped observations, 1984-2012

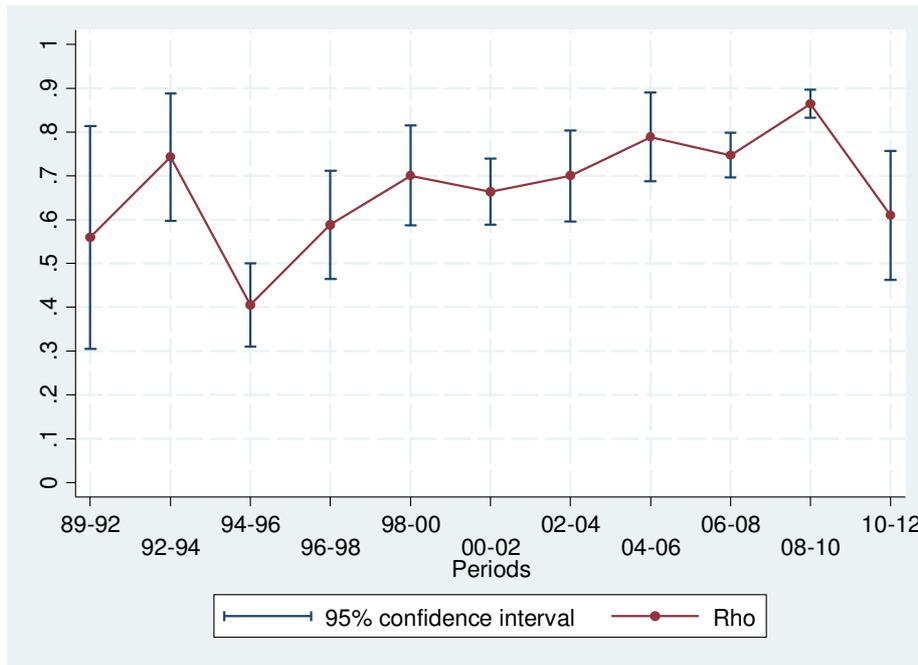
Periods	35 groups			28 groups		
	LB	Rho	UB	LB	Rho	UB
1989-1992	0.31	0.56	0.81	0.35	0.63	0.90
1992-1994	0.70	0.82	0.94	0.60	0.74	0.89
1994-1996	0.31	0.41	0.50	0.25	0.36	0.48
1996-1998	0.13	0.41	0.70	0.47	0.59	0.71
1998-2000	0.59	0.70	0.81	0.39	0.57	0.75
2000-2002	0.59	0.66	0.74	0.58	0.65	0.73
2002-2004	0.60	0.70	0.80	0.62	0.73	0.85
2004-2006	0.69	0.79	0.89	0.55	0.75	0.95
2006-2008	0.68	0.85	1.01	0.70	0.75	0.80
2008-2010	0.90	0.97	1.03	0.83	0.86	0.90
2010-2012	0.46	0.61	0.76	0.75	0.83	0.91

Note: all parameter are statistically significant $p < 0.01$. LB and UB refer to lower bound and upper bound from 95% Conf. Interval. Each estimate represents coefficient from a different regression.

An alternative criterion of twenty-eight groups was used as a robustness check. These groups stem from aggregating the two categories with the highest educational levels described above. This alternative produced fewer groups (g) with a larger number of observations (n_g) each. Rho estimates from this alternative grouping criteria appear very consistent with the previous approach; however, the estimates from the 35 group-observations appear to be the most efficient and will be used in the construction of synthetic panels except for 2006 and 2008. **Graph 2** shows the resulting rho estimates and the 95% confidence interval and describes a clear upward trend only interrupted around 1996 and 2012. It is reassuring that both grouping criteria follows the same trend.

Graph 2. Rho estimates and 95% confidence interval

³⁵ As described by Verbeek (2008) there is no general rule to judge whether the number of observations within each cell is large enough to use asymptotics based on $ng \rightarrow \infty$. In his scholarly review, for instance, Proper, Rees and Green (2001) use cells of around 80 observations whereas Alessie, Devereux and Weber (1997) use more than one thousand observations. Antman & Mackenzie (2007, 2007b) used one hundred observations as a reference.



A final remark regarding the implications for the mobility profiles to be obtained. This growing trend suggest that the baseline information have an increasing importance in the determination of the synthetic income except for the period around the first economic downturn. This is because both the idiosyncratic component of the synthetic income, the innovation terms, as well as the returns of time invariant characteristics from the baseline became more persistent (Eq. 1 illustrates the importance of baseline characteristics on these two terms: ρ_{y00} , and ρ_{e00}). This diverging pattern is a relevant distinction between both periods of economic crisis. In other words as the AR(1) grows, the prevailing conditions in each baseline turn out to be more deterministic (less mobile is a society). This pattern is stronger in the second crisis (where $0.8 < \rho < 0.90$) than in the first one ($0.3 < \rho < 0.50$).

2.2.4 Calibration parameters

The rho estimates, and their 95% confidence interval, allow obtaining the set of calibration parameters that reproduce the distribution of residuals in the target period (t). **Table 2** shows the average of the calibration parameters, $\bar{\theta}$, obtained over $i=100$ independent optimization processes. Each set of parameters, $\theta_i = \{\pi_1, \sigma_1, \pi_2, \sigma_2, \rho_1\}$, minimizes the squared difference between the calibrated approximation and the actual CDF of targeted residuals. These optimizations stem from alternative values of rho each of which was randomly drawn within the 95% confidence interval from a normal distribution. These statistics suggest that the distribution of innovation terms, obtained by the combination of the two normal variables, described in the

table for each period, departs from a normal distribution with mean of zero and standard deviation of one.

Table 2. Calibration parameters by period
Average from one hundred optimization processes

Period	μ_1	μ_2	σ_1	σ_2	ρ_1
1989-1992	-0.10	-0.04	0.79	0.76	0.48
1992-1994	-0.08	-0.03	0.73	0.61	0.43
1994-1996	-0.07	-0.04	0.71	0.72	0.46
1996-1998	-0.05	-0.04	0.79	0.80	0.48
1998-2000	-0.08	-0.05	0.69	0.67	0.49
2000-2002	-0.05	-0.04	0.68	0.70	0.50
2002-2004	-0.05	-0.03	0.81	0.68	0.46
2004-2006	-0.11	-0.04	0.73	0.69	0.44
2006-2008	-0.05	-0.03	0.86	0.72	0.47
2008-2010	-0.22	-0.03	1.11	0.67	0.42
2010-2012	-0.06	-0.03	0.80	0.77	0.44

Once obtaining all the inputs for the construction of synthetic panels 100 simulations were performed to compute the expected value of mobility measures. Graphs A2 in appendix show the kernel distribution for each synthetic income (terminal year) along with the cross-sectional distribution. In all cases the estimates for each synthetic panel closely approximates the level and the shape of the distribution.

3. Trends of income mobility in Mexico

Income mobility can be broadly conceived as a transformation from an initial, or first, income distribution to a second, or terminal, income distribution. There are, however, several perspectives on this concept. We followed the categorization of income mobility concepts described in Jäntti & Jenkins (2015) & Fields (2010) to contextualize the type of mobility examined here. This taxonomy follows four categories: positional change, income growth, long-term inequality, and income risk. See **Annex 1** for a brief description of the mobility indicators used.

3.1 Mobility and positional change

The notion of *positional change* refers to a change in the concentration of individuals at different points along the income distribution. This concept of relative mobility refers to the exchange of observational units between positions: “changes in income affect positional mobility only insofar as these changes alter each person’s position relative to the position of others” (Jäntti & Jenkins, 2015). One device to examine this notion of mobility is the transition matrix, which assigns each individual into a number of categories depending on their income of origin (O) and destination (D). The transition matrix simply cross-tabulates the relative frequencies. Each matrix cell, m_{01} ,

then refers to the relative frequency of individuals in each quantile in period 0 (origin or baseline) and the corresponding quantile in period 1 (or destination).

Table 3 shows the estimated transition matrix using quintiles defined on the real income limits of each baseline. Results appear in single columns for each synthetic panel (instead of the typical matrix form) to save space and facilitate longitudinal comparison. The first two columns of the table specify the quintiles of origin and destination respectively. Here $m_{0i}=20\%$, indicates that each quintile of origin concentrates 20% of the total population. For example, the first quintile for the 1989-1992 panel would be $12.0+4.7+2.2+0.8+0.2=20$. A case of perfect immobility corresponds to a situation where the percentage of every cell equal zero except for those in the leading diagonal (in this case: $m_{11}, m_{22}, \dots, m_{55}$) which equal 20%. Any departure from this position describes positional mobility.

Table 3. Transition matrix by synthetic panel, 1984-2012.
Percentage of population by quintile of origin and destination

Quantile		Sub periods / synthetic panel										
Q. O.	Q. D.	1989-1992	1992-1994	1994-1996	1996-1998	1998-2000	2000-2002	2002-2004	2004-2006	2006-2008	2008-2010	2010-2012
1	1	12.0	15.7	16.3	12.3	13.6	14.7	14.4	13.9	13.9	16.7	12.8
1	2	4.7	3.2	2.9	4.5	4.9	4.0	4.1	4.2	4.1	2.4	4.3
1	3	2.2	0.9	0.7	2.2	1.1	1.1	1.1	1.3	1.4	0.7	1.9
1	4	0.8	0.3	0.1	0.8	0.3	0.2	0.4	0.5	0.5	0.3	0.8
1	5	0.2	0.1	0.1	0.2	0.1	0.1	0.1	0.2	0.2	0.1	0.2
2	1	5.0	6.0	9.4	5.6	3.8	5.5	5.9	5.0	6.0	7.1	5.7
2	2	5.9	8.0	6.7	6.0	8.4	7.7	7.3	7.4	6.8	8.8	6.0
2	3	5.0	4.4	2.9	4.8	5.4	4.7	4.4	4.9	4.5	2.8	4.6
2	4	3.1	1.3	0.9	2.8	2.0	1.8	2.0	2.0	2.2	1.1	2.8
2	5	1.0	0.4	0.1	0.8	0.3	0.3	0.4	0.6	0.5	0.5	0.9
3	1	2.0	1.8	4.2	2.4	1.0	1.7	2.1	1.8	2.4	2.4	2.5
3	2	4.3	4.9	7.0	4.5	4.6	5.3	5.2	4.3	4.9	6.2	4.5
3	3	5.8	7.7	5.6	5.6	7.3	6.7	6.2	6.9	6.0	7.7	5.5
3	4	5.4	4.6	2.7	5.1	5.9	5.0	4.9	5.3	5.1	2.9	5.2
3	5	2.5	1.1	0.5	2.4	1.3	1.3	1.5	1.8	1.6	1.1	2.4
4	1	0.7	0.6	1.4	0.8	0.3	0.5	0.6	0.7	0.7	1.0	0.9
4	2	2.0	1.7	4.3	2.4	1.4	2.2	2.2	1.7	2.1	2.1	2.4
4	3	4.4	5.0	6.5	4.6	4.3	5.1	4.6	4.1	4.4	6.0	4.3
4	4	6.9	8.6	5.8	6.6	8.9	8.1	7.6	8.3	7.8	8.2	6.7
4	5	6.1	4.2	2.0	5.6	5.2	4.3	4.9	5.4	5.0	3.2	5.8
5	1	0.1	0.1	0.2	0.2	0.1	0.1	0.1	0.2	0.1	0.2	0.1
5	2	0.5	0.2	0.9	0.6	0.2	0.3	0.3	0.4	0.4	0.6	0.5
5	3	1.5	0.8	2.8	1.7	0.7	1.1	1.0	0.9	1.1	1.2	1.5
5	4	4.1	3.9	6.1	4.4	4.0	4.4	3.9	3.5	4.2	4.9	4.2

5	5	13.8	15.1	10.0	13.1	15.0	14.1	14.7	15.2	14.2	13.4	13.6
Total		100	100	100	100	100	100	100	100	100	100	100

Note: Q.O_ Quintile of origin, Q. D_ Quintile of destination. Expected value from 100 optimizations.

The table shows contrasting patterns in upward and downward mobility in the extreme tails of the income distribution. Perhaps the simplest way to examine the transition matrix is by observing the share of population who moved or remained at the bottom or at the top part of the distribution. The pattern is one of less (upward) mobility for the poorest quintiles around both periods of economic downturn (around 1996 and 2008). On the contrary, the pattern is one of more (downward) mobility for the richest quintiles around the same periods. In short, both periods of economic turmoil appear associated with more downward mobility at the top and less upward mobility at the bottom.

Two intuitive measures of exchange mobility summarize this information. The first of these measures uses the Pearson correlation, r , which describes the direction and strength in the association on (log) incomes between each pair of years. The second relies on the Beta coefficient, β obtained from an OLS regression of the (log) synthetic income in first period on the (log) income of the baseline. These measures are connected by the ratio of the standard deviations, σ in both years according to the following expression: $r = (\beta \sigma_0 / \sigma_1)$. This means that the correlation coefficient adjusts for the inequality observed in each year, which is useful when the marginal distribution of income varies in time. These measures of persistence are the base for intuitive measures of mobility where a perfect linear relationship between the incomes in both periods ($r=1$ for instance) refers to immobility.

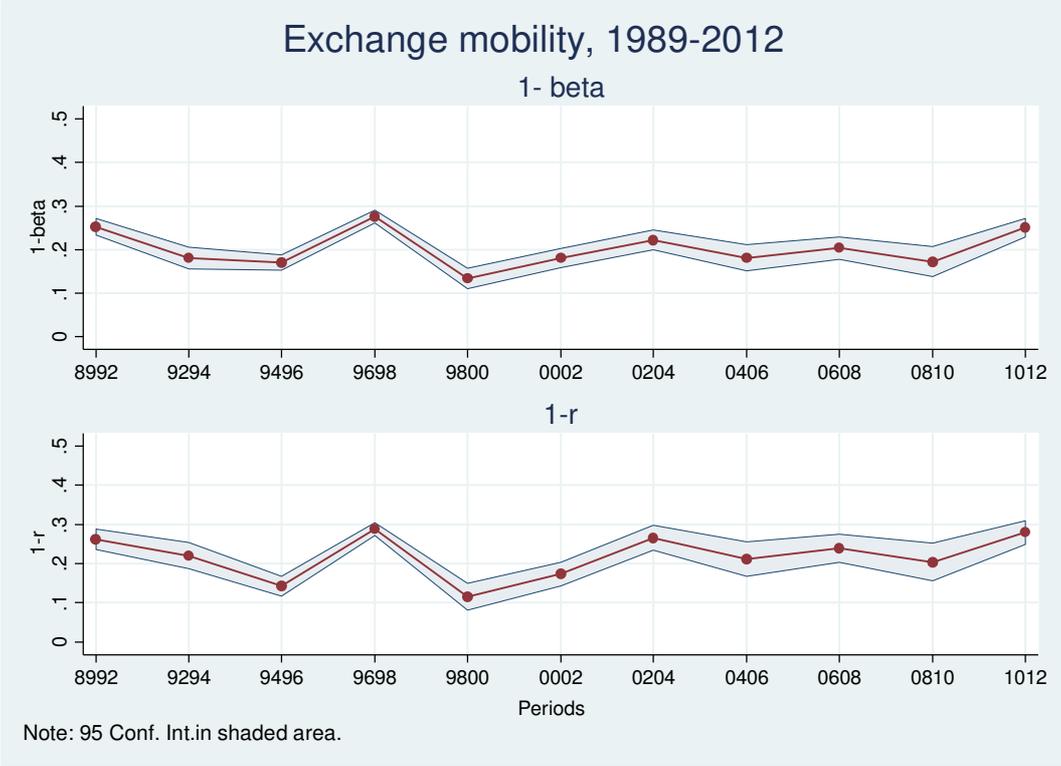
Graph 3 shows two simple measures of mobility from the complement of these indicators ($1-b$ and $1-r$) for the continuum of sup-periods from 1989 to 2012. Four remarks are in order. Firstly, both indices describe a parallel trend that suggests low levels of mobility (around 0.2) except for the sharp increase right after the economic downturn of 1995 (around 0.3). After this point, the mobility trends returned to a stable trend. Interestingly the second period of economic downturn does not seem to depart from that trend except for the following period, 2010-12, where mobility seem to rise slowly again.

Secondly, a gap between these indices, in favour of the $1-r$ index, appears right after the brief period of economic slowdown during 2000-02. A gap like this suggest that inequality in the terminal year fell relative to the baseline ($r < (\beta \sigma_0 / \sigma_1)$ provided that the mobility stems from its complement) which that is consistent with the trends on income inequality in Mexico (see Campos, Esquivel & Lustig, 2012). Thirdly, recent stable trends on income mobility appear consistent with similar trends for the USA – Mexico’s neighbour and most important business

partner. Bradbury (2011) also obtained a downward trend in the 1-beta estimates from around 0.30 in mid 80's to 0.25 in mid 90's using a ten-year length panels from the Panel Study of Income Dynamics.

Lastly, a cautionary note on the length of these sub-periods: mobility appears larger in the first period, 1989-92, however Gittleman and Joyce (1999) document the sensitivity associated to the length of alternative time-intervals. They indeed find that this type of positional mobility increases as the interval widens. This means that the figures from the first period (with a 3-year length interval) might not be strictly comparable with the rest. Because of this, the analysis here focused on periods with a homogeneous two-year length: from 1992-2012.

Graph 3



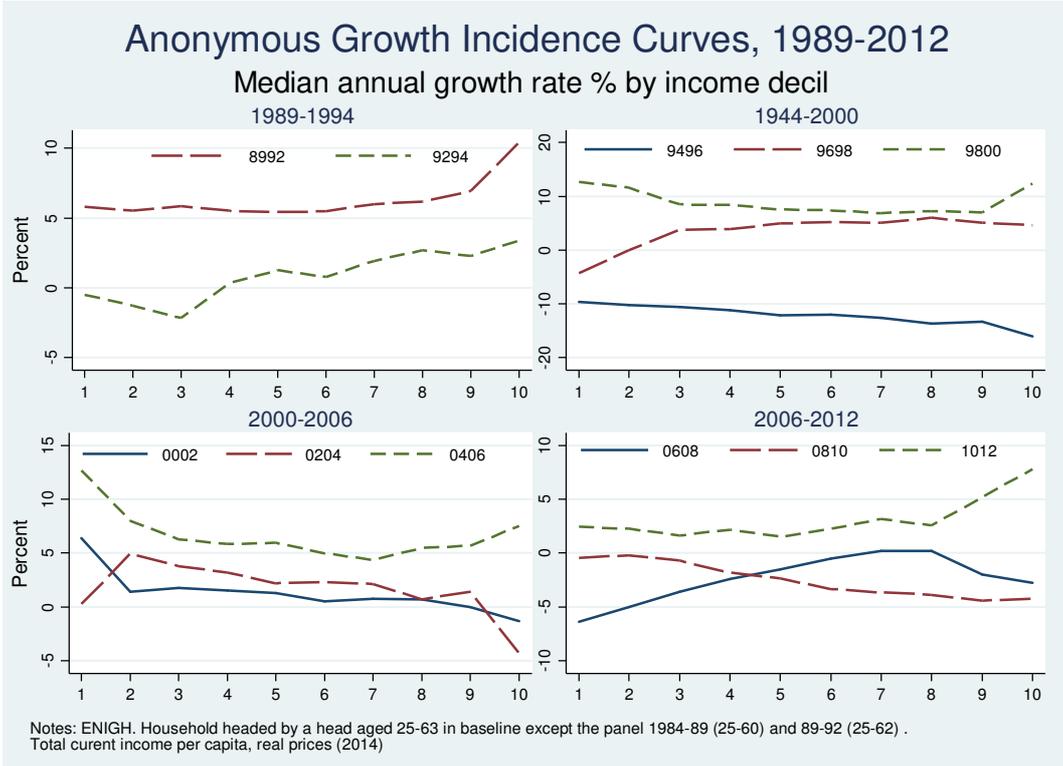
3.2 Mobility and income growth

A second notion of mobility refers to *income growth* and relies on aggregate measures of changes in income observed at individual level between two points in time. Growth here is defined as the distance between the first and the second period. This measure adds new information relative to the *positional change* approach as it takes into account the direction of the change. The Growth Incidence Curves (GIC) are one useful device being used to examine the distributional changes

between the initial and the terminal points. These curves associate to every quantile the mean or the median income growth of all individuals in that quantile.

An upward GIC indicates pro-rich growth, hence refers to a process that increases inequality, whereas a downward GIC indicates pro-poor growth, therefore promoting equality. In the absence of longitudinal data this procedure is often performed by computing income growth from group-based data, e.g. deciles, from cross-sectional surveys.³⁶ **Graph 4** shows twelve cross-sectional GIC with data at decil level. For the ease of comparison, each curve is clustered in four larger sub periods: on around a 6-year interval. According to these graphs the growth incidence was mainly pro-rich from 1989-1994 and mainly pro-poor from 2000-2006. There is no clear pattern for the rest. These type of graphs, however, are *Anonymous* GIC as they ignore the initial income distribution and by doing so neglects mobility.³⁷

Graph 4



The analysis here follows a *Non-anonymous* approach introduced in Bourguignon (2011) where GIC are to be considered on both the initial and terminal incomes. With longitudinal data this yields *non-anonymous* GIC (NAGIC) which, simply plot income growth conditional on the each

³⁶ Lakner & Milanovic (2015), for instance, constructed a global panel by the use of country year average decil income from 1998 to 2008 to examine growth incidence curves and other inequality measures.

³⁷ This is in fact the type of information disseminated by the National Institute of Statistics in Mexico (INEGI) to describe the change in income from one year to other when a new household income survey is available.

baseline's income distribution. **Graph 5** shows the corresponding set of curves with synthetic panels.³⁸ Some remarks are in order. Firstly, a notable contrast emerges between the NAGIC and the GIC graphs. The former seem to follow a downward slope suggesting that (positive or negative) growth spells contributed to equalizing the distribution of income. Negative sloped NAGIC were also found by Hungerford (1993), for United States using three panels from the PSID of around 10 year-length each from 1969 to 1998, and by Jenkins and van Kerm (2011) in Britain using four panels from the BHPS of 4 year-length each from 1992 to 2005.³⁹

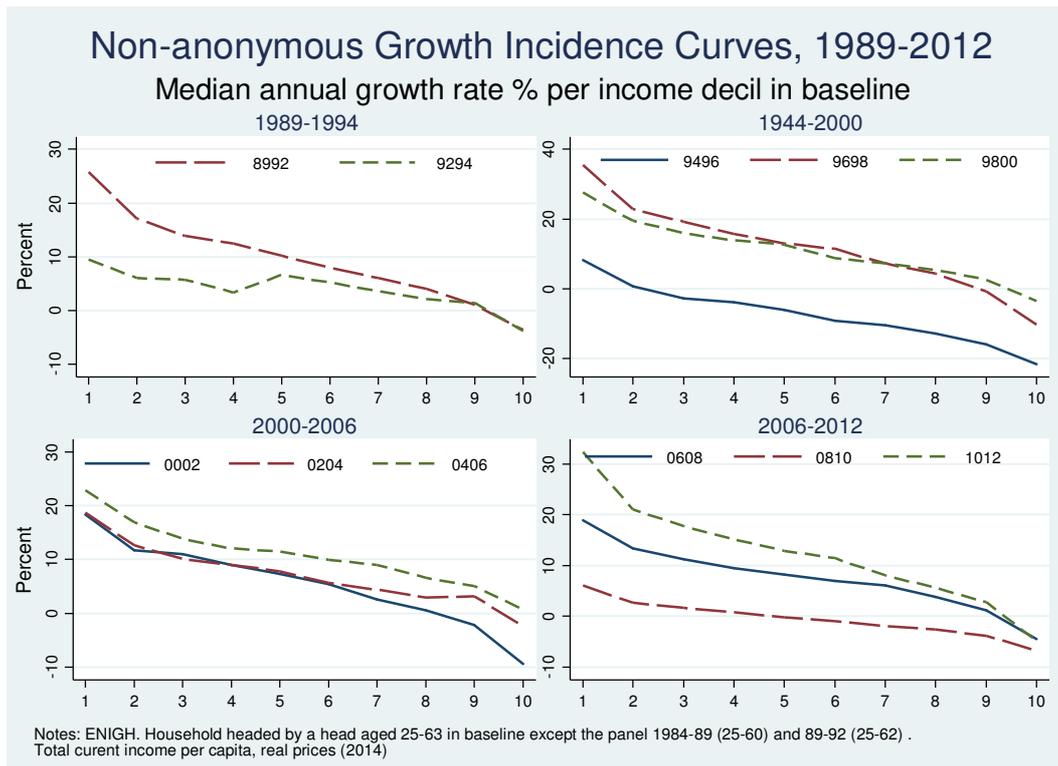
Secondly, it is reassuring that their pattern, e.g. shape and level, differ over time.⁴⁰ These patterns are already useful to form societal judgements on the structure of growth experiences and because of that already have a descriptive value about the distributional impact of growth. Take for instance the curve for 1994-1996, the period around the economic downturn of 1995. It is clear that it lies everywhere below the rest meaning that there is first-order dominance according to the social welfare literature jargon. In line with Jantti & Jenkins (2015), the use of NAGIC from synthetic panels can be justified when the interests is in changes in the slopes of the curves rather than the levels themselves.

Graph 5

³⁸ NAGIC shows the growth of the observation in the median of each decile observed in the baseline. GIC, the previous graph, shows the growth of the observation at the median of each decil in their respective cross-section distribution.

³⁹ PSID stands from the U.S Panel Study of Income Dynamics (PSID). BHPS: British Household Panel Survey.

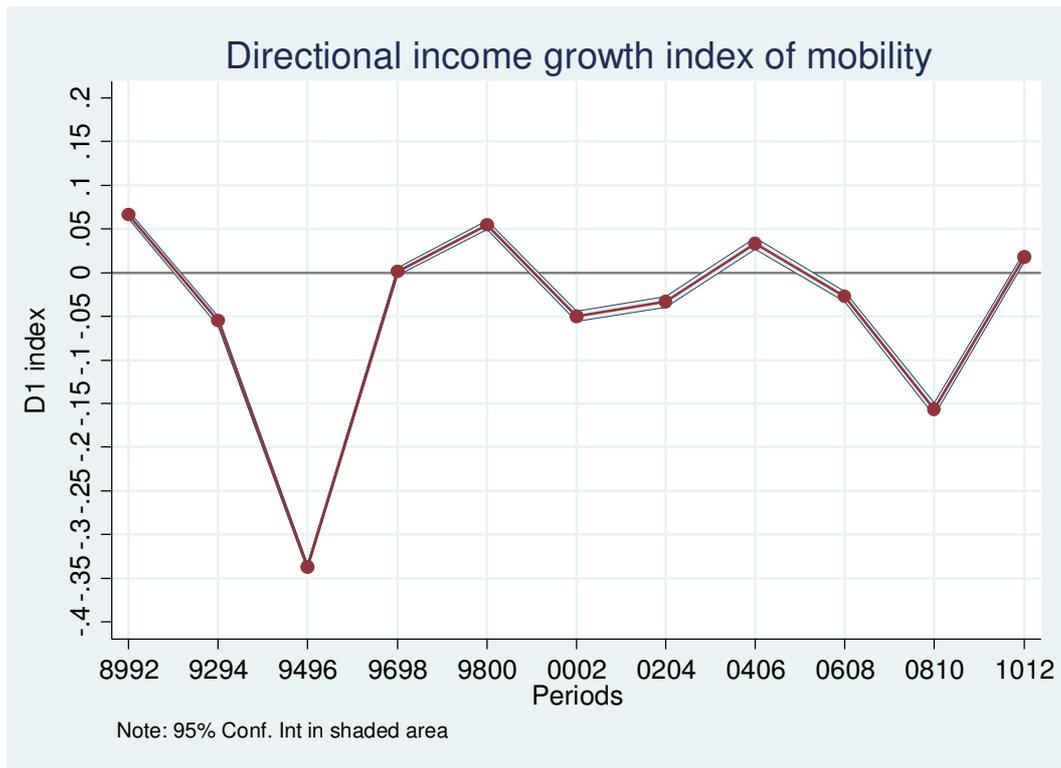
⁴⁰ This might be a consequence of a regression through the mean (also discussed by Jenkins and van Kerm (2011) or by the random drawing of innovation terms. The later however is obtained by multiple repetitions, 100 times here, from an equal number of independent optimization processes. These repetitions are used to compute the expected value of mobility measures so that these results are not driven by the set of specific drawings.



Thirdly, one might wonder which growth episodes are preferred to others. Under the first-order dominance criteria, there is no single answer as the curves with the highest levels, 1996-98 and 1998-00, cross each other. There is no Pareto-superiority. This means that the income of the first four deciles did not grow as fast in 1998-00 as it did right after the crisis in 1996-98. On the other extreme, the episodes associated with economic downturn, 1994-96 and 2008-10, shows the lowest levels in the whole period as expected. There is no Pareto-inferiority either (See Graph 1 in Annex).

We now examine the D1 index of *directional income growth* from Fields and Ok (1999), as this might be the most well-known aggregate measure of directional mobility (Jäntti & Jenkins, 2015). This index is concerned with ‘the extent to which incomes are rising or falling’ and so the direction stems simply from $d(y_0, y_1) = \log(y_1) - \log(y_0)$. The index is $D1 = (1/n) \sum d(y_0, y_1)$ with a straightforward interpretation: there is more/less income movement when this measure increases/decreases (Fields, 2010). **Graph 6** shows the evolution of directional movement over the whole period. The index firstly confirms the low-level mobility trends and the abrupt downward mobility during both episodes of economic slump particularly in 1995.

Graph 6



3.3 Mobility and long-term inequality

The last approach of mobility to be examined on this paper is concerned with the long-run effect of mobility in the reduction of inequality. It relies on the average income on two points of time relative to cross-sectional inequality. Measures of this type of mobility rely on aggregate measures of inequality and because of that the direction of mobility (upward or downward) is not directly examined in this last set of indexes.

The paper follows the seminal work of Shorrocks (1978) who proposed a measure of income rigidity, R . This measure stem from the ratio of inequality on averaged incomes to the weighted average of cross-sectional inequality as follows: $R_s = I(y_m) / \sum [w_i \cdot I(y_i)]$. Here $I(\cdot)$ refers to some measure of inequality; y_i is the cross-sectional income in some period 'i'; and y_m is the longitudinal average of initial and final income for each individual. The weights, w_i , stem from the proportion of aggregate income received in each period ($w_i = \mu_i / \mu$) and sum to unity. In complete rigidity, this measure of rigidity equals unity and inequality remains the same in both periods. Mobility is conceived as the complement of rigidity: $M_s = 1 - R_s$.

Fields (2010) followed a variant on this approach with an index of 'Mobility as an Equalizer of Longer-term Incomes'. The rigidity measure is now defined by the ratio of inequality on averaged incomes to the cross-sectional inequality in the baseline: $R_f = I(y_m) / I(y_i)$. Similarly, the

corresponding mobility index is $M_f = 1 - R_f$. With complete rigidity, $I(y_m)=I(y_i)$, there is zero equalization of longer-term incomes relative to initial income. The index is unbounded but takes a positive (negative) value to indicate that the average incomes between two points in time are more (less) equally distributed than the base-year income. This indicator describes to what extent the income changes that took place during a specific period make the distribution of incomes more equal than the initial distribution.

Graph 7 plots these indexes using the Gini index as a measure of inequality. Both describe a parallel trend. This trend is examined by three sub-periods, of similar length each.⁴¹ The focus however is on the two most recent periods for comparability in length of the synthetic panels. Between 1992-2000, the mobility worked to *equalize longer-term incomes relative to the base*. Both indexes reached a peak during the economic crisis and lost its momentum during the economic recovery. In the second period, from 2000 onwards, the low and stable levels of mobility that took place appear to have *almost no effect on longer-term inequality*. The level of these indexes is consistent with those computed from Hungerford (2011) for the United States. This author used PSID data for two periods using a 10-year length panel. The Fields index for the periods 1979-1988 and 1989-1998 are 0.02 and 0.08, the corresponding Shorrocks index appear slightly larger (0.109 and 0.111, respectively).

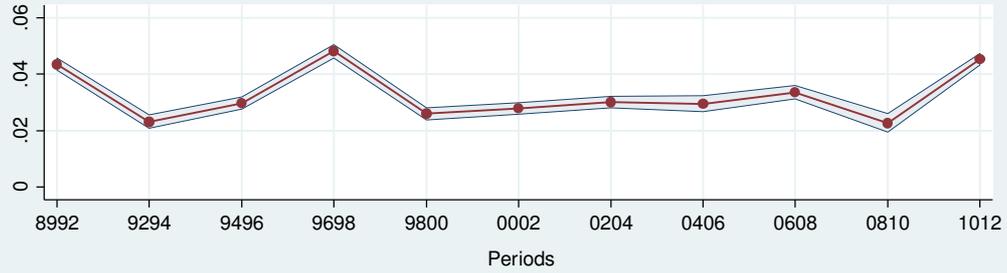
The previous empirical evidence provided an overview of the income dynamics that was only available through the scarce availability of actual survey panel data in Mexico. Finally, these results show a potential utility of this approach for making the analysis of income mobility more feasible given the available series of cross-section in most developed and developing countries.

Graph 7

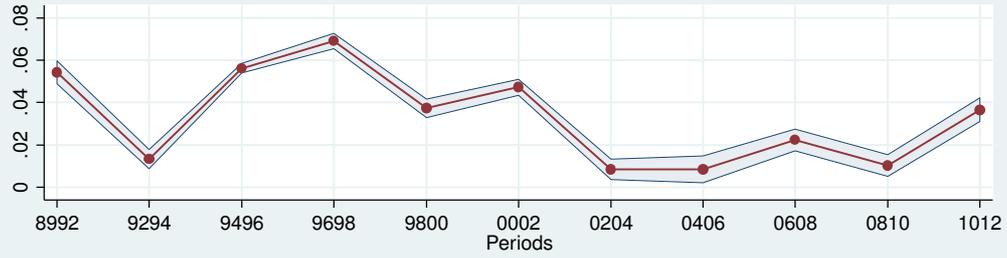
⁴¹ The first period, between 1989-1994, corresponds to a decline in mobility and both indices are remarkably close.

Mobility as an equalizer of longer-term incomes

Shorrocks' index



Fields' index



Note: 95% Conf. Int in shaded area. Both indexes are Gini based.

4. Concluding remarks

The paper examined long-run trends of income mobility by the construction of multiple short-term synthetic panels from cross-sectional surveys in Mexico. This strategy allowed using only the contemporaneous parameters in the construction of such panels following a methodology described in Bourguignon & Moreno (2017). During the period of analysis, the Mexican economy went through multiple stages of the economic cycle with two important periods of economic slowdown: an internal in 1995 and a global in 2008. The complex idea of economic mobility was examined here by three notions of income mobility widely used in the literature: *positional* movement, *directional* movement and *mobility as an equalizer of longer-term incomes*. Several devices were employed here to describe the trends and pattern with cross-sectional data at household level.⁴²

The analysis documents low levels of short-run economic mobility for most periods of analysis. The exception being the period of economic downturn occurred in mid 90's. The mobility patterns observed during this economic crisis seemed to have *equalized longer-term incomes*. This pattern however lost its momentum with the economic recovery in the following years. Other mobility notions complement these results. In terms of *positional* mobility the pattern is one of less upward mobility for the poorest quintiles and more downward mobility for richer population groups. However, in terms of *directional mobility*, the period is associated with a progressive income fall. All in all, the mobility patterns observed during the economic downturn of 1995 describe an equalization process that compares with *glass ceilings and sticky floors*.

⁴² (1-rho, 1-beta, GIC, non-anonymous GIC, Fields' index of directional mobility, and Shorrocks' as well as Field's index of mobility as an equalizer of longer term incomes).

APPENDIX

List of income mobility indices

Mobility concept	Index	Notes
1 Exchange mobility	1-Beta	Beta is the coefficient from OLS of individual (log) income in period 2 on (log) income of period 1. Range [0,1]. Immobility=0
2 Exchange mobility	Hart	$H = 1 - r$. Mobility as lack of correlation. $r = \beta(\sigma_1/\sigma_2)$ =correlation coefficient. Range [-1,1]. Immobility=0
3 Directional income growth	Fields' D1	$D1 = [1/N \sum(\log(y_{1i}) - \log(y_{2i}))]$. Is the average of individuals' proportional growth. The weighting scheme treats all individuals the same.
4 Reduction in the inequality of longer-term income	Shorrocks' 1-R	$R = I(y_m)/\sum_1^T w_i I(y_i)$ is a measure of income rigidity. $I(y_m)$ is a measure of income inequality in averaged incomes in period 1 and 2. w_k is the proportion of aggregate averaged income in each period. The larger the income change in IR, the less rigid is the income system.
5 Reduction in the inequality of longer-term income	Fields' $m_{equalizer}$	$m_{equalizer} = 1 - I(y_m)/I(y_1)$ To what extent the income changes that took place make the distribution of longer-term incomes more equal than the initial distribution of incomes. $I(y_m)$ is an inequality measure.

Source. Based on Jäntti & Jenkins (2015) and Fields (2012).

Graph A1

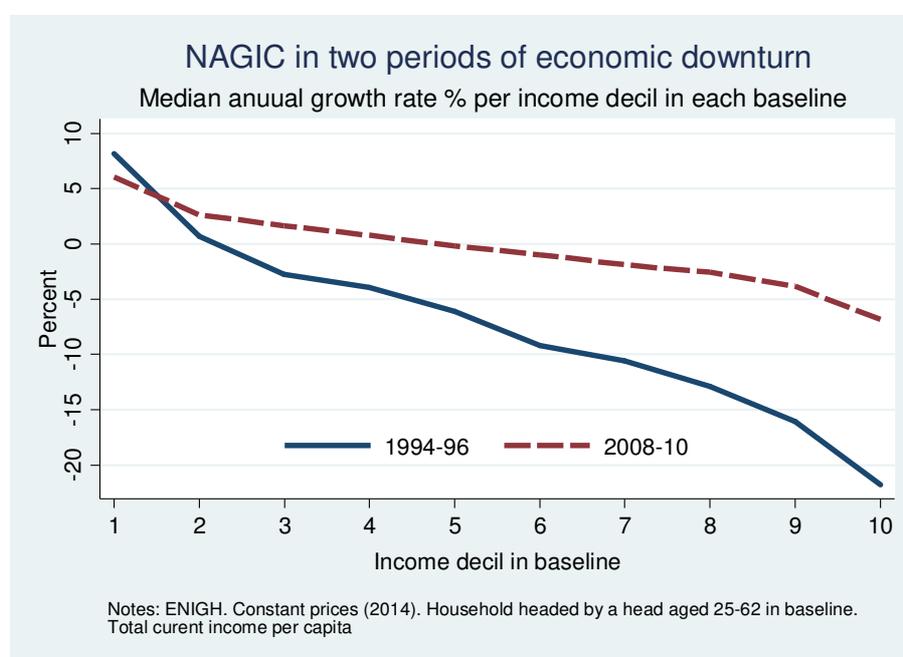


Table A1. Descriptive statistics (1/2)

Mean. Standard deviation in parenthesis

Synt. panel	1989-1992		1992-1994		1994-1996		1996-1998		1998-2000	
	1989	1992	1992	1994	1994	1996	1996	1998	1998	2000
Income (log)	7.612 (0.948)	7.783 (0.972)	7.776 (0.959)	7.798 (0.995)	7.793 (0.993)	7.502 (0.966)	7.497 (0.964)	7.568 (1.010)	7.560 (1.009)	7.749 (0.989)
HH female	0.120 (0.325)	0.129 (0.336)	0.121 (0.326)	0.132 (0.339)	0.127 (0.333)	0.148 (0.355)	0.142 (0.350)	0.156 (0.363)	0.152 (0.359)	0.157 (0.363)
HH birth year	1,948 (10.71)	1,950 (10.80)	1,952 (10.61)	1,952 (10.96)	1,954 (10.74)	1,954 (10.81)	1,956 (10.62)	1,956 (10.87)	1,957 (10.64)	1,957 (10.75)
HH schooling	6.210 (4.984)	6.319 (4.965)	6.497 (4.911)	6.507 (5.058)	6.641 (5.040)	6.765 (5.080)	6.863 (5.051)	6.919 (5.066)	7.033 (5.041)	7.458 (5.114)
Hm <5	0.807 (0.941)	0.820 (0.974)	0.750 (0.922)	0.744 (0.931)	0.723 (0.905)	0.755 (0.933)	0.733 (0.908)	0.692 (0.889)	0.643 (0.847)	0.615 (0.817)
Hm 6-24	2.415 (1.882)	2.004 (1.621)	2.225 (1.738)	2.020 (1.631)	2.128 (1.682)	1.956 (1.620)	2.063 (1.690)	1.859 (1.548)	1.976 (1.610)	1.732 (1.444)
Hm 65+	0.0694 (0.275)	0.0464 (0.226)	0.0556 (0.252)	0.0535 (0.246)	0.0594 (0.259)	0.0495 (0.231)	0.0535 (0.240)	0.0421 (0.214)	0.0458 (0.227)	0.0386 (0.203)
Urban	0.651 (0.477)	0.642 (0.480)	0.642 (0.480)	0.644 (0.479)	0.644 (0.479)	0.618 (0.486)	0.620 (0.485)	0.626 (0.484)	0.629 (0.483)	0.653 (0.476)
HH married	0.832 (0.374)	0.829 (0.376)	0.834 (0.372)	0.810 (0.393)	0.815 (0.388)	0.797 (0.402)	0.803 (0.398)	0.788 (0.409)	0.793 (0.405)	0.787 (0.410)
Observations	9,513	8,588	8,769	10,511	10,498	10,777	10,813	8,256	8,217	8,212

Notes: HH_ household head, household members. Weighted sample Each sub period refer to households with heads aged between 25-62 in each base line.

Table A1. Descriptive statistics (2/2)

Mean. Standard deviation in parenthesis

Synt. panel	2000-2002		2002-2004		2004-2006		2006-2008		2008-2010		2010-2012	
	2000	2002	2002	2004	2004	2006	2006	2008	2008	2010	2010	2012
Income (log)	7.754 (0.992)	7.768 (0.947)	7.764 (0.945)	7.806 (0.935)	7.801 (0.928)	7.975 (0.898)	7.968 (0.894)	7.881 (0.939)	7.874 (0.936)	7.827 (0.909)	7.820 (0.905)	7.881 (0.928)
HH female	0.153 (0.360)	0.181 (0.385)	0.177 (0.382)	0.215 (0.411)	0.211 (0.408)	0.222 (0.415)	0.218 (0.413)	0.226 (0.418)	0.223 (0.416)	0.222 (0.416)	0.219 (0.413)	0.229 (0.420)
HH birth year	1,958 (10.52)	1,959 (10.64)	1,960 (10.49)	1,961 (10.71)	1,962 (10.46)	1,964 (10.50)	1,965 (10.40)	1,964 (10.64)	1,965 (10.40)	1,966 (10.59)	1,967 (10.45)	1,968 (10.92)
HH schooling	7.613 (5.088)	7.401 (5.052)	7.516 (5.025)	7.942 (4.963)	8.074 (4.912)	8.942 (4.556)	8.999 (4.515)	8.284 (4.880)	8.420 (4.824)	8.659 (4.900)	8.767 (4.852)	8.820 (4.808)
Hm <5	0.571 (0.795)	0.581 (0.802)	0.547 (0.785)	0.586 (0.804)	0.546 (0.784)	0.564 (0.794)	0.533 (0.766)	0.529 (0.773)	0.500 (0.753)	0.503 (0.751)	0.482 (0.746)	0.473 (0.725)
Hm 6-24	1.834 (1.517)	1.729 (1.431)	1.817 (1.477)	1.645 (1.399)	1.735 (1.437)	1.572 (1.340)	1.657 (1.369)	1.628 (1.371)	1.720 (1.411)	1.545 (1.324)	1.620 (1.365)	1.444 (1.287)
Hm 65+	0.0421 (0.214)	0.0390 (0.209)	0.0452 (0.227)	0.0439 (0.216)	0.0461 (0.222)	0.0497 (0.235)	0.0521 (0.241)	0.0468 (0.228)	0.0499 (0.239)	0.0434 (0.220)	0.0465 (0.231)	0.0400 (0.203)
Urban	0.656 (0.475)	0.650 (0.477)	0.653 (0.476)	0.649 (0.477)	0.652 (0.476)	0.683 (0.465)	0.682 (0.466)	0.656 (0.475)	0.657 (0.475)	0.656 (0.475)	0.654 (0.476)	0.658 (0.475)
HH married	0.787 (0.409)	0.770 (0.421)	0.773 (0.419)	0.746 (0.435)	0.748 (0.434)	0.732 (0.443)	0.735 (0.441)	0.741 (0.438)	0.744 (0.436)	0.733 (0.442)	0.736 (0.441)	0.715 (0.452)
Observations	8,177	14,040	13,950	18,424	18,222	15,473	15,459	23,724	23,365	21,998	21,652	6,971

Notes: HH_ household head, household members. Each sub period refer to households with heads aged between 25-62 in each base line.

Table A2. Income model by synthetic panel (1/2)

Synt. panel	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1989-1992		1992-1994		1994-1996		1996-1998		1998-2000	
	1989	1992	1992	1994	1994	1996	1996	1998	1998	2000
VARIABLES	Real income (log)									
HH female	-0.190*** (0.0356)	-0.105*** (0.0383)	-0.0991*** (0.0378)	-0.155*** (0.0306)	-0.173*** (0.0306)	-0.147*** (0.0317)	-0.158*** (0.0318)	-0.166*** (0.0353)	-0.189*** (0.0355)	-0.145*** (0.0330)
HH birthyear	-0.0107*** (0.000750)	-0.0124*** (0.000769)	-0.0118*** (0.000761)	-0.0123*** (0.000661)	-0.0123*** (0.000662)	-0.0118*** (0.000671)	-0.0113*** (0.000672)	-0.0113*** (0.000793)	-0.0122*** (0.000798)	-0.0119*** (0.000760)
HH schooling	0.0705*** (0.00170)	0.0875*** (0.00185)	0.0852*** (0.00180)	0.0920*** (0.00158)	0.0898*** (0.00155)	0.0854*** (0.00152)	0.0828*** (0.00151)	0.0810*** (0.00181)	0.0800*** (0.00179)	0.0843*** (0.00167)
Hm 5	-0.211*** (0.00820)	-0.244*** (0.00818)	-0.236*** (0.00833)	-0.249*** (0.00739)	-0.231*** (0.00740)	-0.257*** (0.00733)	-0.241*** (0.00760)	-0.246*** (0.00911)	-0.223*** (0.00945)	-0.238*** (0.00947)
Hm 6-24	-0.118*** (0.00403)	-0.0883*** (0.00467)	-0.116*** (0.00427)	-0.103*** (0.00404)	-0.120*** (0.00387)	-0.123*** (0.00413)	-0.140*** (0.00394)	-0.125*** (0.00500)	-0.142*** (0.00477)	-0.130*** (0.00517)
Hm 65+	-0.229*** (0.0253)	-0.153*** (0.0339)	-0.171*** (0.0301)	-0.163*** (0.0257)	-0.163*** (0.0243)	-0.215*** (0.0271)	-0.215*** (0.0259)	-0.172*** (0.0350)	-0.202*** (0.0329)	-0.243*** (0.0360)
Urban	0.450*** (0.0168)	0.371*** (0.0169)	0.357*** (0.0164)	0.498*** (0.0143)	0.491*** (0.0141)	0.355*** (0.0142)	0.351*** (0.0141)	0.454*** (0.0169)	0.444*** (0.0167)	0.354*** (0.0161)
HH married	-0.284*** (0.0313)	-0.217*** (0.0339)	-0.206*** (0.0330)	-0.259*** (0.0267)	-0.269*** (0.0266)	-0.273*** (0.0282)	-0.274*** (0.0282)	-0.247*** (0.0319)	-0.257*** (0.0321)	-0.223*** (0.0301)
Constant	28.39*** (1.459)	31.51*** (1.496)	30.42*** (1.483)	31.29*** (1.287)	31.51*** (1.291)	30.32*** (1.308)	29.39*** (1.311)	29.24*** (1.546)	31.09*** (1.558)	30.53*** (1.482)
Observations	9,513	8,588	8,769	10,511	10,498	10,777	10,813	8,256	8,217	8,212
R-squared	0.47	0.49	0.51	0.56	0.57	0.52	0.53	0.53	0.53	0.51

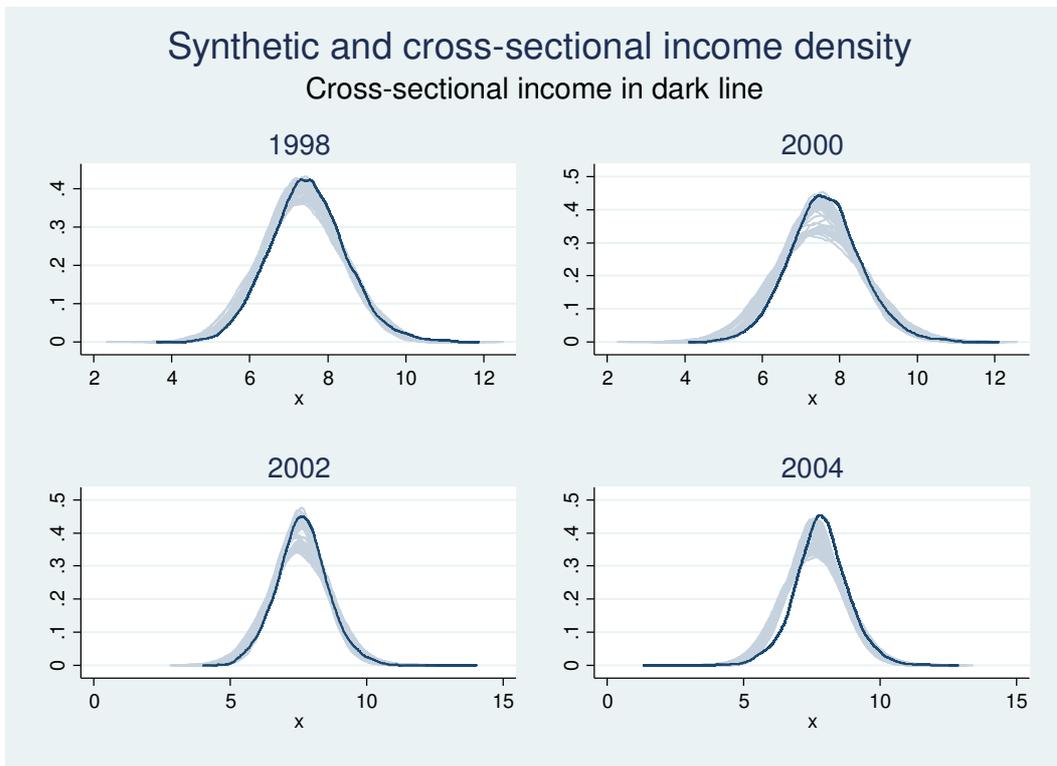
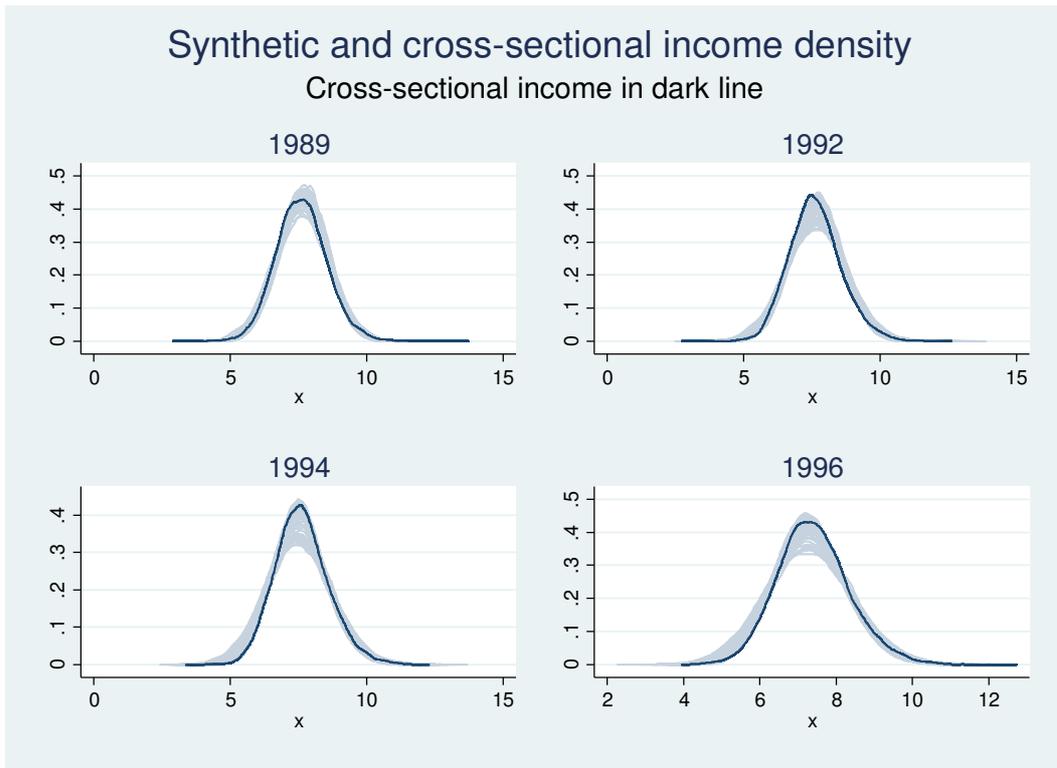
Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. HH_ household head, household members. Include regional effects. Each sub period refer to households with heads aged between 25-62 in base line.

Table A2. Income model by synthetic panel (2/2)

Synt. panel	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
	2000-2002		2002-2004		2004-2006		2006-2008		2008-2010		2010-2012	
	2000	2002	2002	2004	2004	2006	2006	2008	2008	2010	2010	2012
VARIABLES	Real income (log)											
HH female	-0.174*** (0.0324)	-0.139*** (0.0233)	-0.129*** (0.0233)	-0.103*** (0.0182)	-0.087*** (0.0181)	-0.098*** (0.0187)	-0.103*** (0.0185)	-0.127*** (0.0150)	-0.132*** (0.0150)	-0.075*** (0.0156)	-0.079*** (0.0156)	-0.099*** (0.0269)
HH birthyear	-0.012*** (0.00075)	-0.012*** (0.00056)	-0.012*** (0.00056)	-0.015*** (0.00054)	-0.013*** (0.00054)	-0.0131** (0.00058)	-0.013*** (0.00057)	-0.014*** (0.00042)	-0.014*** (0.00045)	-0.014*** (0.00048)	-0.014*** (0.00042)	-0.011*** (0.00081)
HH schooling	0.0826*** (0.00165)	0.0822*** (0.00126)	0.0809*** (0.00125)	0.0944*** (0.00109)	0.0927*** (0.00109)	0.0932*** (0.00121)	0.0913*** (0.00122)	0.0873*** (0.00100)	0.0860*** (0.00101)	0.0843*** (0.000986)	0.0825*** (0.000995)	0.0800*** (0.00191)
Hm 5	-0.209*** (0.00961)	-0.253*** (0.00708)	-0.245*** (0.00713)	-0.244*** (0.00661)	-0.229*** (0.00659)	-0.256*** (0.00707)	-0.230*** (0.00712)	-0.255*** (0.00608)	-0.233*** (0.00624)	-0.255*** (0.00620)	-0.237*** (0.00629)	-0.272*** (0.0119)
Hm 6-24	-0.151*** (0.00494)	-0.126*** (0.00380)	-0.138*** (0.00364)	-0.142*** (0.00363)	-0.157*** (0.00351)	-0.136*** (0.00390)	-0.150*** (0.00380)	-0.124*** (0.00325)	-0.145*** (0.00320)	-0.131*** (0.00339)	-0.148*** (0.00332)	-0.136*** (0.00640)
Hm 65+	-0.249*** (0.0343)	-0.215*** (0.0250)	-0.203*** (0.0234)	-0.205*** (0.0218)	-0.202*** (0.0212)	-0.264*** (0.0237)	-0.261*** (0.0227)	-0.154*** (0.0193)	-0.164*** (0.0185)	-0.143*** (0.0194)	-0.141*** (0.0187)	-0.123*** (0.0400)
Urban	0.344*** (0.0160)	0.457*** (0.0123)	0.450*** (0.0123)	0.363*** (0.0118)	0.360*** (0.0117)	0.344*** (0.0118)	0.342*** (0.0118)	0.360*** (0.0101)	0.353*** (0.0101)	0.338*** (0.0103)	0.337*** (0.0103)	0.387*** (0.0181)
HH married	-0.248*** (0.0294)	-0.213*** (0.0217)	-0.199*** (0.0216)	-0.220*** (0.0173)	-0.210*** (0.0172)	-0.230*** (0.0179)	-0.228*** (0.0177)	-0.238*** (0.0145)	-0.243*** (0.0145)	-0.234*** (0.0151)	-0.225*** (0.0150)	-0.232*** (0.0258)
Constant	31.59*** (1.477)	30.85*** (1.107)	30.31*** (1.111)	33.77*** (0.985)	33.08*** (0.987)	33.06*** (1.054)	33.13*** (1.054)	35.23*** (0.885)	35.03*** (0.892)	34.20*** (0.879)	33.95*** (0.888)	29.33*** (1.611)
Observations	8,177	14,040	13,950	18,424	18,222	15,473	15,459	23,724	23,365	21,998	21,652	6,971
R-squared	0.51	0.54	0.54	0.54	0.55	0.53	0.53	0.50	0.50	0.51	0.52	0.48

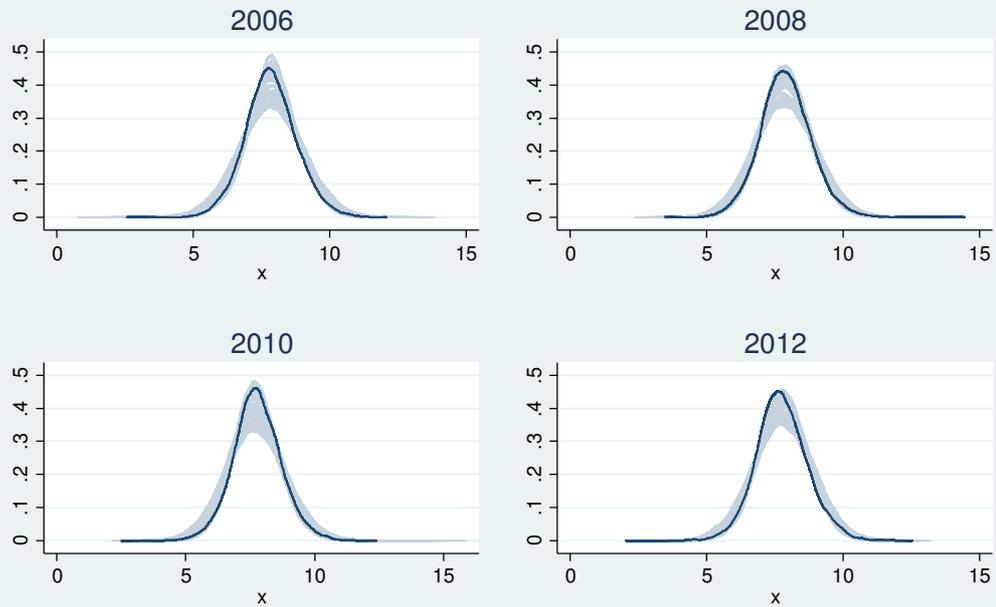
Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. HH_ household head, household members. Include regional effects. Each sub period refer to households with heads aged between 25-62 in base line.

Graph A2. Income density, 1984-2012



Synthetic and cross-sectional income density

Cross-sectional income in dark line



Chapter 3: Intergenerational transmission of education across three generations ⁴³

« La patrie périra si les pères sont foulés aux pieds.
Cela est clair. La société, le monde roulent sur la paternité,
tout croule si les enfants n'aiment pas leurs pères. »

« Le père Goriot »

Honoré de Balzac

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Abstract

This paper addresses endogeneity biases to provide empirical evidence on the intergenerational transmission of human capital across three generations. The endogeneity of paternal schooling is addressed by the use of a two-fold instrumental variable approach. A natural experimental set up from a regional war that occurred at the beginning of the 20th century is exploited to instrument years of schooling of the “grandfather” generation whereas labour market indicators serve as an instrument for the education of the “parents” generation. Using a unique Mexican survey that gathers retrospective information on the three generations, the paper first shows that parental education has a significant effect on their children’s education. It also shows that the IV estimate is larger than the OLS estimate, which implies that accounting for endogeneity unveils a larger importance of familiar background (less educational mobility) than ignoring it. This holds true for both the older and the younger pairs of parent-child links in the three generations at hand.

1. Introduction

This paper examines the effect of grandparental education on their children's and grandchildren's educative outcomes. The endogeneity of paternal schooling (the fact that other factors, like individuals' ability, that influence their decision to accumulate education are also linked to offspring's outcomes) is addressed by the use of a two-fold instrumental variable approach. Firstly, a regional and religious civil war provides a natural experimental set up to instrument the effect of grandfathers' education (G0) on their children's and grandchildren's outcomes. Secondly, local minimum wage when dropping out school are used to instrument the parents' generation (G1), which in turn is used to examine its effect on grandchildren's education (G2). This unified framework allows examining the direct and the indirect effect of education over three generations.

The theoretical foundations of the transmission of human capital across three generations were set in the seminal model of Becker and Tomes (1979) and more recently in Solon (2013). The model is grounded on the parental decision between current consumption and the investments in the human capital of the children. These models predict a negative coefficient of grandparents' education on grandchildren's outcomes, conditional on parental outcomes. This negative sign emerges as a consequence of credit constraints and the substitution between parental and grandparental investments given the level of human capital of the parents' generation. Lindahl, et al. (2014) recently tested these predictions by exploiting a rich set of Swedish administrative data from Malmö city and find a positive effect of grandparental education (by instrumenting parent education with the great-grandparent education) on their grandchildren.

Apart from the empirical validation of these predictions, the literature on intergenerational mobility focus on the association of two adjacent generations with a particular emphasis on the father-son linkage from well-developed countries (Jantti & Jenkins, 2015). The multigenerational literature is still in early stages due mainly to data restrictions (Solon, 2016). For instance, empirical evidence from Nord European countries tend to exploit rich administrative records that are only found in few countries (see Hällsten (2014), Lindhahl, et.al (2015), Møllegaard & Jæger (2015)). Other countries resort to retrospective surveys to overcome these limitations (see Mare (2014) and Pfeffer (2014)). Studies exploring more than two generations are scarcer and largely rely on cross-sectional correlations.

In search for causality, the literature on intergenerational mobility of education has recently moved away from cross-sectional OLS estimates and has turned to the use of alternative identification strategies to elicit the effect of two adjacent generations (Black & Devereux, 2011). These strategies range from the use of twins and adopted children to natural experiments often

taking an instrumental variable approach. Under the IV approach, most studies exploit changes in education laws that increase the length of compulsory schooling as described in Holmlund et al. (2011) and Black & Devereux (2011). Two recent studies stand out in clear contrast. Maurin & MacNally (2008) exploited the cohort variation in college attendance from the 1968 student riots in Paris that lead to a one-off larger pass rates to higher education, while Carneiro et al. (2013) exploited the variation in the direct and opportunity cost of education across counties and cohorts to identify the effect of maternal education on children's' outcomes. Both find significant effects of parental education on children's grade repetition and tests performance (math and reading) respectively.

This paper exploits a unique dataset, the "*Encuesta de Movilidad Social Inter-generational*" (EMOVI) on a national representative sample of adults aged 25-64 in Mexico, which contains information on the education level of the "parents" generation and also asks them about the education level of the "grand-parent" generation and their children (the "grand-children" generation). Children's education is collected independently of their residency status. These key features allows examining educational mobility across three generations.

To examine the effect of grandparental education (G0) on their offspring (G1 and G2) the study follows two identification strategies: the first one relies on the geographic distribution of a religious conflict whilst the second, a robustness check, uses historical records of the territorial variation of the Church in the provision of education three decades before the uprising. It is argued here that the so-called *Cristero* conflict differently affected the human capital accumulation of the grandparent generation and test for this by implementing a difference-in-difference-in-differences approach. Individuals that were at school age (primary school) or that were born during this insurrection and were living in a rural area of a region affected by the conflict are to be considered as 'treated' group while everyone else are the reference group. This external source of variation will be used later on as an instrument of the grandparents' education to determine the effect of grandparents' education on the parents' generation and the unconditional effect on the grandchildren's generation. Similarly, to examine the effect of parental education (G1) on the (grand) children's education (G2), the study exploits labour market indicators, which is often used in labour economics literature. Here minimum wage per state when dropping out school is used to instrument parental education.

Once equipped with a set of identification strategies for each of the first two generations the paper examines the intergenerational transmission of human capital across three generations. More specifically the paper studies the effect of grandparental education on their grandchildren's education, conditional on parental education under an instrumental variable approach. The analysis first shows that parental education is the most important family background in the

children's years of education though it seems to play a lesser role in successive generations. This conclusion holds for any of the two contiguous pairs of parent-children links (G01 and G12). Beyond the findings of two contiguous generations, results also suggest that the influence of the grandparents' educative legacy, conditional on parental education, does not seem to reach the second generation.

The contributions of this paper to the literature on the intergenerational mobility run in several directions. Firstly, the analysis explicitly addresses endogeneity biases to examine the effect of the grandparental education on grandchildren's education conditional on parental education. Secondly, the study focuses on a shock on grandparents' childhood in a period where the average schooling was very low. This means that the long run effect of grandparental education is larger than the marginal effect often identified by studies that exploit changes in compulsory schooling laws affecting a specific part of the education distribution (these reforms are originally addressed to population with low or intermediate education levels). The findings from a middle-income country extend the current knowledge from Nordic or highly developed countries.

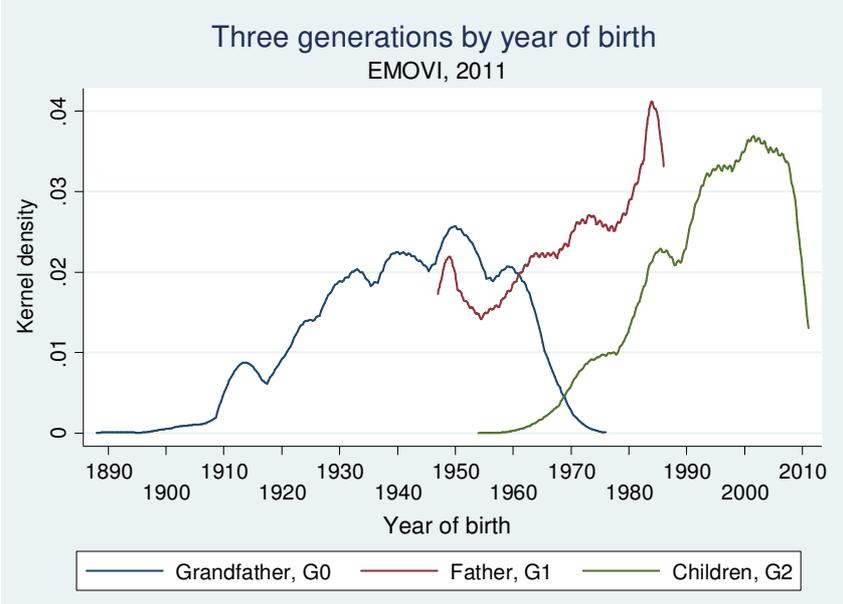
The paper is organized as follows. The second section describes the survey and the sample used. The third section describes the general approach to examine both the *intergenerational* and the *multigenerational* transmission of education in the literature, which corresponds to an autoregressive process of first or higher orders. The fourth and fifth sections examine the effect of parental education on their offspring for the two pairs of parent-child links at hand, i.e. G01 and G12 respectively. Section six examine the conditional effect of grand parental education on the grand-children education through an AR(2) with a multi-equation approach taking advantage of the two sets of instruments at hand. Section seven discusses the implications of these results in a procedure often used to extrapolate the long-run effect of grandparental education in the absence of data on three generations. The last section concludes. The annex contain a detailed description of the effect of the civil war on the affected generation (the grandparents' generation). This appear in the annex as the focus of the paper is on the multigenerational transmission of education on top of the effect of a civil war on the affected generation.

2. Data and sample

The study uses a Mexican survey "*Encuesta de Movilidad Social Inter-generational*" (EMOVI by its Spanish acronym from now on), which consists on a random sample of the population collected in Mexico in 2011. The survey's goal is to determine the extent to which parents' resources and living conditions influence their offspring's socioeconomic position. The survey is deliberately designed to gather retrospective information on the ancestors of a national representative sample of adults aged 25-64 in Mexico. This data also contains a rich set of retrospective information on the respondents, as well as contemporary information on their children. The EMOVI 2011

contains data of eleven thousand individuals. **Graph 1** presents a graphical description of the full sample on these generations whereby the respondents of the survey are to be referred to as first generation, G1, or the parents' generation interchangeably.

Graph 1. Density of individuals by year of birth within each generation



An earlier survey was collected in 2006, but it covered mostly men (women were only interviewed if living alone) and only asked educational data for the respondents' co-resident children but not for their parents.⁴⁴ A more recent survey was recently collected but was not available at the time of writing. Therefore, the 2011 data represent a unique survey that allows us to investigate the intergenerational transmission of education within three generations of household members (grandparents, parents, and grandchildren) along several dimensions. In fact, no other Mexican dataset gathers similar information.

The EMOVY 2011 survey gathers information on several characteristics regarding both parents of the respondents. This cross-sectional survey collects information about the respondents' education, earnings, assets and other relevant socio-demographic data. The survey also collects retrospective information about the respondent's parent's socioeconomic status (G0). The dataset is somewhat less complete regarding the respondent's children's data (G2), although it collects information about their schooling independently of their co-residency status. This attribute makes this survey suitable for this analysis as traditional household surveys would be biased due to the non-random selection of children, that are often still at school when co-resident (Emran, Greene & Shilpi, 2015).

⁴⁴ The sample is only representative of the Mexican male population aged 25-64. Similarly the set of questions regarding the respondents' mother is limited (it does not ask for the year of birth for instance).

The sample used is comprised by the cohort of grandparents in school age or older during the *Cristero* war with parents who themselves have children who are out of school age. **Table 1** shows descriptive statistics where panel A, B and C contains outcome indicators for the grandparents, parents and grandchildren, respectively. Panel C contains data from around 1960 individuals from the second generation (G2) which corresponds to around 780 families in Panel A and B. A more detailed description of the data and the groups being compared appear in the Annex (in particular table A3 in the first annex)..

Table 1

Descriptive statistics, EMOVI Survey (2011)

Variable	Obs.	Mean	Std. Dev.
A. Grand-parents' generation, G0			
Outcome variables			
Grandfather's schooling	772	2.05	3.34
Grandmother's schooling	607	1.68	2.86
Number of children	786	5.71	3.25
Year of birth	786	1917	3.7
B. Parents variables, G1			
Parents' schooling	782	6.22	4.48
Dummy for lagging in Prim. school	786	0.51	0.50
Number of children	786	2.86	1.71
Male	786	0.46	0.50
Year of birth	786	1955	6.83
C. Grand-children variables, G2			
Grandchildren's schooling	1962	9.72	3.87
Male	1962	0.53	0.50
Year of birth	1962	1984	8.43

Source: EMOVI (2011). Sample of grandparents in school age (around 6-12) or older during the *Cristero* war with parents who themselves have children being out of school age at the time of the survey.

3. The general approach to the intergenerational transmission of education.

Intergenerational mobility is often measured by estimating a first-order auto regression process between two generations (Solon, 2016). The empirical literature on intergenerational mobility focus on the father-son associations with a particular emphasis on Nordic countries (see Björklund and Salvanes (2011), Black & Deveroux (2011), and Holmlund, et.al (2011), Solon (1999) and Jäntti & Jenkins (2015)). When examining the effect of any parental-child link, or the unconditional effect of grandparents' education on grandchildren's education, the literature follows a bivariate regression approach that relates some indicator of the ancestors' education (s) with that of the offspring's generation:

$$s_{\tau} = \alpha + \alpha_1 s_{\tau-1} + \alpha_2 x_{\tau} + \varepsilon \quad (Eq. 1)$$

Where τ refers to some index generation, $\tau+1$ refers to their offspring, x is a vector of controls, which include birth year and sex for generation τ and ε is a random error term (Lindahl, et al., 2015).

To take into account the unequal distribution of education within each generation the literature on intergenerational transmission of income or education tends to standardize the outcome variables to net out the inequalities within each generation. This procedure exploits the relationship between the correlation coefficient (ρ) and the OLS regression coefficient ($\beta = \frac{\text{Cov}(y_0, y_1)}{\text{SD}(y_0)}$), where SD stands for the standard deviation of two generations (0 and 1 respectively). This expression suggest that in a stationary world (where the outcomes of both generations are equally distributed) the correlation coefficient and the OLS coefficient are equal. Standardized variables (mean zero and standard deviation of one) allows dealing with the fact that each generation possesses different distributions.⁴⁵

Multigenerational studies are scarcer and largely rely on cross-sectional correlations. Hällsten (2014), Lindahl, et.al (2014) and Lindahl, et.al (2015) examined the transmission of education across four generations in Sweden while Møllegaard & Jæger (2015) and Kroeger & Thompson (2016) examined three generations in Denmark and the United States respectively.⁴⁶ Similarly, when examining the intergenerational transmission of human capital the literature follows an OLS model:

$$s_{\tau} = \alpha + \alpha_1 s_{\tau-1} + \alpha_2 s_{\tau-2} + \alpha_3 x_{\tau} + \varepsilon \quad (Eq. 2)$$

Where, τ refers to an index generation, both τ and $\tau+1$ refers to their offspring and, x is a vector of controls for the three generations considered. Finally, studies on longer series of generations resort to intergenerational associations with surnames data (Clark & Cummins (2014) and Collado et al. (2013)) or with detailed genealogical data like Mare & Song (2014). This type of literature however work with aggregated data (no direct family link) and these focuses on income.

4. The effect of grandfather's education (G0) on their offspring education (G1 and G2)

This paper exploits a natural experiment from an armed conflict that occurred in Mexico at the beginning of the 20th century to provide causal evidence on the multi-generational transmission of human capital across three generations. *La Cristiada* was a massive armed conflict that lasted three years from 1926-1929. This religious conflict can be briefly summarized by a massive rural

⁴⁵ This is relevant as the average education for the index generation is around 2 years while it is almost 10 for the second generation.

⁴⁶ Adermon, et al (2017) followed a similar approach to examine wealth transmission with four generations from Malmö city in Sweden.

rebellion in the western and central states of Mexico after the enforcement of anticlerical laws that emerged from the Mexican Constitution of 1917.

The conflict did not start until 1926, one decade after the new constitution was reformed, when the Catholic Church suddenly suspended its religious worship service as a way of protesting against the legal restrictions to its ministry and to secular policies severely implemented during the second half of President Plutarco Elias Calles' administration (1924-1928). The revolt was known as the *Cristero* rebellion as the government mocked the rebels' battle cry *¡Viva Cristo Rey!* (Long live Christ the King!). **Annex 1** shows a detailed description of the conflict. It also documents that the conflict affected differently the human capital accumulation of the affected generation according to their place and year of birth using a difference-in-difference-in-differences approach.

This section use this natural experiment setup to examine the effect of grandfather's education on their children's (G01) and grandchildren's education (G02). In particular, the section builds on the regional variation of the conflict and makes use of a two-stage least squares instrumental variable (IV) approach to elicit the causal effect of the grandparents' education on their offspring. The empirical estimation follows two identification strategies hinging on attributes that are exogenous to parental and children ability. The first strategy relies on the geographic distribution of the insurgency, whereas the second strategy uses the importance of the Catholic Church in the provision of education long before the uprising.⁴⁷

4.1 First identification strategy: The regional variation of the conflict

The regional variation of the conflict, as captured by the place and the year of birth of the affected cohorts, is used as instrument for the grandparents' years of schooling in the first stage. Older cohorts, born before the *Cristero* uprising, were chosen as comparison group as younger cohorts, born after the conflict, would most likely be affected by its consequences. In a general IV framework the first stage is the regression of the causal variable of interest on covariates and instruments (Angrist and Pischke, 2008). The first stage then is the defined as follows:

$$\hat{S}_0 = \alpha + \beta_1 \text{Cristero} + \beta_2 \text{Rural} + \beta_3 \text{Cohort} + \beta_4 \text{Cristero} * \text{cohort} + \beta_5 \text{Cristero} * \text{rural} + \beta_6 \text{Cohort} * \text{rural} + \beta_7 \text{Cristero} * \text{rural} * \text{cohort} + X_\tau' \beta + \varepsilon \quad (\text{Eq. 3a})$$

⁴⁷ The IV approach is an appropriate methodological procedure as it allows addressing three potential statistical problems related to endogeneity: omitted variable problem, the reverse causality problem, and errors in measurement. In the case of education, the omitted variable problem appears as the educational choice might be correlated with characteristics that cannot be observed in the data (like ability or propensity to exert effort). The reverse causality problem here arises as highly educated parents tend to be associated with highly educated children but it is difficult to disentangle how much of this is due to nature (the genetic transmission for instance) or nurture (the care and environment provided by a high/low educated parents). Finally, the error-in-measurement problem is less of a problem for education, as people tend to accumulate human capital in early stages and tend to know their own educational attainment accurately (see Pfeifer, 2014).

Where; ‘Cristero’, c , is a dummy variable for individuals in *Cristero* region (comprised by a set of states engaged in conflict as described in the **Annex 1**); ‘rural’, r , is a dummy for individuals living in rural areas (equals 0 for urban areas) and; ‘cohort’, t , variable introduces the time dimension in a dummy for children in school age at the moment of the conflict (being 0 for older children –out of school age during the revolt). Here, the coefficient of the interacted variable ‘*Cristero*rural*cohort*’ (CRT1 onwards) identifies the effect of the revolt on the grandparents’ education, S_0 . X refers to a set of exogenous covariates which includes the sex, the year of birth and state fixed effects of the offspring $\tau \in \{1,2\}$ for the parents (G1) or the grandchildren (G2) respectively. This is a common set of variables used in the academic literature as surveyed by Holmlund, Lindahl & Plug (2011) so we stick to these for international comparisons.⁴⁸

4.2 Second identification strategy: The supply shock in educational inputs

The second identification strategy exploits other intrinsic characteristic of the conflict. The law enforcement of the anticlerical legislation of 1926 configured an unprecedented situation for the Mexican clergy traditionally accustomed to the unbinding legislations from the past. The second identification strategy then relies on the fact that the impact on educative outcomes does not depend solely on the regional intensity of the conflict, but on the presence of the Catholic Church in the provision of public education. In particular, this second identification strategy exploits the fact that the stringent application of the educative provisions, preventing the clergy to manage primary schools (Article 3 of the Mexican constitution of 1917), implied a sharp reduction in the number of active schools.

Similarly, the functional form of the first stage is as follows:

$$\hat{S}_0 = \alpha + \beta_1 \text{Church} + \beta_2 \text{Rural} + \beta_3 \text{Cohort} + \beta_4 \text{SChurch} * \text{cohort} + \beta_5 \text{SChurch} * \text{rural} + \beta_6 \text{Cohort} * \text{rural} + \beta_7 \text{SChurch} * \text{rural} * \text{cohort} + X_\tau' \beta + \varepsilon \quad (\text{Eq. 3b})$$

Where; ‘SChurch’ refers to the share of schools managed by the Church as observed in the statistical records of 1895 (30 years before the conflict started). Similarly, the coefficient of the interacted variable *Church*rural*cohort* (CRT2 onwards) identifies the effect of the enforcement of the educative provisions on the grandparents’ education, S_0 . A key attribute on this identification strategy is that it departs from the war incidence, and more importantly, it introduces heterogeneity in the effect captured by the IV.⁴⁹

4.3 The effect of grandparents’ education on their direct offspring, G01

⁴⁸ Under the instrumental variable framework the geographic distribution of insurgency, that is the instrument, must be correlated with the causal variable of interest that in this case is the average years of schooling as described by graph A1 and table A5 in the appendix.

⁴⁹ Other robustness checks were performed using alternative definitions of children in school age and states in conflict with negligible differences with respect to the two identification strategies described.

Under this instrumental variable approach the second stage, or reduced form, estimate the effect of the ancestors' education on their offspring's education. In particular, for any parental-child link, either G01 or G12 (in **Section 4.4**), or for the unconditional effect of grandparents' education on grandchildren's education (G02 in **Section 5**), the reduced form corresponds to a bivariate regression:

$$s_{\tau} = \alpha + \alpha_1 \hat{s}_{\tau-1} + X'_{\tau} \beta + v \quad (\text{Eq. 4})$$

Where s_{τ} refers to the educative outcome of generation τ and, $\hat{s}_{\tau-1}$ is the estimated education of the grandparent obtained from the first stage.⁵⁰ X here refers to a set of exogenous covariates, which includes the sex, the year of birth and state fixed effects.

Table 2 shows both the results from OLS and the reduced form for the grandfather-parent link. The table shows the first and second stage results for both identification strategies. Each estimate represents the coefficient from a different regression. The OLS results in column 1 show a statistically significant positive relationship between the grandfathers-fathers years of education. The coefficient for grandparental education is around 0.45. These results are consistent with related empirical evidence. Behrman, et al. (2001) found an intergenerational educative persistence of 0.50 for Mexico using a more restricted sample from urban employment surveys whereas Hertz et al. (2007) showed that the regional Latin-American average is the highest relative to other regional averages.⁵¹

Table 2
The effect of grandfather's education (G0) on parents' education (G1)

Using the regional variation of the conflict (IV1) and prominence of the clergy (IV2) as instruments

Variable:	Years of education (standardized)		
	(1)	(2)	(3)
	OLS	IV 1	IV 2
Reduced form			
G. Father Ed. (G0)	0.435*** (0.0317)	0.710*** (0.129)	0.649*** (0.122)

⁵⁰ The IV estimates yield the Local Average Treatment Effect (LATE) rather than the Average Treatment Effect (ATE). Under this approach, the instrument can be considered as a treatment indicator that randomly assigns individuals between the treatment group and the control group. Therefore, the IV estimates equal the ATE only when the instrument perfectly predicts the endogenous variable but this would only happen in the remote case where all individuals are compliers. Here the IV estimate captures only the impact of parental education on their children's outcome for the subgroup of parents for which the instrument has an impact.

⁵¹ These regions are: Asia, Africa, Eastern countries, Western Europe and USA. The LA average in Hertz et al. (2007) is obtained from a sample of adults aged 20-69 from seven countries: Colombia, Peru, Ecuador, Chile, Brazil, Panama and Nicaragua.

Observations	768	768	768
Adj. R-squared	0.335	0.266	0.293
First stage			
CRT 1	-	-1.10**	-
	-	(0.463)	-
CRT 2	-	-	-1.56
	-	-	(1.638)
Adj. R-squared	-	0.159	0.161
F-stat	-	8.7	6.7
Sex, G1	Yes	Yes	Yes
Birthyear, G1	Yes	Yes	Yes
Wealth at 14, G1	Yes	Yes	Yes
State fixed eff. at 14, G1	Yes	Yes	Yes
Number of children, G0	Yes	Yes	Yes

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Restricted sample of grandparents in school age, or older, during the civil war regardless of having grandchildren. Each estimate represents the coefficient from a different regression. First stage include main effects (c r t) and interactions (tc tr cr).

The IV results confirms a negative first-stage relationship between the grandparents' years of education and their exposition to conflict. In the current context, these estimates suggest that a drop in the grandfathers' education by a year is associated with a reduction on the parents' education. This relationship is strongly significant and unambiguously negative. The causal relationship described by the IV results are larger in absolute value than OLS's, at around 0.65-0.70, which also appears in line previous studies (see Holmlund, Lindahl & Plug (2011), Maurin & MacNally (2008)).⁵²

This higher order of magnitude is confirmed by the second identification strategy in column 3. Unsurprisingly, the IV estimates are less efficiently estimated than OLS's however all the parameters are strongly significant. The fact that the IV estimate of intergenerational persistence of education is higher than the OLS estimate suggest that the later under-estimate the true causal effect of parents education (Angrist & Krueger (1991) and Verbeek (2012)).⁵³

4.4 The effect of grandparents' education on their indirect offspring, G0-G2

⁵² Of course the literature vary according to the identification strategy country of analysis and time period (Black & Deveroux, 2011).

⁵³ See Angrist & Krueger (1991) and Verbeek (2012). This result is empirically well known since the early work of Behrman & Taubman (1985) who contrast OLS intergenerational estimates of education with 2SLS and IV estimates with data from three generations. In that study, uncle's education is used as instrument for the fathers' education.

Similarly, **Table 3** shows the OLS and the IV estimates of the unconditional effect of the grandfather's education on the second generation. This exercise reports the two instruments described above. The independent variable refers to the instrumented grandparental education whereas the dependent variable is the educative outcome of the second generation.

Table 3

The effect of grandfather's education (G0) on grandchildren's education (G2)
Using the regional variation of the conflict (for G0) as instruments

Offspring: Dep. Var.:	Grandchildren's years of education (G2) Years of education (standardized)		
Indep. Var	(1) OLS	(2) IV 1	(3) IV 2
Reduced form			
Grand-Father (Std) Ed. (G0)	0.148*** (0.0353)	0.287 (0.215)	0.269 (0.177)
Observations	1,897	1,897	1,897
Adjusted R-squared	0.156	0.142	0.145
First stage			
CRT 1	-	-2.188*** (0.648)	-
CRT 2	-	-	-6.629*** (1.785)
F-stat	-	4.6	4.8
Observations	-	1,897	1,897
Adjusted R-squared	-	0.289	0.296
Sex, G2	Yes	Yes	Yes
Birthyear, G2	Yes	Yes	Yes
Wealth, G1	Yes	Yes	Yes
State fixed eff.	Yes	Yes	Yes
Number of children, G1	Yes	Yes	Yes

Note: Robust standard errors in parentheses. Clustered by family. *** p<0.01, ** p<0.05, * p<0.1. EMOVI (2011). Each estimate represents the coefficient from a different regression. Std: standardized. First stage include main effects (c r t) and interactions (tc tr cr).

The OLS estimate appears positive and statistically significant but with a much lower coefficient, 0.15, as compared with the previous estimates. The magnitude of this coefficient is around one third of the estimated influence of the grandfather on the parents' generation (0.15 vs 0.45 for this and the previous generation). Interestingly both the instruments are slightly positive but none appear statistically significant.

5. The effect of parents' education on their offspring, G1-G2

This section resorts to labor market indicators to instrument parental education. The literature uses several instruments to estimate the causal effects of additional years of education, for

instance: twins or siblings' information (Card, 1999); changes in the legislation of compulsory school as well as data on state and quarter of birth (Angrist & Krueger, 1991); the direct, or monetary, costs of schooling (Carneiro et al (2013) and the opportunity cost of schooling- through the proximity to a four-year college- (Card, 1995).

Labor market indicators has recently been used to instrument years of schooling. Labor market indicators can affect educational attainment by an income or a substitution effects. Arkes (2010) for instance used unemployment rates to estimate the returns to schooling arguing that, on the one hand, with higher unemployment rates, earnings will be lower so families may need their teenage children to quit school and work (income effect) leading to lower educational attainment. In the same context, on the other hand, jobs are scarcer, lowering the opportunity cost of attending school, which increase the rate of return to schooling and therefore increasing educational attainment (substitution effect). The ambiguity of the labor market indicators then stems from which of these two effects dominates over the other either the "additional worker" (income) effect or the "discouraged worker" (substitution) effect. Similarly, Card (1999) used this IV to estimate the returns of education.

We exploit this source of variation to instrument parents' generation education (G1). The educative outcome S_1 of the parents' generation (G), the first stage, is defined as follows:

$$\hat{s}_1 = \beta_0 + \beta_1 Z + X' \beta + \varepsilon \quad (Eq. 5)$$

Where Z refer to two alternative instrumental variables. In this case: grandfather's education and labor market indicators. Grandfathers education is an interesting instrument when assuming an AR(1) approach like the one followed by Becker and Thomes. This approach has also been employed to test this model with data on three generations.

Graph 2. Historical records of labour market indicators in Mexico 1940-1972



The instrument to be used here refers to the minimum wage per state and year when the parental generation decided to drop out the school. This instrument appears appealing in our context as it is completely independent of any ancestors education which will prove useful in the next section when all these three generations are to be used simultaneously. Minimum wages in Mexico was introduced in 1934 during the presidency of Abelardo Rodriguez. At the beginning, this indicator was defined by each state to reflect the different cost of living. **Graph 2** describes this state and time variation by the contrast between the state with the largest and the smallest minimum wage on a yearly basis. This external source of variation will be used to instrument the parental education.⁵⁴

The second stage corresponds once more to a bivariate regression as described in **Equation 4** before. **Table 4** contains the results of the first and second stage. The OLS results in column 1 show a statistically significant positive relationship between the (grand) children’s years of education and their parents’ education. The OLS estimates suggest a statistical significant intergenerational persistence of education or around 0.3è.

Table 4. The effect of parents’ education (G1) on children's education (G2)

Using siblings education and adolescence information to instrument G1's education

Dep. Var.:	Grandchildren's education (standardized), G2		
	(1)	(2)	(3)

⁵⁴ Data obtained from INEG (1985). Estadísticas Historicas de Mexico Tomo 5. Primera edicion, Agosto 1985.

	OLS	IV 1	IV 2
Reduced form			
Parents (std) education (G1)	0.373*** (0.0334)	0.416*** (0.0923)	0.450*** (0.0673)
Observations	1,893	1,893	1,828
Adjusted R-squared	0.242	0.241	0.248
First stage			
G0's (std) education		0.359*** (0.0429)	
Min wage _(t,s)			0.106*** (0.00645)
Observations		1,893	1,828
Adjusted R-squared		0.368	0.448
F-stat		125.9	65.5
Sex, G2	Yes	Yes	Yes
Birthyear, G2	Yes	Yes	Yes
Wealth, G0	Yes	Yes	Yes
State fixed eff.	Yes	Yes	Yes
Number of children, G1	Yes	Yes	Yes

Min wage: refers to real minimum wage when dropping-out school (t) in a given state (s). Robust standard error in parentheses. Clustered by family. *** p<0.01, ** p<0.05, * p<0.1. Each estimate represents the coefficient from a different regression. Std: standardized.

The IV estimates shows a positive first-stage relationship between the parents' years of education and their labour market indicators (columns 2 & 3). The causal estimate from the reduced form suggest a larger relationship, of around 0.45, than the OLS estimate -around 0.37. This suggests that an increase in the parents' education by one year substantially increases their children education by around 0.45 standard deviations above the mean years of education. When comparing these results with those of the previous generation the magnitude of these estimates suggest some change in educative mobility in Mexico during the XX century (the figures from both generations changed around 0.60-0.70 to 0.45 for IV). These results implied a trend of educative mobility (less persistence) although this patter is smaller than the pattern implied by the OLS. OLS in this case overestimates mobility compared with the IV estimate.

6. The 'conditioned' effect of grandparents' education on their grandchildren, G0-G2

This section refers to the theoretical models of Becker and Tomes (1979), more recently in Solon (2013), which have strong predictions for the associations of outcomes across multiple generations These models predict a small negative correlation coefficient for the grandchild

generation (G0 on G2) conditional on parental status (G1). Although the analysis of the multigenerational transmission of education is still scarce, some studies examine the effect of grandparents' education on grandchildren's conditional on parents' generation. . The unified framework at hand then appears appealing to provide empirical evidence on the intergenerational transmission of education from an emerging country provided that most of the evidence stem from well-developed and Nordic countries.

Behrman and Taubman (1985) found no empirical basis for this prediction based on survey data from the USA as the coefficient of grandparental education appears positive (around 0.04) but not statistically significant.⁵⁵ They instrumented parental education with siblings' education but not addressed the endogeneity in grandparental education. Lindahl et al. (2014) used rich administrative records to follow four generations in the city of Malmö in Sweden. Their study instrumented the parental education with the education from the previous generation (both the great-grandparental education and the grandparental education). They found a positive and statistically significant estimate of grandparental education on grandchildren education. Finally Kroeger & Thompson (2016) examined the grandmother-granddaughter educative link for the USA where they found a statistically significant OLS coefficient of 0.23.

This literature provide empirical evidence to an AR(2) model for the intergenerational transmission of human capital. Here we follow a similar approach with a different strategy. The strategy is slightly different because with the two instruments at hand, the estimation of **Equation 2** can be performed under a multi-equation approach like the following:

$$s_2 = \alpha + \beta_1 \hat{s}_1 + \beta_0 \hat{s}_0 + X' \beta + v \quad (Eq. 6)$$

Where s_2 is the educative outcome of any of these generations and X consists of a set of exogenous covariates like gender, birth year and state fixed effects. This means that **Equation 6** is to be jointly estimated along with two regimes of **Equation 4** for \hat{s}_0 and for \hat{s}_1 respectively. The former is a structural equation whereas the later are reduced form provided the instruments for the identification of the schooling for parental and grandparental generations - as described by **Equations 3 and 5** respectively. This estimation is performed by maximum likelihood seemingly unrelated regression following Roodman (2011).

Table 5 shows both first and second stage. Many interesting issues emerges from this table. Firstly, similarly to Lindahl et al (2014) and Behrman and Taubman (1985), from Sweden and the USA respectively, the OLS coefficient for the parent education is positive and statistically significant. The coefficient for the grandfather is also positive though not statistically significant

⁵⁵ This is the NAS-NRC sample composed by veterans born between 1917 and 1927 which appear very similar to the period examined here.

(in this regards this is only similar to Behrman and Taubman). Secondly, the instrumented coefficients for parental education suggest a stronger relationship than the one described by the OLS estimates (0.42 for IV vs 0.35 for OLS). The order of magnitude for the instrumented coefficient is larger than the OLS for these contiguous generations. Contrary to Lindahl, both of these IV estimates also confirms a negative and not statistically significant relationship between separated generations. This is interesting as testing for a negative sign in this framework can be seen as a way of testing for the presence of credit constraints (Lindhal, op cit.) which here appears as a tentative interpretation that separates the Mexican results from these other well-developed countries.

The IV estimate for the grandfather education remains not statistically significant though it unveils a larger importance of direct familiar background (less educational mobility) than predicted by the OLS estimates. All in all, these results indicate that the influence of the grandparents' educative legacy did not remain further away from the first generation. These conclusions remain regardless of the identification strategy implemented. No causal effect can be inferred for the grandchildren education, which suggests that the persistence of some part of the current inequality in this emerging country can be traced back to the preceding generation only.

Table 5. Intergenerational transmission of education across three generations, Mexico

Using the regional variation of the conflict (IV1 & IV2) as instrument for G0 education and adolescence and siblings information to instrument for G1 education

Dep. Var.: Offspring: Indep. Var / Method:	Grandchildren's education, G2	
	Standardized years of education	
	(1) OLS	(2) IV 1
Reduced form		
Parent standardized years of Ed., G1	0.353*** (0.0369)	0.418*** (0.0512)
Grandfather standardized years of Ed., G0	0.0239 (0.0357)	-0.0150 (0.159)
Observations	1,893	1,936
Adjusted R-squared	0.268	0.242
First stage, G1		
Min wage _(t, s)	-	0.177*** (0.00813)
F-stat	-	45.6
Observations	-	1,936
Adjusted R-squared	-	0.606

First stage, G0		
CRT 1	-	-1.713***
	-	(0.650)
F-stat	-	10.95
Observations	-	1,936
Adjusted R-squared	-	0.342
Sex, G2, G1	Yes	Yes
Birthyear, G1, G2	Yes	Yes
Wealth, G0, G1	Yes	Yes
Number of children, G0, G1	Yes	Yes
State fixed eff.	Yes	Yes

Note: robust standard errors in parentheses. Clustered by family. EMOVI (2011). Each quadrant represent the coefficient from a different regression. First stage include main effects (c r t) and interactions (tc tr cr).

7. Discussion. The direct Vs the extrapolated effect on long run mobility (G02)

The evidence from previous sections is already useful to assess a popular method often used in related studies to extrapolate the long term transmission of education by the use of two contiguous generations. This method assumes that the correlation between the index generation (G0) and the second generation (G2) tend to be the square of that between G0 and G1. This discussion has also been recently rekindled in Solon (2013) who claims no basis for this last presumption. This section then provides empirical evidence on a causal approach.

As recently reviewed by Lindahl et al (2014) and Stuhler (2013) there are at least two important reasons why researches may have misleadingly extrapolated the long run intergenerational persistence by the use AR(1) only from two contiguous generations. Firstly, important biases in this extrapolation (a lower than geometric decline in intergenerational persistence) stem from the direct influence of the grandparental involvement in the upbringing of their grandchildren.⁵⁶ Secondly, distributional changes of the outcome variable across generations might introduce another relevant bias in predicting the long run mobility from a simple AR(1) specification.

Table 4 allow comparing the estimated effect of grandfather education on their grandchildren education with the extrapolated result which is often used in the literature. The association between the index generation (G0) and the second generation (G2) is relatively smaller than what would be expected if we were to predict this association based on the estimate from the adjacent generations involved (G1-G2). According to **Table 3** the OLS estimate for the persistence between

⁵⁶ In our context the survey in use does not allow to capture the complexity of this relationship.

G02 is 0.15 with OLS and 0.27 with IV whereas the extrapolated figures are very close with OLS=0.14 (0.37×0.37 , from the interaction of the estimates of G12 in **Table 4**) but differ with the IV estimates= 0.200 (0.45×0.45 in **Table 4**). It is reassuring that this discrepancy is larger with the IV estimates.

These results contrast with the empirical evidence from Sweden, as reported from Lindahl et al (2014), where the direct association between the great-grandfather and the father (using older generations than the cohorts used in our study) appears larger than what would be expected from this extrapolation. However our estimate do appears in line with the Swedish estimates for the more contemporaneous generations as the direct association between the grandfather and the grandchildren (around 0.14) also appears slightly different than the extrapolated figure (around 0.12)⁵⁷ reported there. These generations are closer to G0 and G2 used here.

8. Conclusion

The use of three generations allowed comparing medium and long run trends of economic mobility over most of the last century. Differently to the bulk of the multigenerational literature, this paper uses data from an emerging country and controls for endogeneity biases to examine the transmission of human capital. The paper examined the direct effect of parental education on the children's education and the conditional effect of grandparental education on the grandchildren's education.

The causal or IV estimates for the grandfather-parent link as well as for the parent-children link unveils a larger importance of familiar background than what would be obtained by OLS. The IV estimates for these adjacent generations are larger than the OLS estimates, which suggest that this causal examination implies less mobility than conventionally observed. Interestingly, the effect of grandparental education turned out not to be statistically significant once conditioned on parental education. The findings however suggest that the influence of the grandparents' educative legacy in Mexico did not to go beyond its direct effect on the first generation (contrary to empirical evidence from well-developed countries where this coefficient is positive though not always statistically significant).

The findings from a middle-income country extend the current knowledge from Nordic or highly developed countries. Indeed the influence of grandparental education might vary from cultural differences across societies or among social groups as recently suggested by Solon (2016). Finally, the use of a regional civil conflict to instrument the education level of ancestors constitutes a secondary contribution with a potential application to other countries provided that most nations have experienced internal wars in the last century (Blattman & Miguel, 2010). In this regards,

⁵⁷ Cfr Table 2, P. 14. Op. cit.

Mexico was also an interesting case of study because, like many other countries, it is coping with extreme inequalities and with rising regional conflicts from drug cartels and insecurity with potential long run consequences on the wellbeing of future generations.

ANNEX 1

The *Cristero* conflict and the grandparents' education (G0)

Historical background

In January 1926 a Mexican archbishop was put in prison after endorsing a public statement in a national newspaper against the enforcement of secular legislation from the Constitution of 1917. In reaction a countrywide civic association, named the *National League for the Defense of Religious Liberty*, called for a general uprising while the Catholic hierarchy claimed for a peaceful resistance. However, as the anticlerical measures became stricter the clergy protested by suspending sacramental worship on July 1926 leading to a severe armed conflict where thousands of individuals, mainly peasants from rural areas rose to defend their faith, their communities and the church (Meyer (1973a), Buttler (2013), and Aspe (2015)).

The revolt was known as “*La Cristiada*”, or *Cristero* war, after the rebels' battle cry *¡Viva Cristo Rey!* (Long live Christ the King!), and constituted the major conflict between the Catholic Church and the Mexican State during the 20th century. The stringent enforcement of constitutional provisions in 1926 configured an unprecedented situation for the Mexican clergy accustomed to the unbinding legislations from the past. The *Cristero* war spread over western and central states of Mexico and constituted a multilevel conflict: both a local-regional guerrilla war and a national-international diplomatic dispute (Andes, 2014) that came to its end in 1929 after mutual concessions between the Mexican government and the Catholic hierarchy.

The incidence of the war

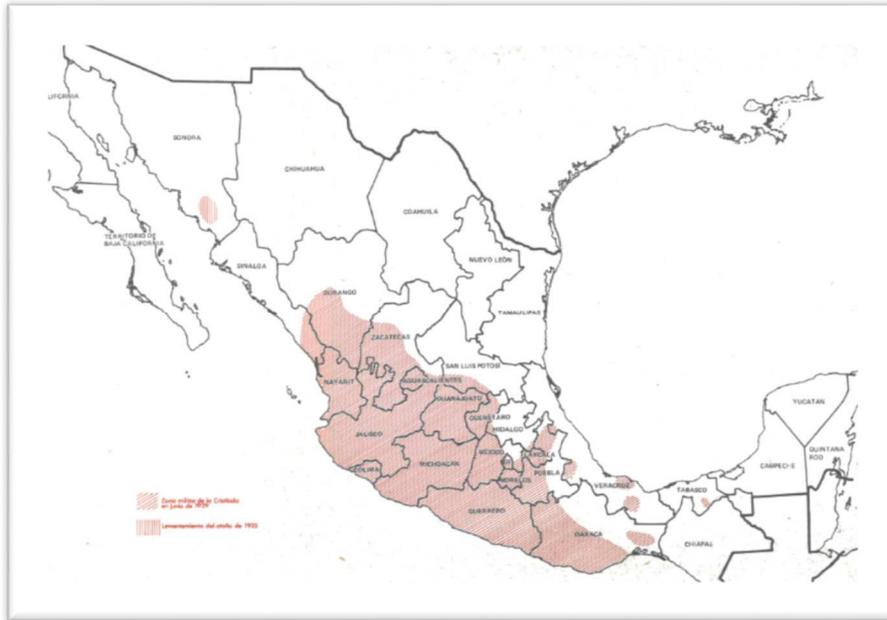
The conflict produced around 250 thousand deceases (Aspe (2015) and Meyer (2014)) where only 90 thousand corresponded to combatants (Andes, 2014).⁵⁸ **Map A1** shows the incidence of the revolt in a region comprised by at least twelve states in western and central in Mexico. This western territory gathered half (48%) of the total population of 15 million according to the 1910 Census.⁵⁹ The conflict adopted the form of guerrilla warfare in rural localities. Meyer (1973b and 1973c) examined this conflict through the use of official and *Cristero* sources producing one of the most comprehensive historic studies on this matter. He was able to quantify the number of *Cristero* troops by state confirmed by independent sources.⁶⁰

Map A1. Regional distribution of the *Cristero* war

⁵⁸ This was clearly a civil war as, according to Buttler (2013), a significant sector of the population remained loyal to the regime, which armed its supporters – the beneficiaries of land reform known as *agraristas*- and sent them into battle alongside the federal army.

⁵⁹ This is the closest data available before the uprising. The next population census was carried out until 1930.

⁶⁰ These other sources were the U.S. Department of State Records, Clark memorandum on military situation and military records.



Source: Meyer (1973a)

Meyer (2014) extended his research on the number of combatants yielding around 50 thousand fighters whose regional distribution appears in **Table 2**. In absolute terms, the rebels' troops were stronger in four western states (Jalisco, Michoacán, Guanajuato and Zacatecas) whereas these troops were much more stronger in relative terms, i.e. the share of rural population engaged in the conflict, in three states (Colima, Aguascalientes and Nayarit) but weaker in other central (DF, México and Morelos) and southern states (Oaxaca, Puebla, Veracruz). These two criteria, territory spread and the density of combatants, allows defining a *macro* region that experienced the greater intensity of the *Cristero* war. This region is comprised by the states of Aguascalientes, Jalisco, Michoacán, Guanajuato, Colima, Nayarit and Zacatecas that contained 27.2% of the total Mexican population in 1910.

Table A2

Regional distribution of *Cristero* fighters by state (1926-1929)

State	Fighters	% Rural Pop.	State (s)	Fighters	% Rural Pop.
Michoacán	12,000	1.3%	Durango	2,000	0.4%
Jalisco	10,000	0.9%	Aguascalientes	1,200	1.6%
Guanajuato	4,000	0.4%	Guerrero	3,000	0.5%
Zacatecas	5,400	1.2%	Oaxaca	1,500	0.1%
Nayarit	2,500	1.5%	Morelos, México, DF	1,000	0.1%
Colima	2,000	3.8%	Puebla, Tlaxcala,		
			Veracruz	1,000	0.0%

Sources: *Cristero* fighters from Meyer (1973c) and Meyer (2014). Rural population from 1910 Census (INEGI, 1910). Rural population refers to areas outside the state capital.

The effect of the conflict on the affected generation

First identification strategy

The first methodological approach exploit the conflict characteristics and relies on the influence of this insurgency on the grandparents' education determined by three characteristics: the affected cohort, the affected areas and the geographical distribution of the conflict. Firstly, the effect of the conflict on the grandparental generation is expected to be larger in the states directly engaged in the conflict. This incidence is presumably larger in states with the higher share of combatants relative to their rural population which led us to a small set of states from central and occidental region. Secondly, the effect is expected to be larger in the rural areas where the *Cristero* troops were able to engage in guerrilla war due to the disproportionate number of federal forces (see Meyer (1973a), Buttler (2013) and Jrade (1982)). Finally, given the low level of education that characterized these cohorts, it is speculated that the war and the enforcement of the constitutional amendments more negatively affected the human capital accumulation of children in school age corresponding to primary education.⁶¹

It is argued here that the largest effect of the war is to be found on younger cohorts in school age that might have been prevented to enroll or complete elementary education. The focus then are children that were born during the conflict or that were in school age in primary education (aged 7-12). The most affected cohorts were those born between 1917 and 1929. The oldest cohort encompasses those children that were enrolled in the 2nd year of primary education at the beginning of the struggle in 1926. Conclusions are robust to selecting other cohorts in close age intervals.⁶² Given the nature of the conflict, it is expected that the children most negatively affected were those living in rural localities, as they were more prone to be exposed to this civil war.

The objective now is to identify the effect of the *Cristero* conflict on the grandparents' educative achievement. To show that the conflict differently affected the children according to their place and year of birth, the empirical strategy exploited the regional variation of the conflict under a difference-in-difference-in-differences (DDD) specification. In this setting, older cohorts, those born before this uprising, were selected as comparison group as younger cohorts, born after the conflict, would most likely be affected by its direct or collateral consequences.⁶³ Following Imbens & Wooldridge (2007) the empirical implementation is as follows:

⁶¹ In addition to small proportion of individuals enrolling in higher levels of education, the number of secondary schools was also very limited at the time, and most of them were located in urban areas.

⁶² Very consistent effects are found when using a more restricted sample of cohorts that was at school age during the conflict. To gain precision we stick to the most ample sample reported here.

⁶³ Under a similar objective and following a triple difference approach Singh and Shmyyakina (2016) found a substantial and statistically significant negative effect of localized insurgencies on children's educational attainment.

$$S_0 = \alpha + \beta_1 \text{Cristero} + \beta_2 \text{Rural} + \beta_3 \text{Cohort} + \beta_4 \text{Cristero} * \text{cohort} + \beta_5 \text{Cristero} * \text{rural} + \beta_6 \text{Cohort} * \text{rural} + \beta_7 \text{Cristero} * \text{rural} * \text{cohort} + \varepsilon \quad (\text{Eq. A1})$$

where ‘Cristero’ is a dummy variable for individuals in *Cristero* region (comprised by a set of states engaged in conflict as described above), ‘rural’ is a dummy for individuals living in rural areas (equals 0 for urban areas), and ‘cohort’ variable introduces the time dimension in a dummy for children in school age at the moment of the conflict (being 0 for older children –out of school age during the revolt). **Table A3 and A4** shows descriptive statistics for these groups and variables. The outcome variable is grandparents’ education, S_0 .

Table A3. Descriptive statistics for the Diff-in-Diff-in Differences implementation

EMOVI Survey (2011)

Variable	Obs	Mean	Std. Dev.
Grand-fathers			
Cristero*rural*cohort (crt)	786	0.154	0.361
Dummy cristero region (c)	786	0.240	0.428
Dummy rural area (r)	786	0.822	0.383
Dummy affected cohort (t)	786	0.762	0.426
Cristero*cohort (ct)	786	0.170	0.376
Rural*cohort (rt)	786	0.622	0.485
Crister*rural (cr)	786	0.218	0.413
Grand-mothers			
Cristero*rural*cohort (crt)	616	0.175	0.381
Dummy cristero region (c)	616	0.247	0.431
Dummy rural area (r)	616	0.812	0.391
Dummy affected cohort (t)	616	0.810	0.393
Cristero*cohort (ct)	616	0.130	0.336
Rural*cohort (rt)	616	0.472	0.500
Crister*rural (cr)	616	0.216	0.412

Source: EMOVI (2011). Sample of grandparents born during the Cristero war or older.

Table A3. Summary statistics for groups used in the implementation of Diff-inDiff-in-Differences

	Above school age during the conflict						Born or at school age during the conflict					
	Rural children living in Cristero region			Rural children living out of Cristero region or urban children.			Rural children living in Cristero region			Rural children living out of Cristero region or urban children.		
	N	mean	sd	N	mean	sd	N	mean	sd	N	mean	sd
Grand-fathers sample												

G0 Schooling	160	2.44	4.04	357	1.46	2.73	324	1.24	2.09	1254	2.34	3.43
G1 Schooling	160	5.69	4.16	357	5.98	4.75	330	6.01	4.27	1285	5.97	4.50
G2 Schooling	135	9.96	3.79	320	9.63	4.09	284	9.15	3.91	1235	9.82	3.81

Grand-mothers sample

G0 Schooling	202	0.85	1.70	642	1.79	2.74	281	1.25	2.09	970	1.63	2.81
G1 Schooling	208	6.41	4.06	655	6.10	4.53	282	5.54	4.32	987	5.89	4.57
G2 Schooling	161	9.60	3.83	611	9.80	3.89	258	9.30	3.93	944	9.78	3.86

Source: own computation with EMOVI (2011)

A key assumption in this approach is that the trends of the groups under analysis possess similar trends. For illustrative purposes, **Graph A1** plots a visual inspection. The graph plots the average educative trends for two groups. The first group refers to ‘affected’ children, in rural and *Cristero* areas, while the second group refers to ‘unaffected’ children, in rural and *Cristero* areas but above school age at the moment of the conflict plus children in rural areas out of the region in conflict. The time dimension of the chart refers to the affected cohorts (in school age at the moment of the conflict) and the unaffected cohorts (older cohorts and hence out of school age at the moment of the conflict). Some interesting facts emerge from this chart. First, that there was not a seemingly difference in years of schooling between these two cohorts before the conflict outbreak. Second, that *La Cristiada* seems to have altered the human capital accumulation process creating a significant difference between these two groups after the conflict. The graph shows that human capital accumulation was negatively affected in the insurgent regions.

Graph A1

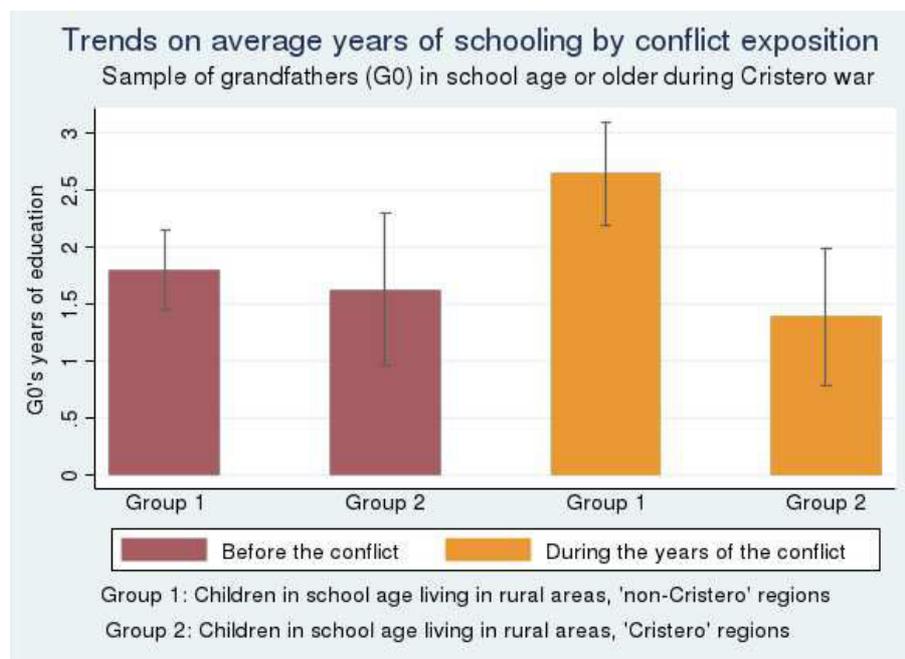


Table A5 presents results of a baseline specification of Eq. 1 for the grandfathers’ and the grandmothers’ education (using standardized years of education). The estimated coefficient for

the affected boys is negative and statistically significant. This means that children exposed to the conflict accumulated less education as compared with those not affected by the conflict. These results seem reasonable considering the length of the conflict though the effect might constitute a lower bound provided that the education system did not immediately reestablished immediately after the conflict. The coefficient for the females is not statistically significant provided that this group already accumulated less years of education in comparison with their masculine counterparts. More importantly, this table confirms that the effect on the educational outcomes varies according to the age and the place of residence at the time of the conflict for the male cohort considered.

Table A5

The effect of <i>Cristero</i> civil war on grandparents' education (G0)		
Variable:	(1)	(2)
	Years of education (standardized)	
Generation:	Grand-Father	Grand-Mother
Cristero*rural*cohort (crt)	-1.172** (0.470)	0.00571 (0.210)
Dummy cristero region (c)	-0.876*** (0.253)	-0.875*** (0.268)
Dummy rural area (r)	-0.512** (0.260)	-0.809*** (0.188)
Dummy affected cohort (t)	0.457 (0.291)	0.255* (0.138)
Cristero*cohort (ct)	0.767* (0.434)	-0.000305 (0.192)
Rural*cohort (rt)	-0.214 (0.302)	-0.0722 (0.122)
Cristero*rural (cr)	1.070*** (0.299)	0.817*** (0.291)
Observations	772	510
Adj. R-squared	0.082	0.099

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Other non-contemporaneous outcomes were examined to assess side effects of this conflict. The analysis here refers only to fertility (number of children) and wealth holdings of grandparents. These resources refer to their wealth rank, decil, computed by Principal Component Analysis, PCA, from the rich set of the assets reported by the survey respondent when he or she was at age 14. **Table A6** reports the interacted term of interest (crt) that confirms a negative effect on the grandfathers' years of schooling. This analysis controls for age, ethnicity condition and includes state fixed effects. Results suggest no effect on fertility and in the future wealth of the affected

cohort for both the grandfathers and grandmothers. The identification of the effect of grandparents' education on their offspring, to be shown latter on, builds on these results.

Table A6

The effect of Cristero war on grandparents' outcomes (G0)

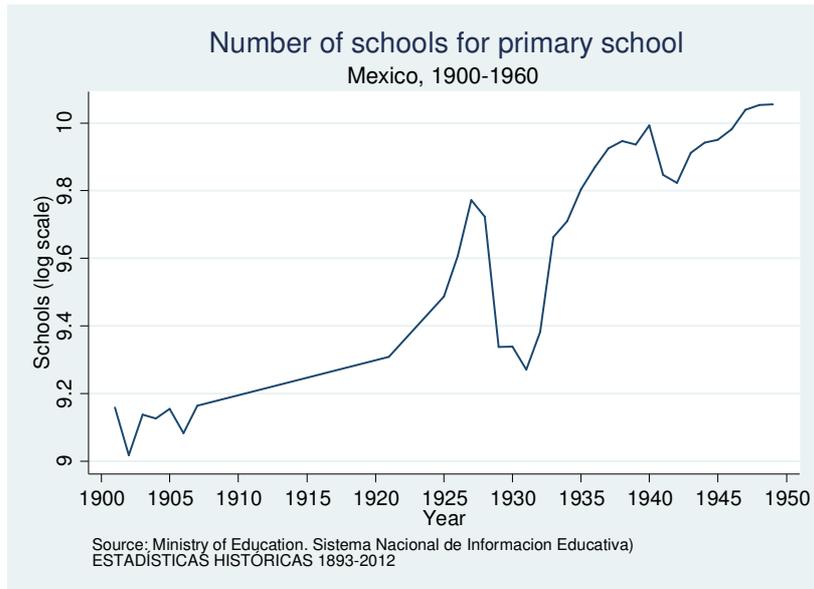
Generation VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Grand-Father (G0)			Grand-Mother (G0)		
	Education (Std)	Children	Wealth	Education (Std)	Children	Wealth
Cristero*rural*cohort (crt)	-1.068** (0.470)	0.305 (1.976)	0.269 (1.978)	0.00553 (0.219)	-0.655 (0.908)	-0.00929 (0.727)
r, c, t,tr, tc, rc	Yes	Yes	Yes	Yes	Yes	Yes
Birhtyear, G0	Yes	Yes	Yes	Yes	Yes	Yes
Ethnicity, G0	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects, G0	Yes	Yes	Yes	Yes	Yes	Yes
Observations	772	786	774	510	616	607
Adj. R-squared	0.091	0.044	0.150	0.116	0.068	0.154

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Wealth corresponds to the PCA of assets reported by G1 at age 14. Std_ standardized.

Second identification strategy

The second identification strategy exploits intrinsic characteristics of the conflict. The law enforcement of the anticlerical legislation of 1926 configured an unprecedented situation for the Mexican clergy traditionally accustomed to the unbinding legislations from the past. This strategy exploits the fact that the stringent application of the educative provisions, preventing the clergy to manage primary schools (Article 3 of the Mexican constitution of 1917), implied a sharp reduction in the number of active schools. This strongly affected schools administered by the Catholic Church that had had an important role in the provision of education during the three previous centuries. **Graph A2** shows historical administrative records for the total number of primary schools during the first half of the 20th century describing a harsh reduction in a clear u-shaped trend during the *Cristero* conflict. This pattern illustrates an important supply shock in at least one relevant educational input, the stock of primary schools, and exemplifies the potential effect of these low previsions as it took nearly ten years to return to pre-conflict levels.

Graph A2



The conflict then might have prevented children to enroll in school or, for those already in school, it might have increased the probability of interrupting education due to the abrupt shutdown of schools -or their physical destruction. This suggests that the legal enforcements of 1926 and the *Cristero* conflict are likely to have affected the human capital accumulation of children in school age. The effect on educational outcomes might have taken place through several channels. As the violence escalated, and the number of casualties increased, the negative impact on schooling could have also been stronger in the insurgent areas not only due to the destruction of schools but also because of shortages of civilian and religious educators/teachers. This is a special characteristic of this conflict as only around 35% of the casualties concerned to combatants. Indeed, detailed historiographical research, Andes (2014), Aspe (2015), and Meyer (2014), finds that a substantial number of priests were killed, imprisoned or deported during the conflict.

The effect of the war on schooling then would presumably be larger in states where the historic provision of education by the clergy was more important. **Table A7** shows the share of religious schools by state in 1900 and illustrates the preeminence of the Church as school administrator. This indicator reveals the heterogeneous influence of the clergy in public affairs and particularly its strength in the provision of education. On average almost one out of five schools was managed by the clergy ranging from 5 to 55% percent in Guerrero and Guanajuato respectively. This is the basis of the second identification strategy that relies on the fact that the impact on educative outcomes does not depend solely on the regional intensity of the conflict, but on the historical dominance of the Catholic Church in the provision of public services.⁶⁴

Table A7

⁶⁴ Historical data stems from the official records from the Mexican Statistical office at the beginning of the XX century as described in Peña (1991).

Number of schools managed by the government or by the clergy, by state, Mexico 1900

State or territory	No. of schools by type of management:				State or territory	No. of schools by type of management:			
	Gov.	Clergy	Total	Clergy %		Gov.	Clergy	Total	Clergy %
Aguascalientes	46	31	77	40.3%	Puebla	1091	79	1170	6.8%
Campeche	80	6	86	7.0%	Querétaro	158	47	205	22.9%
Coahuila	99	33	132	25.0%	San Luis P.	355	312	667	46.8%
Colima	45	24	69	34.8%	Sinaloa	335	14	349	4.0%
Chiapas	126	29	155	18.7%	Sonora	176	2	178	1.1%
Chihuahua	98	26	124	21.0%	Tabasco	130	36	166	21.7%
Durango	133	87	220	39.5%	Tamaulipas	193	37	230	16.1%
Guanajuato	274	344	618	55.7%	Tlaxcala	248	18	266	6.8%
Guerrero	382	19	401	4.7%	Veracruz	694	125	819	15.3%
Hidalgo	594	84	678	12.4%	Yucatán	342	10	352	2.8%
Jalisco	446	365	811	45.0%	Zacatecas	400	70	470	14.9%
Edomex	1031	89	1120	7.9%	Fed. District*	354	191	545	35.0%
Michoacán	300	254	554	45.8%	N. Baja Cal.*	94	38	132	28.8%
Morelos	234	31	265	11.7%	S. Baja Cal.*	11	0	11	0.0%
Nuevo León	316	88	404	21.8%	Nayarit*	32	24	56	42.9%
Oaxaca	688	94	782	12.0%					

Source: *Cuadro sinóptico y estadístico de la República Mexicana* in Peñafiel (1900). Notes: Public schools includes three levels of government (federal, state, municipality). Federal administration only. The modern state of Quintana Roo was part of Yucatan state back in ninetieth century.

The correlation between this indicator and the number *Cristero* fighters by state is 0.44. This also serves a robustness check, as it does not solely rely on the specific states involved in the armed struggle, but also on the regions across the country where the clergy had maintained its customary influence in the provision education, and where the application of secular provisions had a harsher effect.

Similarly, the empirical implementation is as follows:

$$S_0 = \alpha + \beta_1 S_{Church} + \beta_2 Rural + \beta_3 Cohort + \beta_4 S_{Church} * cohort + \beta_5 S_{Church} * rural + \beta_6 Cohort * rural + \beta_7 S_{Church} * rural * cohort + \varepsilon \quad (Eq. A2)$$

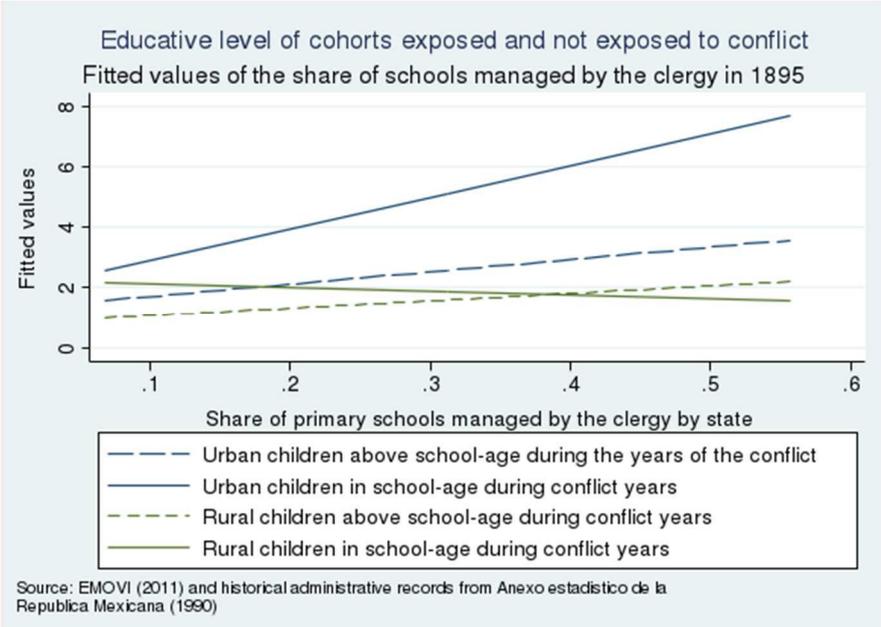
where ‘S_{Church}’ is the share of schools managed by the Church as observed in the statistical records of 1895 (30 years before the conflict started). Once more ‘rural’ is a dummy for individuals living in rural areas (equals 0 for urban areas), and ‘cohort’ variable introduces the time dimension in a dummy for children in school age at the moment of the conflict (being 0 for older children –out of school age during the revolt). A key attribute on this identification strategy is that

it departs from the war incidence, and more importantly, it introduces heterogeneity in the effect captured by the IV.⁶⁵

Graph A3 illustrates this second approach as it displays the years of education of individuals exposed and not exposed to the conflict over the state variation of the share of primary schools managed by the clergy as observed in 1985 (30 years before the uprising). The effect of the conflict on the affected cohort (in solid lines that corresponds to individuals in school age during the conflict) confirms a divergent process relative to the unaffected cohort (in dotted lines that corresponds to individuals above school age during the conflict) that was characterized by a parallel trend between the urban and the rural areas. The regression line of the most directly affected group of individuals, rural population in school age during the conflict, shows a negative first-stage relationship whereas the group less likely to be affected by the insurgency, urban population in school age during the conflict, shows a positive relationship, as anticipated.

To wrap up, the upward slope of the dotted lines (cohorts above school age during the conflict) describes a positive relationship between years of schooling and share of primary schools managed by the clergy whereas the divergent trajectory observed by the solid lines describes the effect of the school destruction on the affected generations. The difference between the dotted and the solid lines illustrates then the associated loss on education.

Graph A3



⁶⁵ Other robustness checks were performed using alternative definitions of children in school age and states in conflict with negligible differences with respect to the two identification strategies described.

Final remarks

« Soit dit en passant, c'est une chose assez hideuse que le succès. Sa fausse ressemblance avec le mérite trompe les hommes. Pour la foule, la réussite a presque le même profil que la suprématie. Le succès, ce ménechme du talent, a une dupe : l'histoire... Prospérité suppose Capacité. »

« Les Misérables »

Victor Hugo

This dissertation provided inputs and examined long-run trends of economic mobility. This research firstly addressed a methodological issue to tackle the scarce availability of longitudinal data. The first chapter provides a methodological approach and discusses the construction of synthetic income panels. Our results seemed of sufficient quality to envisage a systematic application of this methodology with sequences of two cross-sectional household surveys over a longer time span so as to study a possible evolution in the income mobility of the population.

Having applied this approach to Mexico, the analysis documents low levels of short-run economic mobility over three decades -between late 1990's and early 2010's. The mobility patterns observed during the *Tequila* economic crises of 1995 seemed to have equalized longer-term incomes. In particular, the mobility patterns observed during the economic downturn describe an equalization process that compares with *glass ceilings and sticky floors*: less upward mobility for the poorest quintiles and more downward mobility for richer population groups. The structure of income growth experiences observed during this period suggested a trend of progressive income fall.

Complementarily, the longest trends of economic mobility examined, by the use of educative trends on three generations, extended the analyses over most of the last century. This research finds that parental education has a significant effect on their children's education. This holds true for both the older and the younger pairs of parent-child links in the three examined generations. The causal channel examined unveiled less mobility than conventionally observed by the literature that do not address endogeneity issues. Interestingly, the effect of grandparental education on the grandchildren's generation turned out not to be statistically significant once conditioned on parental education. This means that the influence of the grandparents' educative legacy in Mexico did not to go beyond its direct effect on the first generation.

The findings from a middle-income country extended the current knowledge from Nordic and highly developed countries. Indeed the influence of individual origins might vary from cultural differences across societies or among social groups. In this regards, Mexico was also an interesting case of study because, like many other countries, it is coping with extreme inequalities and with rising regional conflicts from drug cartels and insecurity with potential long run consequences on the wellbeing of future generations.

This empirical evidence might prove useful for other countries. These results brings useful inputs for the design of compensatory policies in periods of economic crises. As for policy implications, the trends of mobility emerging from this research may well constitute a *defining challenge of our time* (as described in the introduction) and because of that, it may worth monitoring this piece of evidence in a systematic way. This sort of empirical evidence may had been the motivation that leaded to the creation of the "The Social Mobility Commission" by the UK government with the explicit goal to promote "social mobility". Empirical evidence is needed to feed these deliberations.

This work may well be an attempt to generate a keen audience demanding this type of information. If anything, this dissertation might be simply an attempt to encourage the demand for long run longitudinal analysis on human wellbeing.

Paris, Winter, 2018

Bibliography:

- Adermon, Adrian, Mikael Lindahl, and Daniel Waldenström. 2015. "Intergenerational Wealth Mobility and the Role of Inheritance: Evidence from Multiple Generations." Unpublished manuscript.
- Andes, Stephen. 2014. "The Vatican and Catholic Activism in Mexico and Chile: The Politics of Transnational Catholicism, 1920-1940". Oxford University Press. United Kingdom.
- Angrist, Joshua & Krueger, Alan. 1990. "Does Compulsory School Attendance Affect Schooling and Earnings?" Quarterly Journal of Economics. Volume 106, Issue 4 (Nov., 1991), 979-1014. MIT Press
- Angrist, Joshua & Pischke, Jörn-Stephen. 2008. "Mostly harmless econometrics: An empiricist's companion". Princeton university press.
- Antman and McKenzie. 2007. "Poverty traps and nonlinear Income Dynamics With Measurement Error and Individual Heterogeneity" Journal of Development Studies, Vol. 43, No. 6 (August 2007). Routledge.
- Antman and McKenzie. 2007b. "Earnings Mobility and Measurement Error: A Pseudo Panel Approach" Economic Development and Cultural Change, Vol. 56, No. 1 (October 2007). The University of Chicago Press.
- Arellano and Bond. 1991. "Some tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations". Review of economic studies, 58, 277-297.
- Aspe-Armella, María. 2015. "*Una misma fe: identidades distintas: los católicos mexicanos tras los arreglos de 1929*". En Soberanes Fernández, José Luis & Cruz Barney, Óscar (coordinadores). 2015. "Los arreglos del Presidente Portes Gil con la jerarquía católica y el fin de la guerra cristera. Aspectos jurídicos e históricos". Instituto de Investigaciones Jurídicas. UNAM. México.
- Behrman, Jere & Taubman, Paul. 1985. "Intergenerational Earnings Mobility in the United States: Some Estimates and a Test of Becker's Intergenerational Endowments Model". The Review of Economics and Statistics, Vol. 67, No. 1 (Feb., 1985), pp. 144-151. The MIT Press
- Behrman, Jere & Alejandro Gaviria & Miguel Székely, 2001. "Intergenerational Mobility in Latin America," IDB Publications (Working Papers) 6485, Inter-American Development Bank.
- Björklund, Anders & Salvanes, Kjell. 2011. "Education and Family Background: Mechanisms and Policies". In Handbook of the Economics of Education. Volume 3. Edited by Eric A. Hanushek, Stephen Machin and Ludger Woessmann. Elsevier B. V.
- Black, Sandra E., Devereux, P. and Salvanes, P. 2005. "Why the Apple Doesn't Fall Far: Understanding Intergenerational Transmission of Human Capital." The American Economic Review 95, no. 1: 437-49.
- Black, Sandra & Devereux, Paul. 2011. "Recent Developments in Intergenerational Mobility". In Handbook of Labor Economics. Chapter 16. Volume 4, Part B, Pages 773-1823 (2011). Edited by David Card and Orley Ashenfelter. Elsevier B. V.

- Blattman, Chris. & Edward, Miguel. 2010. "Civil War". *Journal of Economic Literature* 2010, 48:1, 3-57.
- Bradbury, K., 2011. "Trends in U.S. Family Income Mobility, 1969-2006". Working Paper 11-10, Federal Reserve Bank of Boston, Boston, MA. Version October 2010, 2011.
- Bourguignon, Goh and Kim. 2004. "Estimating individual vulnerability to poverty with pseudo panel-data". World Bank Policy research paper 3375. August 2004.
- Bourguignon, F. 2011. Non-anonymous growth incidence curves, income mobility and social welfare dominance. *Journal of Economic Inequality*. No. 9, 605-627. Springer.
- Bourguignon & Moreno. 2017. On synthetic panels. In Moreno (2018). Chapter one. PhD thesis dissertation. Paris School of Economics. France.
- Browning, Deaton and Irish. 1985. A Profitable approach to Labour supply and commodity Demands over Life Cycle, *Econometrica*, 50. Number 3. May 1985.
- Butler, Matthew. 2013. "Popular Piety and Political Identity in Mexico's *Cristero* Rebellion: *Michoacán*, 1927-1929". A British Academy Postdoctoral Fellowship Monograph published for the British Academy by Oxford University Press. United Kingdom.
- Campos, R., Esquivel, G., and Lustig, N. 2012. "The Rise and Fall of income Inequality in Mexico, 1989-2010". United Nations University. Working paper No.2012/ January 2012 USA
- Card, David. 1999. "The Causal Effect of Education on Earnings". *Handbook of Labor Economics*. 3. 1801-1863. 10.1016/S1573-4463(99)03011-4.
- Carneiro, P., Meghir, C. and Parey, M. 2013. "Maternal Education, Home Environments, And The Development Of Children And Adolescents". *Journal of the European Economic Association*, 11: 123-160.
- Chadwick, L. and Solon, G., 2002. "Intergenerational income mobility among daughters". *The American Economic Review*, 92(1), pp.335-344.
- Chávez-Juárez, and Wanner. 2012. "Determinants of Internal Migration in Mexico at an Aggregated and a Disaggregated Level" (March 26, 2012). Available at SSRN: <http://ssrn.com/abstract=1978806>
- Clark, Gregory and Cummins, Neil. 2014. "Surnames and Social Mobility in England, 1170-2012". *Human Nature*. December 2014, Volume 25, Issue 4, pp 517-537.
- Collado, D., Ortuño-Ortín and Romeu. 2012. "Long-run intergenerational social mobility and the distribution of surnames." manuscript, Universidad de Alicante.
- Coubés, M., Zavala, M., Zenteno, R. 2005. "*Cambio demográfico y Social en el México del siglo XX*". *Una perspectiva de Historias de Vida*. El Colegio de la Frontera Norte, 2005.
- Cross, P. & Manski, C. 2002. "Regressions, Short and Long," *Econometrica*, Econometric Society, vol. 70(1), pages 357-368, January

Cruces, Lanjow, Luccetti, Perova, Vakis and Viollaz. 2011. "Intra-generational Mobility and Repeated Cross-Sections: A three country validation exercise". The World Bank. Latin-American and the Caribbean Region. Poverty, Equity and Gender Unit. December 2011. Policy Research Working Paper 5196.

Cruces, G., Lanjouw, P. Lucchetti, L., Perova, E., Vakis, R. and Viollaz. M. (2015). "Estimating Poverty Transitions Repeated Cross-Sections: A Three country Validation Exercise". *Journal of Economic Inequality*, 13:161–179.

Dang, H. and Dabalen, A. 2017. "Is Poverty in Africa Mostly Chronic or Transient? Evidence from Synthetic Panel Data". World Bank Policy Research Working Paper 8033. Washington, USA.

Dang and Lanjouw. 2015. Poverty Dynamics in India between 2004 and 2012: Insights from Longitudinal Analysis Using Synthetic Panel Data". World Bank Policy Research paper 5916. Policy Research Working Paper 7270.

Dang and Lanjow. 2013. "Measuring Poverty Dynamics with Synthetic Panels Based on Cross-Sections", June. The World Bank. Policy Research Paper, 6504.

Dang. and Lanjouw, 2016. Welfare dynamics measurement: two definitions of a vulnerability line and their empirical application. *Review of Income and Wealth*.

Dang, Lanjow, Luoto and McKenzie. 2011. "Using Repeated Cross-Sections to Explore Movements in and out of Poverty", January. The World Bank. Policy Research Paper, 5550.

Dang, Lanjow, Luoto and McKenzie. 2014. "Using Repeated Cross-Sections to Explore Movements in and out of Poverty", *Journal of Development Economics* 107 (2014). Elsevier.

Deaton. 1985. "Panel Data from Times Series of Cross-Sections," *Journal of Econometrics*, 30.

Eder, Christoph. 2014. "Displacement and education of the next generation: evidence from Bosnia and Herzegovina". *IZA Journal of Labor & Development*. 3:12. Springer.

Fan, Yanqin & Sherman, Robert & Shum, Matthew. 2016. Estimation and Inference in an Ecological Inference Model. *Journal of Econometric Methods*. 5. . 10.1515/jem-2015-0006.

Ferreira, Messina, Rigolini, López, Lugo, and Vakis. 2013. "Economic Mobility and the Rise of the Latin American Middle Class". Washington, DC: World Bank.

Fields, G. , & Ok, E. 1999. "Measuring movement of incomes" [Electronic version]. Retrieved August, 2017 from Cornell University,

Fields, G. (2010). "But that is not what Economic Mobility is!" Working Paper Cornell University and IZA. Ithaca, NY: Cornell University.

Fields G., 2012. "Does Income mobility equalize longer-term incomes? New measures of an old concept". *Journal of economic inequality* 8(4), 409-427.

Filmer, D. and Pritchett, L. 1994. "Estimating Wealth Effects without Expenditure Data - or Tears: An Application to Educational Enrolments in States of India. The World Bank Policy Research Working Paper. WPS 1994.

Foster, James E. and Jonathan Rothbaum. (2015). "Using Synthetic Panels to Estimate Intergenerational Mobility". Working paper No. 013/2015. Espinosa Yglesias Research Centre.

Gittleman, M. & Joyce, M. 1999. "Have family income mobility patterns changed?" *Demography* 36: 299.

Hällsten, Martin. 2014. "Inequality across three and four generations in Egalitarian Sweden: 1st and 2nd Cousin Correlations in socio-economic outcomes". *Research in Social Stratification and Mobility*, 35 (2014), pp. 19–33.

Hertz, T., Jayasundera, T., Piraino, P., Selcuk, S., Smith, N. and Verashchagina, A., 2007. "The inheritance of educational inequality: International comparisons and fifty-year trends". *The BE Journal of Economic Analysis & Policy*, 7(2).

Holmlund, H, Lindahl, M. and Plug, E. 2011. "The Causal Effect of Parents' Schooling on Children's Schooling: A Comparison of Estimation Methods." *Journal of Economic Literature*, 49(3): 615-51.

Hungerford, T. 1993, "U.S. income mobility in the seventies and eighties". *Review of Income and Wealth*, 39: 403–417.

INEGI. 1910. *Tercer Censo de Población de los Estados Unidos Mexicanos 1910*. Instituto Nacional de Geografía e informática. Gobierno de México. México.

Imbens, Guido & Wooldridge, Jeffrey. 2007. "Whats New in Econometrics?". NBER Summer Institute 2007. Lectures. In: <http://www.nber.org/minicourse3.html>

Jäntti, M. and Jenkins, S. 2015. "Income mobility". In Bourguignon and Atkinson (2014). "Handbook of Income Distribution", volume 2A. Chapter 10. Elsevier.

Jenkins, S. and Van Kerm, P. 2006. "Trends in income inequality, pro-poor income growth, and income mobility". *Oxford Economic Papers*, Volume 58, Issue 3, 1 July 2006, Pages 531–548.

Jenkins, and van Kerm. 2011 "Trends in individual income growth: measurement Methods and British evidence". *Public Economics Programme Papers*, PEP 08. The London School of Economics and Political Science, Suntory and Toyota International Centres for Economics and Related Disciplines, London, UK.

Kroeger, S. and Thompson, O., 2016. "Educational mobility across three generations of American women". *Economics of Education Review*, 53, pp.72-86.

Lakner, C. and Milanovic, B. 2013. "Global Income Distribution: From the Fall of the Berlin Wall to the Great Recession". *Policy Research Working Paper*; No. 6719. World Bank, Washington, DC. World Bank.

Lindahl, Mikael, Palme Mårten, Sofia Massih & Anna Sjögren. 2015. "Long-term Intergenerational persistence of Human Capital: An empirical analysis of Four Generations". *The Journal of Human Resources*. 50, 1. The University of Wisconsin.

Lindahl, Mikael, Palme Mårten, Massih Sofia, and Anna Sjögren. 2014. "A Test of the Becker- Tomes Model of Human Capital Transmission Using Microdata on Four Generations." *Journal of Human Capital* 8(1): 80–96. The University of Chicago. USA

Lustig, Nora. 1992. "MEXICO: The Remaking of an Economy". The Brookings Institution, USA.

- Mare, Robert. 2014. "Multigenerational Aspects of Social Stratification: Issues for Further Research." *Research in Social Stratification and Mobility* 35: 121-28.
- Mare, Robert and Song, Xi. 2014. "Social Mobility in Multiple Generations". September 2014. UCLA.California Center for Population Research On-Line Working Paper Series. PWP-CCPR-2014-014.
- Maurin, Eric. 2002. The impact of parental income on early schooling transitions: A re-examination using data over three generations. *Journal of Public Economics* 85: 301–332.
- Maurin, Eric & Sandra McNally. 2008. "Vive la revolution! Long-term education Returns of 1968 to the angry students", *Journal of Labor Economics* 26: 1-33.
- Meyer, Jean. 1973a. "La Cristiada. 1- La guerra de los cristeros". 2ª Ed. Siglo XXI. México
- Meyer, Jean. 1973b. "La Cristiada. 2- El conflicto entre la guerra y el Estado (1926-1929)". 2ª Ed. Siglo XXI. México
- Meyer, Jean. 1973c. "La Cristiada. 3- Los cristeros". 2ª Ed. Siglo XXI. México
- Meyer, Jean. 2014. « *La rébellion des Cristeros : L'église, l'état et le peuple dans la Révolution mexicaine* ». CLD éditions. Paris.
- Mier, Marta & Rabell, Cecilia. 2005. "Cambios en los patrones de coresidencia, la escolaridad y el trabajo de los niños y los jóvenes". In Coubés, Marie-Laurie, Zavala de Cosío, Maria Eugenia, Zenteno, René. 2005. "Cambio demográfico y Social en el México del siglo XX". Una perspectiva de Historias de Vida. El Colegio de la Frontera Norte, 2005. Chapter 9.
- Ministry of Education. 2015. "Estadística Histórica Nacional". Secretaria de Educación Pública. Mexican Government.
- Møllegaard, Stine, and Mads Meier Jæger. 2015. "The effect of grandparents' economic, cultural, and social capital on grandchildren's educational success." *Research in Social Stratification and Mobility* 42: 11-19.
- Moffit, R. 1993. "Identification and Estimation of Dynamic Models with time series of Repeated Cross-sections". *Journal of Econometrics*, 59, 99-123.
- Pacini, D. Two-sample least squares projection *Econometric Reviews*, Taylor & Francis, 2017, 0, 1-29
- Pekkarinen, Tuomas, Roope Uusitalo, and Sari Kerr. 2009. "School tracking and intergenerational income mobility: Evidence from the Finnish comprehensive school reform." *Journal of Public Economics* 93, no. 7: 965-973.
- Penafiel, Antonio. 1900. "Cuadro sinóptico y estadístico de la República Mexicana". Secretaria de Fomento. Colonización e Industria. Dirección General de Estadística. 1901.
- Peña, Sergio de la. 1991. "La estadística Económica nacional: primeros pasos". *Problemas del Desarrollo. Revista Latinoamericana de Economía*. Vol 22, No 87 (1991). Universidad Nacional Autónoma de México.

- Pfeffer, Fabian. 2014. "Multigenerational Approaches to Social Mobility". A Multifaceted Research Agenda. *Research in Social Stratification and Mobility*, 35, 1–12.
- Prakarsh Singh, Olga N. Shemyakina, 2016. "Gender-differential effects of terrorism on education: The case of the 1981–1993 Punjab insurgency", *Economics of Education Review*, Volume 54, October 2016, Pages 185-210.
- Ramon Jrade. 1985. "Inquiries into the *Cristero* Insurrection Against the Mexican Revolution". *Latin American Research Review* 20 (2). Latin American Studies Association: 53–69.
- Ramon Jrade. 1985. "Church organization and challenges to state power: the case of the *Cristero* Insurrection against the Mexican Revolution". Centre for developing-Area Studies. Discussion paper series No 9. McGill University. Montreal, Quebec, Canada.
- Roodman, D. 2011. "Estimating fully observed recursive mixed-process models with *cmp*". *Stata Journal* 11(2): 159-206.
- Rubalcava, Luis y Teruel, Graciela (2006). "Mexican Family Life Survey, First Wave", Working Paper, www.ennvih-mxfls.org
- Rubalcava, Luis y Teruel, Graciela (2008). "Mexican Family Life Survey, Second Wave", Working Paper, www.ennvih-mxfls.org
- Shahe Emran, & Greene, William and Shilpi, Forhad. 2015. "When Measure Matters: Co-resident Sample Selection Bias in Estimating Intergenerational Mobility in Developing Countries". (July 30, 2015). Available at SSRN: <http://ssrn.com/abstract=2639343>
- Skyt, Helena & Schindler, Beatrice. 2012. "The impact of parents' years since migration on children's academic achievement". *IZA Journal of Migration*. 1:6. Springer
- Solon, Gary. 1984. "Bias in estimation of Intergenerational Earnings Correlations", *Review of Economics and Statistics*, February 1989.
- Solon, Gary. 1999. "Intergenerational mobility in the labor market". Chapter 29. In "Handbook of Labor Economics", Volume 3, Edited by O. Ashenfelter and D. Card. Elsevier Science
- Solon, Gary. 2014. "Theoretical models of inequality transmission across multiple generations". *Research in Social Stratification and Mobility*. Volume 35, March 2014, Pages 13–18.
- Sotelo, Jesús. 1981. "*La educación socialista*" en Solana, Cardiel, Bolaños (Coord.). 1983. "Historia de la educación Pública en México: 1876-1976". Fondo de Cultura Económica. 2ª Ed. México
- Solana, Cardiel, Bolaños (Coord.). 1983. "*Historia de la Educación Pública en México: 1876-1976*". Fondo de Cultura Económica. 2ª Ed. México.
- Stuhler, Jan. 2012. "Mobility across Multiple Generations: The Iterated Regression Fallacy". IZA Discussion Paper No. 7072. December 2012.
- Vakis, Rigolini, and Lucchetti. 2016. "Left Behind: Chronic Poverty in Latin America and the Caribbean". Washington, DC: World Bank.

Verbeek, M. 2008. "Pseudo panels and repeated cross-sections". Chapter 11 in Mátyás and Sevestre, eds., 2008, "The Econometrics of Panel Data", Springer-Verlag Heidelberg.

Verbeek, Marno. 2012. "A guide to Modern Econometrics". WILEY, 4th edition. United Kingdom.

Webpages

Mexican constitution. 1824. "*Constitución Federal de los Estados Unidos Mexicanos: sancionada por el Congreso General Constituyente, el 4 de octubre de 1824*". Biblioteca virtual Miguel de Cervantes. El Colegio de México. Consulted in:

<http://www.cervantesvirtual.com/servlet/SirveObras/ecm/12252743220150495543435/index.htm>

Mexican constitution. 1857. "*Constitución Federal de los Estados Unidos Mexicanos: Sancionada y jurada por el Congreso General Constituyente el día 5 de febrero de 1857*". Biblioteca virtual Miguel de Cervantes. El Colegio de México. Consulted in:

<http://www.cervantesvirtual.com/servlet/SirveObras/ecm/35716152323148053754491/index.htm>

Mexican constitution. 1917. "*Constitución Federal de los Estados Unidos Mexicanos*". Biblioteca virtual Miguel de Cervantes. El Colegio de México. Consulted in:

http://constitucion1917.gob.mx/es/Constitucion1917/Constitucion_1917_Facsimilar

Abstracts

Résumé en Français

La mobilité économique à long terme

La mobilité économique est une des aspirations de toute société moderne, mais comment peut-on savoir la véritable évolution de la mobilité sociale ? C'est-à-dire : 1) peut-on mesurer la mobilité sociale avec les données ou la technologie disponibles aujourd'hui ? 2) Quelles sont les tendances de la mobilité sociale qui a traversées la génération actuelle ? Ou encore 3) à quel point la société actuelle est-elle mobile par rapport aux anciennes générations ? Ce sont les trois questions à la base de cette thèse. Nous soutenons ici que c'est possible de connaître encore plus sur l'évolution de la mobilité sociale en restreignant son analyse à quelques dimensions dans le champ de l'économie : le revenu et l'éducation.

Le première article s'attaque au problème du manque des données nécessaires pour l'analyse des dynamiques du revenu à l'intérieur d'une génération. Il est avéré que les données longitudinales sont rares et très peu disponibles dans la plupart des pays, ce qui est vrai même pour les pays développés ! Nous avons essayé d'assembler ce casse-tête par des approches méthodologiques récentes, telles que les « panels synthétiques », une méthodologie normalement utilisée pour l'analyse des dynamiques de la pauvreté.

Les articles deux et trois décrivent, plus spécifiquement, les tendances à long terme de la mobilité économique pour le revenu et pour l'éducation, respectivement. Le deuxième papier s'occupe de la mobilité intra-générationnelle, tandis que le troisième est dédié à la mobilité intergénérationnelle. Tous les deux répondent aux questions deux et trois posées plus en haut, en cherchant d'améliorer la façon dont la dimension temporaire est incluse dans l'analyse du bien-être économique, ceci avec pour but de reproduire l'effet d'un film fait avec plusieurs clichés.

Cette thèse cherche à élargir le savoir expérimental sur la mobilité économique, vu que la plupart des études ne prennent en compte que quelques années de mobilité intra-générationnelle ou à peine quelque génération. En outre, la plupart des résultats des expériences existantes font référence aux pays scandinaves ou à des pays fortement industrialisés. Pour cette thèse nous avons donc pris l'exemple du Mexique, mais les approches et les principes méthodologiques utilisés pourront être appliqués à n'importe quel autre pays.

Les chemins de nos vies sont dans un mouvement perpétuel : par monts et par vaux. Dans une société démocratique, il semble utile de savoir si notre appartenance sociale nous permet de nous en sortir malgré nos origines, ou si au contraire, notre destin est voué à l'échec à cause d'elles. Il nous faut en effet, des résultats empiriques pour répondre à ces délibérations. Cette thèse est peut-être une invitation osée à mettre en marche cette conversation.

Mots-clefs: mobilité entra-générationnelle, mobilité intra-générationnelle, panels synthétiques, Mexique

Abstract in English

Mobilité économique à long terme

Economic mobility constitutes a social aspiration in many modern societies however do we really know the actual evolution of social mobility? In other words: 1) how can we measure economic mobility with the data available or with the technology at hand? 2) What are the trends of economic mobility experienced by the current generation? Moreover 3) how mobile is a society relative to previous generations? These questions motivate this dissertation. The complexity of these issues may derive in some sort of paralysis but it is claimed here that it may be possible to learn something about its evolution by restricting analysis to a couple of key dimensions within the economic discipline: income and education. This is the scope followed by this research.

The first paper in this dissertation is devoted to deal with the lack of the required data to examine the income dynamics within one generation. It is well known that longitudinal data is often scarce and is seldom available in many countries. This is the case even in well-developed countries! This conundrum has been partially addressed through recent methodological approaches by the so-called synthetic panels.

The second part of this dissertation is entirely devoted to applied research. More specifically, the second and third papers describe long run trends of economic mobility in income and education respectively. The former is devoted to intra-generational mobility while the later is devoted to inter-generational mobility. Each of them address the second and third interrogations referred above. In a way this dissertation attempts to improve the addition of the time dimension in the analysis of economic wellbeing. It attempts to produce the effect of a motion picture by the use multiple snapshots. The trends contained herein are far from being perfect and complete but they are based on the use of extensive data and multiple methods covering three decades and the same number of generations in each case.

This research expects to expand our knowledge on the empirics of economic mobility as most of the studies refer to few years of intra-generational mobility or to a couple of generations only. Furthermore, most of the empirical evidence available refers to Nordic and highly industrialized countries. Mexico is the canvas of this work but the approaches and principles followed here could be easily mimicked elsewhere.

The roads of our lives are constantly moving: *rising and falling*. In a democratic context, it is useful to know, whether our society provides the chance to get ahead regardless of our origins, or whether this chance is ruled or doomed by them. Empirical evidence is needed to foster these deliberations. This dissertation may well be an invitation to sustain this kind conversation.

Keywords: inter-generational mobility intra-generational mobility, synthetic panels, Mexico.