Medición de la Movilidad Económica y Social

Aplicación a la Economía Argentina

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Resumen

Siendo la movilidad económica un fenómeno de largo plazo por naturaleza, su medición requiere de un panel largo de variables como salarios, ingresos o gastos de consumo de las personas o de los hogares. Pero la falta de tales datos y la existencia de sesgos debido a los errores de medición ponen algunos reparos en el uso de datos longitudinales. Sin embargo, es posible usar un pseudo-panel dinámico que estime consistentemente la movilidad individual aún en presencia de errores en los ingresos reportados. Aplicando este método a datos de ingresos en Argentina, en el primer capítulo de la tesis se halla una moderada movilidad de ingresos durante el período 1985-2004.

En el segundo capítulo se usa la metodología de regresión por cuantiles para explorar heterogeneidades en la movilidad intrageneracional de ingresos en Argentina. Esta metodología permite detectar diferencias en la dependencia de ingresos a través de la distribución condicional de ingresos. El resultado obtenido más consistente es que el ingreso obtenido por el individuo en el período anterior es la variable que mejor explica los ingresos corrientes del individuo ubicado en el centro y en los alrededores de la distribución condicional de ingresos, pero no en la cima o en la base de ésta. También se halla que al incluir el nivel de educación el vínculo entre los ingresos pasados y presentes disminuye, lo que sugiere que la educación juega un importante rol en explicar la dependencia de ingresos.

En el tercer capítulo se estima el grado de movilidad intergeneracional en Argentina buscando si existen diferencias de movilidad entre adolescentes y adultos jóvenes. Usando una nueva base de datos, la Encuesta de Empleo y Educación de la Juventud (CEDLAS-INDEC), se pueden obtener estimaciones de movilidad no sesgadas para los jóvenes mayores. Las estimaciones develan una menor movilidad intergeneracional para los adultos jóvenes con respecto a los adolescentes, un resultado que es robusto para varias especificaciones del modelo. También se encuentra que la mayor inmovilidad de los adultos jóvenes no es uniforme a través del nivel educativo de sus padres ni del género del joven.

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Introduction

In the last few decades, economists have increasingly emphasized that the static distribution of economic well-being falls short in acquiring a proper appraisal of the fairness and progressiveness of the society. Since the aspiration to progress seems inherent to human nature, the present and the expected welfare will differ throughout an individual's lifetime as long as he is able to improve his position within the distribution of income, through a combination of hard work, effort, and luck. However, each country's degree of economic and social mobility determines if such a difference would actually occur and also to what extent. The purpose of the mobility analysis is precisely to study this dynamic evolution of individual well-being. Mobility is valuable also for the economic efficiency and social cohesion it entails (Conconi et al. 2007). On the one hand, when mobility is low, potentially productive people will be restricted by the low initial socioeconomic circumstances they suffer from and will not be as productive as they could have been with better education and health facilities. On the other hand, social tolerance for the current inequality depends on the progress prospect of the individuals who lie at the bottom of the income distribution, so is the social cohesion needed for the sake of stability especially to maintain the democracies of the developing countries. An additional reason to be interested in social mobility is related to the need for an equality of opportunity for children. The intuitions suggest that an increased degree of intergenerational mobility translates into more equal opportunities.

Fields (2005) points out that the literature on income mobility is fundamentally unsettled because mobility is quite multifaceted and the term "income mobility" evokes several different ideas to varied researchers. The author also considers that this particular subject still requires an open discussion among researchers and policy makers alike, especially, with regard to the aspects of mobility that are most important from the point of view of economic well-being (Fields et al. 2007a). Hence, in conducting an empirical research, it is necessary to be explicit about the concept of the mobility used. According to Fields (2005), mobility presents six different notions. Among them, time dependence or persistence measures the extent to which economic well-being in the past determines the individuals' economic well-being in the present. This particular concept is employed in this present study as well. This notion of time dependence allows an estimation of the extent to which the incomes of rich and poor individuals converge over time, in an intra-generational context as well as through parents and children in a generational context.

The interest in assessing economic mobility at an empirical level has been closely related to the increasing inequalities that exist in the labor markets in industrialized countries between the period of the seventies and the nineties. This growing inequality would be less consequential as long as it was accompanied by a significant degree of individual mobility. The empirical studies regarding the transmission of poverty also deserve a particular mention in the field of mobility. This is because reducing the degree of child poverty has been an important concern for public policy in a number of countries in both North America and Europe during the nineties (Corak 2004). The available empirical literature regarding economic mobility in developed countries is vast; the available surveys may be found in Atkinson, Bourguignon, and Morrisson (1992), Maasoumi (1998), Solon (1999), Fields and Ok (1999), and Morgan (2006) who offer an illuminating analysis on the common intellectual foundations of mobility research in the fields of sociology and economics. In developing countries, the concern regarding economic mobility is also associated to their accustomed problem of inequality. The academic interest on the dynamic aspects of an individual's welfare has increased in Latin America, based on the fact that the countries in there are still the most economically unequal in the world and due to the substantial macroeconomic instability they experienced in the last two decades. However, for developing economies, the scant amount of suitable data has limited the amount and scope of mobility studies; the research in Latin America is not an exception in this regard. Fields et al. (2007a) present a review of intra-generational mobility studies, just as Behrman et al. (2001) provide for intergenerational mobility research.

Measuring income mobility in the notion of time dependence has been broadly grounded in the seminal work of Lillard and Willis (1978) and MaCurdy (1982); further, its evaluation involves estimating an autoregressive model, which in its simplest version consists of a dynamic linear model linking the current income to the one in the immediate past. In this simple framework, the regression coefficient (β) is a measure of immobility or the persistence degree and 1- β is called "regression to the mean". It shows that an individual may be expected to be closer to the mean income at present than in the past, or with regard to his parents, by the fraction 1-β (Goldberger, 1989). Complementing the unconditional convergence between the incomes of rich and poor individuals over time is also possible by adding some observable determinants. This way, the mobility coefficient estimates the extent to which the poorer and the richer individuals who are observationally equivalent (at least in terms of characteristics like age, gender, and education) reveal income patterns that converge over time. This statistical characterization of mobility is indeed well suited to estimate generational mobility, where incomes correspond to each generation.

The empirical task has been anything but easy due to the many challenges that the unbiased measurement of mobility entails. Since economic mobility is a long-term phenomenon by nature, for conducting a study based on intra-generation or on two consecutive generations wherein it is regarding the mobility existing between the parents and their children, the measures of individual well-being, such as, earnings, incomes, wealth, or even better, consumption, for a considerable span of the individual's life are required. Throughout the individuals' life, the movements in earnings are transitory, thus, mobility estimated over several periods may be different from that which could be predicted by using a one-year interval panel (Gottschalk 1997). In the presence of a long panel, it is possible to approximate the individual earnings in the long term by calculating the average of these earnings over all the periods observed in the panel. For the measurement of mobility the presence of a long panel is required, which is a resource quite uncommon in developing countries.

Panel datasets are not free from the difficulties that can distort the measurement of mobility (see Ashenfelter et al. 1986; and Antman and McKenzie 2007), thus, the presence of the longitudinal data does not eliminate all the issues that are entailed in measuring mobility. On the one hand, the common problem of measurement error overrates the estimated mobility caused due to the well-known attenuation bias toward zero; on the other hand, the non random attrition from the panel might understate the degree of mobility when mobile households attrite from the sample.

To deal with the measurement error problem, some authors (e.g., Fields and Sánchez Puerta 2006; Fields et al. 2007b; and Albornoz and Menendez 2007) base their estimations on a predicted measure of permanent earnings. By following this method, they not only avoid the problem of measurement error but also the mobility associated with the transitory changes that occur in the earnings (Fields et al. 2006). However, the predicted earnings are not well suited to study the conditional convergence; as, on the one hand the problem of multicollinearity may possibly arise, and on the other, the conditional equation that draws on the permanent earnings would provide an unclear interpretation (Fields et al. 2007b). Antman and McKenzie (2007) develop an alternative approach by implementing the use of age cohorts of people (that is, groups of individuals selected from cross-sectional surveys); based on the process of calculating the average required for the construction of a pseudo-panel, the measurement error at the individual-level encountered in the cross-sectional survey is cancelled. In addition, the pseudo-panels rely on cross-sectional surveys, which are usually available over longer periods even in developing countries, and therefore allow an extension in the length of the mobility study, making also international comparisons easier. Non-random attrition also becomes much less of an issue since each household needs to be observed only once. These features are relevant for Latin American countries in which cross-sectional surveys but not long panels are available (see Calónico 2006; and Cuesta, Ñopo, and Pizzolitto 2007). However, the cohort method is not free from limitations and presents some disadvantages regarding the use of true panels. The major one is that switching the analysis from the level of individual or household earnings to the average cohort earnings excludes the possibility of considering any intra-cohort income mobility (Fields et al. 2006).

Beyond those measuring complexities, a question arises about the accuracy of measuring the mean income mobility. If people do not vary beyond their distinguishable differences, measuring the mean effect of the past incomes over the current one suffices. However, if the differences existing among dissimilar types of people are not observable, the inter-temporal linkage present between the incomes may vary depending upon the position held by each individual in the conditional distribution of incomes. If the degree of mobility at the lower end of the income distribution is different from the mobility at the remaining income distribution, the mean mobility might not represent the mobility of any individual at all.

By considering the possibility of different mobility patterns apparent across the income distribution, it becomes evident that the mean (OLS) techniques are not enough to describe them. Thus, several different approaches are empirically used to capture the mobility differences present across the income distribution. Among them the Markov-chain approach has been widely adopted by authors, since it facilitates a measure of income persistence as well as explains who moves where. In addition, the transition matrices allow a significant flexibility in characterizing mobility by admitting asymmetries and other non-linearities; further, this approach has much greater appeal than parametric regression since it does not require any assumptions about the functional form. However, the use of transition matrices is complicated by the phenomenon of the so-called floor-ceiling effects. Thus, based on the way the transition matrices are constructed, it is not possible to ascertain if the higher income persistence found at the very top and bottom of the conditional distribution are by design. In addition, there is the problem of reducing such a probability matrix to a scalar variable that characterizes the overall extent of mobility. However, it is possible to overcome the limitations of the transition matrices and to employ a more flexible estimation framework than OLS by using semi-parametric techniques, such as, Koenker's quantile regression. This approach makes the measurement of the effect of the explanatory variables at any point in the conditional distribution of the response variable possible by allowing the examination of the differences that exist between the individuals at the top of the conditional earnings distribution and those at the bottom.

The degree to which the economic status is transmitted from the parents to the children unveils, in a broad sense, the degree of equality of life chances present in a society. In a mobile society, the family background like the education level of the parents and their family income might not be relevant in determining a child's future socioeconomic level. For these reasons, appraising intergenerational mobility is highly relevant from the political and social view, as well as an active field in the empirical research. The path of measuring generational or social mobility in developing countries is paved by empirical challenges principally due to the gap that existed between data requirements and existent data; actually, since, ideal data sets for intergenerational studies rarely exist even in developed countries (Corak 2006).

To overcome the lack of available appropriate longitudinal data, some researchers attempted to measure the intergenerational mobility in Latin American countries by using data of the achievements of teenagers at school obtained by the standard household surveys (e.g., Behrman, Birdsall and Székely 1998; Andersen 2001; Dahan and Gaviria 2001; Fernández 2006; and Conconi et al. 2007). This approach seems to be quite important and effective since it allows undertaking comparisons among countries and over time, contributing to understand the mechanisms underlying the intergenerational transmission of economic status. Based to the data collected by conducting these surveys, the studies that utilize this survey data strongly focus on the achievements of teenagers at school, revealing practically nothing about the mobility patterns of young adults. Nevertheless, if the family background affects the marginal decisions of education of young people beyond adolescence differently, the achievements of twenty-year-olds reveal just a small part of the intergenerational mobility story. However, several cross-sectional surveys are found that include retrospective questions on family background like parental education and occupation. This data can be used to estimate the measure of social mobility for adults.

The present thesis consists of three papers that deal with the measurements of economic mobility in Argentina, with an emphasis on the different approaches that helped in circumventing some of the above mentioned data and methodological constraints. To this end, the standard econometric techniques were applied herein to explain the parameters of economic and social mobility that exist throughout the lifetimes of individuals as well as among parents and their children.

Chapter I of the present study, focused on "Estimating Long Term Mobility in Argentina with Pseudo-Panel Data" in order to obtain an accurate measure of the intra-generational earnings mobility in the absence of long panels, as well as to avoid its overestimation caused by the common problem of the occurrence of measurement errors in the declared earnings. By applying this method, this study finds out the parameters of long- term earnings mobility that existed in Argentina between the period of 1985 and 2004.

Chapter II of the study, named as "Uncovering Mobility Patterns in Argentina using Quantile Regression", applies several quantile regression methods to estimate the intra-generational income mobility models in Argentina. This methodology allowed the detection of the differences that exist in the incomes' dependence across the conditional income distribution. The most consistent result obtained herein was that the individual's past income was a more important explanatory variable for the current individual's incomes at the middle of the conditional income distribution than at the top or at the very bottom of it. It also found that including the education level of the individuals in the analysis diminishes the link between the past and the present income suggesting that education plays a significant role in explaining the dependence of incomes.

Chapter III, named as "Exploring Intergenerational Social Mobility in Argentina", investigates the degree of generational income mobility in the country by exploring the measurement differences that exist in the social mobility present between children and young adults, without the common biases that arise when using household surveys. For this purpose, a new and original source of information on labor and educational issues was used. The estimations unveil a reduced amount of intergenerational mobility for young adults with regard to teenagers, a result that is robust for several specifications of the model. It is also found that immobility in young adults is not uniform across the parents' educative level.

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Chapter I

Estimating Long Term Mobility in Argentina with Pseudo-Panel Data

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Abstract

The degree of mobility in the individual earnings complements the picture of well-being in societies where inequality is constantly broadening. It seems particularly interesting to estimate mobility in the presence of a highly unstable macroeconomic environment like the one that has characterized Argentina in the last few decades. Since economic mobility is a long-term phenomenon by nature, its measurement requires the presence of a long panel, however, using longitudinal data is complicated by the lack of availability of such data and the existence of biases due to the measurement error problem. However, it is possible to use a dynamic pseudo-panel that consistently estimates the measures of absolute and conditional mobility in the presence of a reporting error. Applying

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this method to the earnings data in Argentina, the present paper determines the long-term earnings mobility between the period of 1985 and 2004.

1.1 Introduction

Recent empirical literature provides sound evidence regarding the distressing growth in the levels of inequality and poverty in Latin American countries[i]. By using the cross-section data obtained from household surveys, the literature shows that the inequality in the distribution of income became worse in the last two decades. However, since the literature evaluates inequality in a static context, it fails to uncover whether it is the same individual who remains poor or rich throughout the entire period of study. Nevertheless, it is quite clear that in the presence of mobility, the individual position in the distribution of income may not remain the same with time, moreover, the degree of individual well-being, which depends on the expected evolution of its position in the income ladder may also alter with time (Bowlus and Robin 2004). Consequently, since two societies with identical inequality and poverty levels but different degrees of mobility perform quite distinctly in terms of the welfare of the individuals, the diagnosis of inequality and poverty may fall short to evaluate the social welfare of the countries effectively. Hence, the degree of income mobility of the people in Latin America needs to be estimated to complement the well-being picture drawn in the static cross-section frame. It appears to be relevant for some countries like Argentina, in particular, that once stood out in Latin America for offering eminent opportunities of progress to its people[ii].

The present paper looks at the status of the earning mobility in Argentina for a twenty-year period (1985–2004). For this purpose, the paper uses pseudo-panel data. The concept of mobility, defined as time dependence along the lines of Fields (2005) categorization, is modified here in order to show the degree that the cohorts' earnings in the past determine their average earnings in the present. The analysis is based on the Argentinean survey *Encuesta Permanente de Hogares (EPH)*, collected by the *Instituto Nacional de Estadística y Censos (INDEC)*. The present study specifically uses the data from Greater Buenos Aires (GBA) since this is the largest set of available information both on the basis of the expanse of the observations made and of temporal length. This paper contributes to the existent empirical literature regarding the status of earnings mobility in Argentina by adopting a methodological approach that allows the estimation of mobility by avoiding the problem of measurement error. The duration of the period considered here is a major contribution of the paper to the literature. Since mobility is essentially a long term phenomenon, estimating the earnings mobility over a period of twenty years makes it possible to obtain a more accurate measurement of the possibilities of the economic progress of the people. Along with this, a two-decade period also allows analyzing the changes that occur in the degree of mobility in different sub-periods. This fact is quite important for studying the earnings mobility in developing countries, which are almost always affected by the significant macroeconomic instability and substantive policy changes. It also contributes to complement the results already obtained in the literature, by offering another way to assess the degree of earnings mobility in the country.

In analyzing inequality in a dynamic frame, panel data arises as a data structure capable of capturing whether it is the same individual who is poor/rich over time, or not. Longitudinal data sets have been broadly used in the literature to estimate the degree of the individuals' earnings, incomes, or wealth mobility (e.g., Hart 1976; Schiller 1977; Lillard and Willis 1978; Jianakoplos and Menchik 1997; and Jarvis and Jenkins 1998). This is also the approach adopted by the few researchers who attempt to estimate the income dynamics in Argentina, like Fields and Sánchez Puerta (2006); Albornoz and Menéndez (2007); and Fields et al. (2007b). However, there are several issues that caution the researcher about using true panels to estimate the income or earnings mobility. One of these issues is the length of the panel available. As long as the movements in the incomes are transitory, the degree of mobility over several periods may be different from what it could be predicted by using a one-year interval panel (Gottschalk 1997): hence, although the annual mobility can be strong yet small when the period of analysis is extended more. Observed from this perspective, using a longer panel is better, however, it increases the amount of difficulties that arise due to attrition and the lack of representativeness that attrition produces (Ashenfelter, Deaton, and Solon 1986).

Another issue that cautions the researcher about using panel data relates to the common problem of measurement errors. Measuring earnings mobility with data provided by surveys, in which the earnings are registered after what the surveyed people say, would overrate the degree of estimated mobility due to the attenuation bias toward zero in the estimated slope coefficient as a consequence of the measurement errors that occur in the earnings variable. In order to deal with this potential bias, some authors (e.g. Fields and Sánchez Puerta 2006; Fields et al. 2007b, and Albornoz and Menendez 2007) base their estimations on a predicted measure of permanent earnings. In this way, they avoid the problem of measurement error, and they also eliminate the transitory changes that occur in the earnings and in the degree of mobility associated with them, since without further imposition of the specific autocorrelation structure is not possible to separate both these phenomena from each other (Fields et al. 2006). Notwithstanding, this procedure is restricted to the estimation of unconditional mobility (Fields et al. 2007b). Undoubtedly, the presence of a good quality panel data covering long periods of time and alternative measurements on the earnings variables would attenuate those methodological constraints (Fields et al. 2006), but the lack of these suitable panel data in most Latin American countries imposes severe limitations on the examination of the dynamics of the individual earnings.

In light of the methodological caveats that affect the use of panel data, there seems to be room to explore alternative methodologies. Recently, Antman and McKenzie (2007) have fruitfully implemented the use of cohorts of individuals in their study; that is, groups of individuals selected through random sampling from different surveys. Building pseudo-panels based on cohorts of individuals facilitates tracking down the specific groups of individuals through their randomly selected representatives in consecutive years. The use of pseudo-panels has several advantages with regard to true panels. First, as they are constructed from cross-sectional surveys, which are usually available over longer periods; the time dimension of the mobility studies can be extended herein. Second, they facilitate a scope of international comparisons (see Calónico 2006; and Cuesta, Ñopo, and Pizzolitto 2007). Both these features are relevant for Latin American countries where cross-sectional surveys and not long panels are available; hence, this facilitates the application of the pseudo-panel techniques to determine the measurements and to conduct the comparison of mobility across these countries. Third, a remarkable advantage of pseudo-panels is that they help to deal with the problems associated with measurement errors and sample attrition present even with true panels for a long period. This is based on the fact that the construction of a pseudo-panel involves the process of calculating averages, which considerably eliminates the measurement error that occurs on an individual-level in the cross-section. Certainly, the cohort method is not free from limitations and presents some disadvantages regarding the use of true panels. The main disadvantage is that switching the analysis from an individual or household earning to the average cohort earning excludes the possibility of considering any intra-cohort income mobility (Fields et al. 2006).

There are enough valuable reasons to study the long term mobility in Argentina. From the seventies to the end of the nineties, the successive cohorts that enter the labor market faced lower paths of earnings and growing earnings volatility. Besides, the unemployment rate considerably rises during these years, reaching about a quarter of the amount of labor force at the beginning of the year 2002. Likewise, the enlargement of the earnings gap that exists between the individuals that lie above the earnings distribution and the individuals that lie at the bottom in the last two decades is a well documented fact (Gasparini, Marchionni, and Sosa Escudero 2001). During those years, two notorious macroeconomic crises had hit the economy and strongly reduced the real incomes of the individuals. Despite the fact that the incomes on average rapidly recovered afterward, the recovery was not even and many workers were not able to reach their former level of income. Hence, based on the evolution of the incomes of anonymous individuals, there is enough empirical evidence that suggests that the income distribution worsened in Argentina. However, this evidence does not show the degree of persistence of the inequality that exists in the income and whether the individuals are still in the same place within the income distribution or have moved. It is particularly interesting to analyze the degree of mobility in Argentina since the country underwent deeply institutional transformations and sharp changes of rules during the nineties. The changes broadly turned the economy toward becoming more market-oriented; further, they specifically provided added flexibility to the labor market. Hence, the Argentinean case facilitates a natural experiment for analyzing if a more market-based economy system allows added degree of income mobility besides the documented increase in the income inequality. In particular, it seems appealing to analyze whether the labor market offered opportunities of economic progress for the workers, who managed to evade unemployment during those years.

Given that earnings mobility is still a nascent area of research in Latin American countries, there are just a few studies conducted in Argentina. Fields and Sánchez Puerta (2006) analyze the degree of earnings mobility that existed during the economic expansion as well as the subsequent contraction that occurred in Argentina at the end of the nineties. They explored and identified the most favored individuals during the phase of economic prosperity and also those who experienced significant loss during the crisis. The major results of their study confirm the "structural convergence hypothesis" given by them; which means that those individual who showed a better state of earnings at the beginning of the period experienced the worst changes, both in the growth years and in the recession ones, as the variable "earnings at the beginning of the period" was the only statistically and economically significant one. Likewise, Fields et al. (2007b) find no support for divergent mobility in Argentina. The relationship that exists between income dynamics and its determinants over time was the marrow of the paper written by

Albornoz and Menéndez (2007). Therein, they modeled the dynamic variability of the degree of individual earnings as a first-order Markov process by performing multiple regression analysis among five one-year panels in order to derive structural patterns from the dynamics of the household income over time. They did not find a stable pattern for the relationship that existed between predicted income and the subsequent income mobility. Recently, Calónico (2006) and Cuesta et al. (2007) use the pseudo-panel approach to study long term income mobility in Latin American countries, including Argentina. Both authors use national household surveys, which were further processed and harmonized by the Research Department of the Inter-American Development Bank. However, several differences exist between these two works and the present one. First, the earlier studies used a shorter time span for the analysis, computing mobility for the period 1992–2003. Secondly, Cuesta et al. (2007) used per capita household's incomes for the study, whereas the estimations conducted in the present study used the parameters of the individuals' labor earnings. All in all, both earlier studies found a lower degree of income mobility with regard to the results obtained in the present paper.

Given that the findings mentioned above are not conclusive, it seems that additional work is still required in the measurement of mobility for Argentina.

The results obtained in the present study by the pseudo-panel estimation show some long term earnings mobility in Argentina indicating that the earnings path does converge in the absolute earnings. However, even though they differ in approach, yet these results are consistent with those corroborated by Fields and Sánchez Puerta (2006); and Fields et al. (2007b). Despite the differences that exist between the present study and those conducted by Calónico (2006) and Cuesta et al. (2007), the results obtained here are not entirely dissimilar.

The rest of the present paper is structured as follows: Section 1.2 explains the estimation methodology and the advantages of the cohort technique; it also discusses the alternative models that can be employed for the estimation. The next section, Section 1.3, describes the data and brings forth an analysis of the mean labor earnings conducted by the cohort technique during the studied period. Section 1.4 contains the foremost results of the present paper. Section 1.5 concludes.

1.2 Mobility and Cohort Methodology

1.2.1 The simple model

Grounded in the seminal work of Lillard and Willis (1978) and MaCurdy (1982), the measurement of mobility involves estimating a dynamic linear model by linking the current earnings to its immediate past and some observable determinants:

$$Y_{it} = \alpha + \beta Y_{it-1} + X'_{it}\delta + u_{it}, \tag{1.1}$$

where $y_{i,t}$ is the endogenous variable of interest (earnings or incomes), $y_{i,t-1}$ is the lagged value of the endogenous variable, $X_{i,t}$ is a vector of exogenous explanatory variables, and $u_{i,t}$ is the error term. The sub index i corresponds either to an individual or to a household. The relevant parameter to measure economic (im) mobility is β; a value of β close to one indicates a high temporal dependence in the earnings across the working life of the people. On the contrary, if β < 1, the degree of temporal dependence will be low, suggesting that the individuals do not remain in the same place within the earnings distribution across their working life. This model is general enough to include the case when the value of $\beta < 0$ and the earnings distribution undergoes a reversal across time (Gottschalk and Spolaore 2002).

In order to estimate the dynamic reduced form model given in (1.1), the panel data is considered as the ideal data structure. Nevertheless, as Ashenfelter et al. (1986) and Antman and McKenzie (2007) point out, panel data structures are not free from the difficulties that can distort the measurement of mobility. First, the panel length may cause problems in estimations as long panels are not commonly available in developing countries; and if they are, they probably suffer from the usual problem of attrition. Since the individuals who leave the panel may experiment earnings changes that are not randomly distributed in the population, analyzing the changes in the incomes of the remaining individuals will not provide an accurate picture of the dynamics as a whole. Another troublesome aspect related to the temporal dimension of the panels is the time that elapses between the successive waves of the panel. If this time interval is too short, the movement of the earnings of the individuals will mostly reflect the seasonal or short frequency changes that occur in their living standards.

Secondly, there is the potential problem of overestimating the degree of mobility because of the presence of measurement error. Following McKenzie (2004) and Antman and McKenzie (2007), the data-generating process for the current earnings $Y^*_{i,t}$ of an individual i in time t is given by the following equation:

$$Y^*_{i,t} = \alpha + \beta Y^*_{i,t-1} + u_{i,t}\,. \qquad (1.2)$$

However, in practice the researcher find that the observed data are measured with errors. He actually observes,

$$Y_{i,t} = Y_{i,t}^{*} + \varepsilon_{i,t} \,. \tag{1.3}$$

Further, substituting (1.3) in (1.2), provides the following equation in terms of the observed earnings:

$$Y_{i,t} = \alpha + \beta Y_{i,t-1} + \eta_{i,t} \,, \tag{1.4}$$

$$\eta_{i,t} = u_{i,t} + \varepsilon_{i,t} - \beta \varepsilon_{i,t-1} \,. \tag{1.5}$$

By applying the method of least squares to the previous model, a β coefficient that is asymptotically biased will be produced because of several reasons[iii]. In particular, due to the measurement error variance, Var ($\varepsilon_{i,t-1}$); when fixed effects do not exist and the measurement error is classical,

$$\beta^{OLS} \xrightarrow{p} \beta \left(1 - \frac{Var\left(\varepsilon_{i,t-1}\right)}{Var\left(Y_{i,t-1}\right)} \right). \tag{1.6}$$

This is the classical attenuation bias toward zero, which in this case drives to an estimation of earnings mobility, which is comparatively larger than the true one.

1.2.2 Cohort approach

To avoid the occurrence of the above mentioned drawbacks with regard to the use of panel data in the measurement of mobility, several authors argue that the parameter of mobility can also be identified from repeated cross-section data (RCS). This RCS data are obtained from the households' surveys conducted regularly twice a year or at least annually, and are usually collected both in developing countries as well as in the developed ones (Deaton 1997). Given that, with this type of data, the individuals or families that are interviewed each time are not necessarily the same those data have a time series of cross-section structure. Due to this aspect, it is not possible to track the same individuals across time as in the case of true panels; however, it is possible to track specific groups of people through their randomly selected representatives identified in consecutive surveys (Deaton and Paxson 1994; Deaton 1997).

A group that can be tracked across time is known as a cohort, which is defined by the birth year of its members in a way that each cohort is formed by people of the same age. For example, taking into account all the individuals born in 1960, the earnings distribution of the twenty-five-year-olds is obtained in the survey conducted in 1985. Further, by collecting the data from successive surveys——1986, 1987, and so on—the distributions of earning can be obtained for twenty–six-year-old individuals in 1986, twenty-seven-year-olds in 1987, and so on. By using the method of cohorts, the variable tracked across time is typically an average value, even though it can also be used another kind of central tendency value like the median or some percentile. A pseudo-panel, which allows relating the current earnings of each cohort with the past ones, is obtained. This data structure is able to analyze the long term dynamics of the earnings. According to Bourguignon and Goh (2004), although the actual path of earning of individuals cannot be observed, yet if the stochastic earning process shows common features for all individuals belonging to a cohort, these characteristics may be recovered at the aggregate level. Hence, in this way it is possible to estimate those common characteristics in the earning process of the individuals by observing the evolution of the mean and the variance of the earnings within a cohort.

The advantages of using the cohort methodology in dealing with the problem of measurement error make it appealing. Since adopting this particular procedure removes the individual measurement error, the summary statistics of the cohort earnings distribution are more accurate than the ones corresponding to the individuals' data generated from true panels. Moreover, as the interviewed people differ between surveys, the measurement error of one period will correspond to different people in another (McKenzie 2004). An added advantage of the cohort methodology lies in its ability to estimate the degree of mobility for a longer period with regard to the typical shorter length of the true panels. This is a particularly relevant point, since a considerable part of the earnings movements are transitory (Gottschalk 1997), making long term mobility potentially quite different from the one predicted by using short interval data. In addition, by using the cohorts generated from independent samples evades the problem of sample attrition.

As expected, the cohort methodology also presents several limitations. Deaton (1997) points out that the repeated cross section data can provide no information regarding intra-cohort dynamics, because with these data structures it is not possible to know the joint distribution of the characteristics of the cohorts in two adjacent periods. In the words of Antman and McKenzie (2007), using the pseudo-panels facilitates capturing the degree of mobility "due to underlying demographic factors and due to shocks that are common for individuals within a cohort, but it understates mobility due to averaging out the individual-level idiosyncratic shocks". Another concern related to the representativeness of the sample is added by Fields et al. (2007a) who consider that the pseudo-panel methodology can entail certain biases if it fails to track a consistent group of individuals over time due to the occurrence of events like migration, deaths, and household dissolution and creation. All in all it seems that panel attrition could be a more serious problem with regard to sample representativeness.

Hence, on the one hand, by using pseudo-panels would probably underestimate the degree of true mobility, and, on the other, by using longitudinal data it is also possible that the estimation overstates the true mobility due to the presence of the measurement error variance. In addition, due to the short length of the panels available in most Latin American countries, it is not possible to calculate the average earnings from several years ameliorating the measurement errors and improving the estimations (Mazumder 2005). Replacing the declared earnings by the predicted ones does not solve the problem completely. Even though this procedure allows the estimation of the unconditional mobility yet it is not well suited to estimate conditional mobility. Since predicted earnings approximate longer-term earnings but not the initial ones, the conditional equation would have no clear interpretation. Besides, multicollinearity would most likely arise between the variables used to predict the earnings and the other explanatory variables included in the conditional analysis (Fields et al. 2007b).

Therefore, taking into account the advantages and disadvantages of the cohort methodology with regard to true panels for the measurement of mobility, it seems that estimating mobility by using the pseudo-panel could contribute in assessing the degree of earnings or income mobility, complementing or corroborating the estimations obtained by using short panels.

Unlike dynamic panels in which the lagged dependant variable is observable, it is unobservable herein. The individuals surveyed in each sample are not the same; consequently, the inter-temporal covariances are not observable. This makes it impossible to identify and estimate the parameters of model (1). Nevertheless, Deaton (1985) and Browning et al. (1985) have pointed at least one kind of model—linear and fixed effects—which is capable of being identifiable and estimated consistently with the RCS data. In addition, Verbeek and Nijman (1992), Moffitt (1993), Collado (1997), McKenzie (2004), and Verbeek and Vella (2005) discuss the conditions required to obtain consistent estimates in a variety of dynamic linear models by using the pseudo-panels when the dependant lagged variable is not observable. Essentially, the model proposed by each of these authors is a first order autoregressive one, comprising exogenous variables, but as Verbeek and Vella (2005) point out the estimators proposed by each of them and the way to present them is quite different.

With repeated cross section data, the autoregressive simple model discussed above is given as:

$$Y_{i(t),t} = \alpha + \beta Y_{i(t),t-1} + X'_{i(t),t}\,\delta + u_{i(t),t} \qquad i = 1,\ldots,N \qquad t = 2,\ldots,T \qquad (1.7)$$

where the variables have a double sub index: t or t-1 refers to the cross-section and i(t), 1,…, Nt indexes the individual i surveyed in cross-sectional time t.

The estimation procedure suggested by Moffitt (1993) is a two-step least square, where the unobservable $Y_{i(t),t-1}$ is replaced by its predicted value by using the observed data in t-1, which corresponds to different individuals related to the survey in t. Verbeek and Vella (2005) point out that Moffit's estimator may be inconsistent since the consistency of the least squares estimators requires the model error $\varepsilon_{i(t)t}$ to be uncorrelated with the predicted lagged earnings $\hat{Y}_{i,(t)-1}$ and that the prediction error $Y_{i(t),t-1} - \hat{Y}_{i,(t)t-1}$, will not be related to the exogenous regressors. Whereas the first assumption may be defended under the usual IV assumptions, this excludes the possibility of the existence of cohort effects in the unobservable: this is something quite unreal and too restrictive for empirical analysis. Along with this, the second assumption would be inappropriate in the presence of exogenous regressors that are permitted to vary over time.

The estimation procedure adopted by McKenzie (2004) and Antman and McKenzie (2007) consisted of obtaining the cohort average from equation (1.4) over the n_c individuals in cohort c observed at time t. The authors did not use the IV methods since its validity required the selected instruments to be uncorrelated to the earnings measurement error (Wooldridge 2002). This aspect is unavoidable if the expenses are used as instrumental variables since the respondents habitually under declare them. In addition, the instrument should not be correlated to the other components of the error term of the data generating process, which leaves out the possibility of using the education level of the individuals or their possession of land in the analysis, since both these factors are undoubtedly correlated to earnings.

Calculating the average values of the cohort in equation (1.4) across the n_c observed individuals from cohort c in time t, gives the following:

$$\overline{Y}_{c(t),t} = \alpha + \beta \overline{Y}_{c(t),t-1} + \overline{u}_{c(t),t} + \overline{\varepsilon}_{c(t),t} - \beta \overline{\varepsilon}_{c(t),t-1}, \qquad (1.8)$$

where $\overline{Y}_{c(t),t}$ is the sample mean of $Y_{i,t}$ corresponding to the individuals belonging to cohort c observed in time t. Since as is evident in the RCS data, the observed individuals in each cross-section are not the same, the lagged mean $\overline{Y}_{c(t),t-1}$ is unobservable. Nevertheless, below it is shown that it is possible to expect that the unobservable lagged mean $\overline{Y}_{c(t),t-1}$ and the sample mean of the individuals observed in t-1, $\overline{Y}_{c(t-1),t-1}$, do not differ asymptotically. Therefore, it is replaced by the mean value of earnings that corresponds to the individuals observed in the cross-section t-1, obtaining the following regression for the cohorts c = 1, 2, ..., C and periods t = 2, ..., T:

$$\overline{Y}_{c(t),t} = \alpha + \beta \overline{Y}_{c(t-1),t-1} + \overline{u}_{c(t),t} + \overline{\varepsilon}_{c(t),t} - \beta \overline{\varepsilon}_{c(t),t-1} + \lambda_{c(t),t}, \tag{1.9}$$

where,

$$\lambda_{c(t),t} = \beta\left(\overline{Y}_{c(t),t-1} - \overline{Y}_{c(t-1),t-1}\right). \tag{1.10}$$

When the number of individuals in the sample n_c becomes large (100/200 individuals according to Verbeek and Nijman 1992), then $\overline{Y}_{c(t),t-1}$ and $\overline{Y}_{c(t-1),t-1}$ may come close to the population mean for the cohort c in time t-1. Therefore, $\lambda_{c(t),t}$ would converge to zero and can be ignored in the calculation (McKenzie 2004). Further, with large cohorts $n_c \rightarrow \infty$, and assuming that there is no cohort level component in the measurement error, the mean measurement error $\varepsilon_{c(t),t}$,

$$\varepsilon_{c(t),t} = \frac{1}{n_c} \sum_{i=1}^{n_c} \varepsilon_{i(t),t} \xrightarrow{p} E\left(\varepsilon_{i(t),t}\right) = 0, \tag{1.11}$$

The consistency of estimators in McKenzie (2004) and Antman and McKenzie (2007) depend on the relative asymptotic magnitude of T and n_c. With a fixed value of T and only the value of n_c going through infinite, OLS and IV are both consistent estimators provided individual errors do not show cohort effects or temporal effects once controlled by cohort fixed effects and temporal aggregated trend. That is, it is necessary to assume that in the individual error term $u_{i(t)t} = v_{cj} + \eta_{i(t),j}$, $\sigma^2_v = 0$. Verbeek and Vella (2005) emphasize that using the averages of the sample cohort and applying OLS to (1.7) with cohort dummies is similar to using the standard within estimator based upon treating the cohort-level data as a panel. In this way, it is possible to obtain consistent estimators by applying OLS since under the assumption that there is no cohort component in the individual's error term, the error term in (1.9) is a within cohort average of individual error terms that is asymptotically zero. When the value of n_c is large and T is moderated, the least squares and IV estimators will be consistent.

There are two alternative specifications of the same model, with and without fixed effects. The simplest specification assuming the lack of fixed effects is given by the following equation:

$$\overline{Y}_{c(t),t} = \alpha + \beta \overline{Y}_{c(t-1),t-1} + \omega_{c(t),t} \cdot \qquad (1.12)$$

If $\overline{Y}_{c(t),t}$ is the level of earnings of the individuals belonging to cohort c observed in time t, then $\beta < 1$ indicates that the individuals that carry a level of earnings under the average earnings level in time t-1 will experience a quicker rise in earnings than the richest. Hence, without the individual effects a measure of "absolute convergence" is obtained (Barro and Sala-i-Martin, 1999), which indicates the amount the household had moved in the distribution of general earnings. Therefore, this measure becomes closest to the positive idea that mobility can moderate the inequality throughout the life of the people, offering better equality of opportunities.

If the data generating process contains individual fixed effects, it is possible to add fixed effects by cohort and estimate the value of β by the following equation:

$$\overline{Y}_{c(t),t} = \alpha_c + \beta\overline{Y}_{c(t-1),t-1} + \omega_{c(t),t}\,. \qquad (1.13)$$

In including the individuals fixed effects, certain differences are allowed to exist among the earnings that the people generated based in their personal capacity to earn as well as the different opportunities that life offered to each one. The individual differences allowed by α_c correspond to the differences that exist in their level of education, their health status, or the cohort that they belonged to; that is, this includes all those characteristics that influence the personal ability of an individual to acquire better jobs, and hence, higher earnings. Given the personal assets, the value of β measures the speed in which the earnings of those who earn much more or less, because of their personal abilities and the available opportunities, return to the level of their average earnings (Antman and McKenzie 2007); a value of β smaller than one indicates that an individual below their own mean earnings will have a quicker earnings growth than the others (this is called conditional convergence in the growth literature). Hence, by adding individual effects, the convergence speed is expected to increase. This estimator puts the concept of mobility close to the evaluation of efficiency and flexibility of the labor market, in the sense that well-functioning labor markets will reduce the time required for an individual to recover their former income level after a negative transitory earning shock.

1.3 Data

The data base employed in the present paper is taken from the *Encuesta Permanente de Hogares (EPH)* collected by the *Instituto Nacional de Estadística y Censos,* INDEC. The survey conducted in Argentina entailed a six-month rotating panel in which 25 percent of the households rotated every semester so that each one of them could be followed for four periods. It an urban survey; carried out in cities which contained over 100.000 inhabitants, representing 71 percent of the country's urban areas and, approximately, 62 percent of the whole population of the country. The *EPH* provides detailed information regarding the employment, earnings, and demographic characteristics of the households, but unfortunately, it does not provide data about the households' consumption, which would be of significant value to evaluate economic well-being. From the year 1973 till the year 2002, the *EPH* was carried out twice a year (May and October waves) in the most important cities in the country, which were progressively incorporated in the survey. From the year 2003 onwards, some modifications were introduced in the questionnaire and in the frequency in which the survey was collected, that is, nowadays it is conducted every three months.

The data used in the present paper corresponds to the one collected from Great Buenos Aires (GBA), the only urban area in which the size of the population is large enough to allow the construction of cohorts with enough observations for a consistent estimation of the parameters. The other cities in the rest of the country are excluded from this study since they were incorporated eventually into the survey, thus, many of them were absent in the first years of the pseudo-panel. This restriction in the data may not be so serious for Argentina since Great Buenos Aires had historically concentrated almost 55% of the country's entire urban population. The analyzed period includes the years 1985–2004. Although the data is available for Great Buenos Aires since 1974, yet only since 1985 is the information without any interruptions. For most of the studied period, the data corresponds to the punctual October survey, but for the last two years, it was generated from the continuous survey corresponding to the fourth quarter. In order to create a pseudo-panel comprising more observations, the May waves could be included duplicating the quantity of the measurements per year. This is a common tool employed in the empirical literature; for example, Antman and McKenzie (2007) formulated the pseudo-panel with every quarter of every year and Deaton and Paxton (1994) did the same. However, some authors like Winkler (2004) and Margot (2001) consider that it is better to include only an annual measurement due to the difficulty of defining the age of individuals when the figures are collected in two different moments of the same year. In this paper, a preliminary test was carried out with the data and it was decided that both measures would not be included in the creation of the synthetic panel as this leads to a big loss in the goodness of fit. It was further determined that the analysis should be carried out based on the October data every year since the May measurements presented interruptions in the years 1985–1986.

The cohorts are built with employed men that lie in the age group between 21 and 65 years. The age range is restricted in order to keep the results comparable with the empirical literature (Calónico 2006; Fields and Sánchez Puerta 2006; 2007; Cuesta et al. 2007). In this way, the confusions that might arise in the income mobility with regard to fluctuations due to first time entries to the labor force and retirements were avoided in the literature. This is not strictly necessary here since the cohorts only included employed individuals. The reason why only men are included for the study is justified by the literature due to the differences that exist between men and women in the labor market. Further, the behavior of women varies more than men's when it comes to hours and periods of non-employment, hence, to mitigate the impact of the changes in the participation in the labor force it is quite common to focus on a prime-age male sample. The sample is also restricted to employed workers at the moment of the survey. Therefore, the focus of the present paper is on analyzing the opportunities of progress for the individuals who were employed during the analyzed period. They are grouped under five-year bands in order to avoid a low number of observations in each cell and the middle point of the band defined the age of the cohort. Although it would be better to work with the cohorts defined not only by the year of birth of the individuals, but also by other observable characteristics, like the level of education, yet these pseudo-panels that are rather more informative can not be exploited herein. The reason for this is that splitting the cohorts in this way reduces the number of individuals in each cohort, making them inadequate in Verbeek and Nijman's requirements to avoid the bias related to the fact that interviewed people differ between different surveys.

The obtained estimations were based on the information required for eleven cohorts including those that were 7–11 years old in 1985 until those between 57–61 years old in the same year. Given the fact that the youngest cohorts are not observed in the first years and that the oldest ones in the last years, the entire sample showed in Table 1.1 contains 163 annual cohort observations. The moment each cohort enters the sample is at the age of 23; for example, the youngest cohort is not included until 1999. In the entire sample, 5.05 percent of the cells have less than 100 individuals. Given that the relative importance of these cells over the entire sample is small and not systematic, it is decided to keep these observations.

INSERT TABLE 1.1 ABOUT HERE

The *EPH* includes different measurements of incomes. The earnings variable selected to evaluate mobility in a longer period requires its presence in each one of the twenty waves that conform the sample. The information regarding the total amount of incomes is available for the entire period. However, as this concept included those earnings that were received from other sources besides the labor ones, and based on the warnings of some authors like Winkler (2004) that the non-labor concept is not well captured by the *EPH*, this variable is not used. The hourly earnings variable that measures the per-hour earnings received by the individuals in their main occupation is available for eighteen of the twenty years of the period that comes under the analysis.

INSERT TABLE 1.2 ABOUT HERE

Although the hourly earnings variable is missing in the surveys of the fourth trimester of the years 2003 and 2004, yet it could be recovered from the information obtained from other questions of the survey; therefore, it is decided to use this variable. By estimating the earnings mobility instead of the income mobility, it is possible to compare the results obtained here by pseudo-panels with those obtained by Fields and Sánchez Puerta (2006) by using true panels. The comparison with Albornoz and Menéndez (2007) is rather straight because they use total family income including other income sources. The earnings were deflated by the consumer's price index of the month of October for the data generated from the punctual survey and by an average of the index in the fourth quarter of the year for the information generated from the continuous survey. The changes of the monetary sign in the period were also taken in account. For the estimation, earnings variables are taken in log.

INSERT TABLE 1.3 ABOUT HERE

1.3.1 Macroeconomic instability and cohorts' earnings path

Some of the earnings profiles of the cohorts are shown in Figure 1.1a. The path of earnings seems similar among cohorts on a wide outline, in displaying sharp fluctuations in response to the greater or lower price stability and the different shocks that impacted the cyclical evolution of the Argentinean economy. It is noted that in the twenty years of the sample, the cohorts underwent two sharp reductions in their real earnings, the first between the end of the eighties and the beginning of the nineties and the second in the year 2002. In the former period, the fall in the earnings corresponded to the inflationary upsurge that translated into a state of hyperinflation. This happened just before the emergence of the monetary police, known as "convertibility", which introduced a fixed rate of exchange between the peso and the dollar on a one-to-one rate in the beginning of the year 1991. The subsequent stability allowed the majority of the cohorts to recover the level of earnings up to similar levels to the ones before the collapse in the end of the eighties. The shrink in the earnings in the second period was explained by the mega devaluation of the peso in the beginning of 2002 and the inflation it caused, which measured at the consumer level, reached 40 percent in October with regard to the data obtained in the end of 2001. In this case, both the collapse and the succeeding recovery in the earnings have not been homogeneous among the cohorts. It broadly seems that youngest cohorts recover their previous level of earning rather slowly regarding mature ones.

INSERT FIGURE 1 ABOUT HERE

Figures 1.1b, 1.1c, and 1.1d plot the earnings of the cohorts and show their decomposition into cohort, age, and year effects following Deaton (1997). Figures 1.1c and 1.1d do not show clear age and cohort effects in the earnings, rather a noticeable common macroeconomic pattern for all cohorts. The latter is very volatile as is revealed by Figure 1b. Figure 1c shows a weak life-cycle profile for the earnings, and Figure 1.1d shows that the cohort effect improves the degree of earnings only in some cohorts: that is, those cohorts that enter into the labor market before the middle of the seventies. For the rest of them and, with the exception of cohort 4, successive cohorts entering the labor market faced a lower path of earnings than their predecessors.

1.4 Estimation Results

In order to compare the pseudo-panel estimations with those obtained from the true panels, Table 1.4 presents the panel data instrumental variable estimates of the degree of earnings mobility by employing the Arellano-Bond dynamic panel data estimator (Arellano and Bond 1991). These estimations are obtained for a set of ten annual panels covering the years 1991–2002. All the intervals correspond to four *EPH* waves included between the months of May of the first year to the month of October in the second year. In all cases, the value of β is close to zero or even negative, which indicates full origin independence and some sign of reversal earnings distribution across time. As argued above, these results could be biased toward zero due to the presence of the measurement error.

INSERT TABLE 1.4 ABOUT HERE

The annual mobility estimations that were obtained by using the twenty-year pseudo-panel data are shown in Table 1.5. In the first model, the fixed effects per cohort are not included and the point-estimated value of β is 0.663, statistically significant at the 1% level[iv]. As expected, due to the measurement error, the pseudo-panel estimate is larger than the one obtained by using the Arellano-Bond IV method, something quite similar to the results given by Antman and McKenzie with the Mexican data. The estimated value of beta is lower than one and suggests that in the analyzed twenty years period, some annual mobility of the earnings did occur in Argentina. The result obtained indicates the presence of convergence in the earnings growth rate in the analyzed period. For example, an individual whose labor earnings per hour in a year exceed by 10%, the mean value of the labor market would be only 6.63% above average, a year later. This result reveals a high degree of mobility relative to the results derived by Calonico and Cuesta. By including the fixed effects per cohort in the second model lightly decrease the value of coefficient β, making it 0.614, that is, statistically significant at the 1% level. Despite the fact that the results derived by Calonico reveal a less degree of mobility with regard to all the results shown herein, this slight drop in the estimated conditional coefficient regarding the point-estimated value without the fixed effects, is consistent with his results. Therefore, it appears that the conditional convergence does not differ much from the absolute convergence in Argentina, at least in the case of the employed workers.

INSERT TABLE 1.5 ABOUT HERE

By adding several explanatory variables besides the dependant variable, a value of β coefficient equal to 0.629 was produced, which continues to be statistically significant at the 1% level. The obtained value is significantly below one, as the confidence interval of 95% does not include such a value. This result is similar in magnitude to the one obtained by Cuesta who find that the introduction of additional controls reduces the inter-temporal persistence of incomes to a value of 0.74 in Argentina. The coefficients of age and its square present the expected sign, positive and negative, respectively; but none of them are found to be statistically or economically significant. The marginal effect corresponding to the size of the cohort is negative but statistically insignificant. The sign is as expected: to belong to bigger cohorts and therefore, competing with more workers in the labor market would affect the earnings of the individuals negatively, but the marginal effect is null.

Restricting the sample to contain just males of a "prime age" made it possible to focus on men for whom the labor earnings are likely to be the main source of income. Table 1.6 shows the results obtained by the estimation of the models in Table 1.5, by using only the observations which correspond to men who were in the age group of 23 and 49 years throughout the analyzed period. The first noticeable feature is that the results do not change very much with this sub sample. In the model that does not have a cohort fixed effect, the value of β (0.666) is practically identical to the coefficient obtained from the entire sample. By adding dummies by cohort, a slight decline in the value of the coefficient β (0.657) was noted with regard to the entire sample. Finally, the inclusion of several explanatory variables produces a smaller value of β (0.643) and the coefficients of the other covariates barely change. Repeating the analysis by including the observations conducted on zero earnings in a given period (the results are not showed here), a slight enlargement in the value of the β coefficient is recorded; however, even then it remains below one.

INSERT TABLE 1.6 ABOUT HERE

One of the advantages in using pseudo-panels is that the earnings persistence can be examined in periods longer than the ones true panels allow to study, which are reduced to two years at the most in the case of the EPH survey from Argentina. Therefore, the value of absolute mobility is calculated for different time lags, one entailing two years and the other five years. The number of observations diminishes as the period over which the mobility is studied becomes longer; further, due to the absence of available data for the years before 1985, it becomes necessary to consider the two-year mobility from the year 1987 and the five-year one from 1990.

The corresponding results are shown in Table 1.7[v]. The estimation for the two-year period shows a value of β that is remarkably lower than the yearly estimation and, for the longer five-year period the coefficient turns to be negative. These results are similar with those provided by Antman and McKenzie (2007) in the case of Mexico; wherein, they show a considerable enlargement in the earnings mobility as long as the temporal framework is longer, by accelerating the individual earnings convergence to the mean earnings when the mobility is measured in a two-year base and showing reversion signs of the earnings distribution when the temporal framework extends to five years.

INSERT TABLE 1.7 ABOUT HERE

Given that significant macroeconomic instability and changing rules characterized the twenty year period analyzed herein, it is possible that the value of earnings mobility may not be uniform within the entire period. Figure 1.1.a suggests the following division of the entire period in three different moments: before convertibility (1985–1990), during it (1991–2001), and after it (2002–2004). To test the hypothesis that the value of earnings mobility is different in those sub-periods, the absolute mobility model is re-estimated for the entire sample by adding two dummies to identify those sub-periods, and two more explanatory variables to interact with the lagged dependant variable. As is shown in Table 1.8, the inclusion of the sub-period interacting dummies diminishes the value of the β coefficient throughout the period under study. This result suggests that despite the fact that inequality grew during the 1990s, a more market oriented economy favored earnings mobility. Table 1.8 also shows that after the convertibility period (2002–2004) a slight reversal seemed to occur in the earnings. Nevertheless this latter result has to be considered with caution. In the one hand, the deeply macroeconomic crisis that Argentina underwent in those years would certainly require to analyze a larger period regarding the one included herein. On the other, the policies adopted those years and the subsequent years not considered in the present study, involved a return to a more intervened economy.

INSERT TABLE 1.8 ABOUT HERE

1.5 Concluding Comments

In the present study, the earnings mobility over the long term is estimated for Argentina during the period 1985–2004 in order to assess if the earnings converge in the long term and if they converge with regard to the grand mean or only around the individuals' characteristics. Due to the absence of longitudinal data for this long period, a pseudo-panel of earnings is constructed to accomplish those estimations. Several first order autoregressive processes models are estimated with this pseudo-panel.

The results obtained herein show some earnings mobility over the long term in

Argentina, which indicate that the earnings path converges to the general mean. The estimations show that the earnings convergence does not improve much by adding the cohort effects, which suggests that the labor market in Argentina does not substantially contribute to accelerate the speed of the individual' earnings level recovery after a negative shock. This would be suggesting that the added flexibility to the labor market during the convertibility decade was not enough to improve the earnings mobility of the employed. This would be also consistent with the observed heterogeneous per cohort pattern of earnings recovery after the 2001-2002 macroeconomic crisis. There is a remarkable growth in the mobility as long as the temporal framework becomes longer, as well. Thus, the individual earnings convergence with the mean earnings is faster when the mobility is studied on a two-year period and it shows reversal signs as the period studied becomes longer. Besides, the results show that the earnings mobility increase through time, further, slight earnings reversal occurs for the period 2002–2004.

Broadly speaking, the findings in the present paper are congruent with those obtained by Fields and Sánchez Puerta (2006), and Fields et al. (2007b) in the sense that the present results imply some inter-temporal convergence in earnings. The results of the present study also reveals more earning mobility than Calónico (2006) and Cuesta et al. (2007), but adding controls makes the results on conditional mobility rather similar to Cuesta's findings.

In addition, the value of absolute and conditional mobility in Argentina seems to be higher than the one found by Antman and McKenzie (2007) for the Mexican households during a similar period (1987–-2001). Notwithstanding, the comparison should to be considered with some caution because for their estimations, the authors added labor earnings over the household members, therefore, their definition of earnings and their sample scope is wider than the one used herein.

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TABLE 1.1

ANNUAL OBSERVATIONS BY COHORT

Cohort	Years																			
	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
1															326	360	303	164	188	210
2										272	325	326	357	331	304	305	243	138	177	207
3					339	205	234	222	206	216	273	262	293	328	297	309	251	118	176	175
4	322	325	320	355	396	246	256	276	226	233	264	266	270	255	238	292	254	129	156	179
5	316	348	348	351	365	237	249	246	204	217	279	252	252	295	289	236	235	115	119	145
6	343	325	321	346	382	251	261	264	190	183	265	250	242	241	243	234	206	117	113	120
7	318	334	327	315	343	218	226	235	152	172	221	204	230	223	195	189	179	70	99	105
8	260	258	263	261	262	141	140	167	138	130	181	170	179	170	160	119	104	64	81	65
9	263	237	242	258	241	147	144	128	100	79	121	108	116	124	65					
10	238	217	224	199	204	112	103	117	62	52										
11	178	170	139	149	114															

Source. Own calculations based on *EPH*, October waves.

TABLE 1.2

COHORT'S AVERAGE REAL HOURLY EARNINGS

Cohort	Years																			
	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
1															3.088	3.006	3.324	2.679	2.636	2.984
2										3.425	3.376	3.482	3.574	3.965	3.977	4.082	4.157	3.02	3.091	3.157
3					2.614	2.262	2.736	3.734	3.885	4.556	4.559	4.174	4.155	4.599	4.182	4.822	5.39	3.33	3.903	3.647
4	3.865	4.159	3.289	2.794	2.645	2.849	3.969	4.203	4.109	4.769	4.678	4.932	4.138	4.896	5.032	5.537	5.153	3.068	3.659	3.647
5	4.55	4.331	3.717	3.241	3.483	2.967	3.557	5.275	4.704	4.67	5.441	5.355	4.967	5.3	5.231	5.09	5.532	4.051	4.261	3.74
6	5.068	5.221	4.338	3.939	3.434	3.477	4.072	4.851	5.354	5.428	5.604	5.125	5.705	6.72	5.531	5.132	5.494	4.584	4.358	5.582
7	5.574	6.533	4.99	3.789	3.635	3.373	4.017	4.804	4.976	4.944	5.468	5.632	5.477	5.869	5.278	6.034	6.18	4.533	3.977	4.703
8	5.649	5.812	4.492	4.096	3.535	3.339	3.849	4.885	5.007	5.677	5.607	4.977	5.834	5.457	5.433	5.809	5.835	5.225	5.127	3.732
9	5.228	5.868	4.432	3.662	3.57	3.065	3.823	4.453	3.94	4.784	5.265	5.261	5.95	5.015	5.661					
10	5.557	4.724	4.304	3.774	3.216	3.103	4.109	3.758	4.205	5.14										
11	6.592	7.65	4.329	4.101	4.659															

Source. Own calculations based on *EPH*, October waves.

TABLE 1.3

DATA DESCRIPTIVE STATISTICS

Cohort Size	Observations in Pseudo-Panel	Mean	Standard Deviation	Median	Min	Max
Average Hourly Earnings	163	4.48	0.98	4.45	2.26	7.65
Age	163	36.44	8.20	36.00	23.00	52.00
Cohort Size	163	220.93	80.59	233.00	52.00	396.00

Note. All cohort-period observations are averages based on at least 100 individual observations.

Source. Own calculations based on *EPH,* October waves, years 1985-2004.

TABLE 1.4

INDIVIDUAL MOBILITY MEASURED WITH SHORT PANELS

Real Individual Earnings (Log)	One Year Panel									
	1991/92	1992/93	1993/94	1994/95	1995/96	1996/97	1998/99	1999/00	2000/01	2001/02
Annually Lag of Individual Earnings (Log)	-0.06 (0.057)	-0.48 (0.067)	-0.21** (0.070)	0.01 (0.078)	-0.16** (0.073)	-0.07 (0.094)	0.2** (0.098)	0.14 (0.100)	0.04 (0.076)	-0.23** (0.105)
Nº observations	327	347	339	428	310	243	958	868	791	509
** p<0.05										
*0.05<p<0.10										

Note. The estimations correspond to Arellano-Bond (1991) instrumental variables estimator. Arellano-Bond IV can not be estimated for 1997/98. The number in parentheses is the homoskedastic standard error.

Source. Own calculations based on *EPH,* October waves.

TABLE 1.5

INDIVIDUAL MOBILITY MEASURED WITH PSEUDO-PANELS

Real Individual Earnings (Log)	Model 1	Model 2	Model 3
Annually Lag of Individual Earnings (Log)	0.663**	0.614**	0.629**
	(0.0566)	(0.0619)	(0.0633)
Cohort Fixed Effect	No	Yes	No
Age	-	-	0.024
			(0.0009)
Square Age	-	-	-0.000
			(0.0002)
Cohort size	-	-	-0.000
			(0.0002)
Cohort-annual observations:	152	152	152
Adjusted R squared:	0.473	0.469	0.472
** p<0.05			
* 0.05<p<0.10			

Note. All cohort-period observations are averages based on at least 100 individual observations. The number in parentheses is the homoskedastic standard error.

Source. Own calculations based on *EPH,* October waves.

TABLE 1.6

INDIVIDUAL MOBILITY MEASURED WITH PSEUDO-PANELS:

MEN 23 - 49 YEARS OLD

Real Individual Earnings (Log)	Model 1	Model 2	Model 3
Annually Lag of Individual Earnings (Log)	0.666**	0.657**	0.643**
	(0.0638)	(0.0684)	(0.0739)
Cohort Fixed Effect	No	Yes	No
Age	-	-	0.071
			(0.0123)
Square Age	-	-	-0.000
			(0.0001)
Cohort size	-	-	-0.000
			(0.0002)
Cohort-annual observations:	110	110	110
Adjusted R squared:	0.498	0.477	0.4867
** p<0.05			
* 0.05<p<0.10			

Note. All cohort-period observations are averages based on at least 100 individual observations. The number in parentheses is the homoskedastic standard error.
Source. Own calculations based on *EPH*, October waves.

TABLE 1.7

MOBILITY OVER DIFFERENT TIME INTERVALS:

MEN 23 - 49 YEARS OLD

Real Individual Earnings (Log)	Yearly	2 - Year	5 - Year	Yearly	2 - Year	5 - Year
Lagged Log of Individual Earnings	0.666**	0.274**	-0.275**	0.657**	0.243**	-0.373**
	(0.0638)	(0.0859)	(0.0827)	(0.0684)	(0.919)	(0.0847)
Cohort Fixed Effect	No	No	No	Yes	Yes	Yes
Cohort-annual observations:	110	104	86	110	104	86
Adjusted R squared:	0.498	0.081	0.105	0.477	0.184	0.155
** p<0.05						
* 0.05<p<0.10						

Note. All cohort-period observations are averages based on at least 100 individual observations. The number in parentheses is the homoskedastic standard error.
Source. Own calculations based on *EPH*, October waves.

TABLE 1.8

MOBILITY PATTERN ACROSS TIME

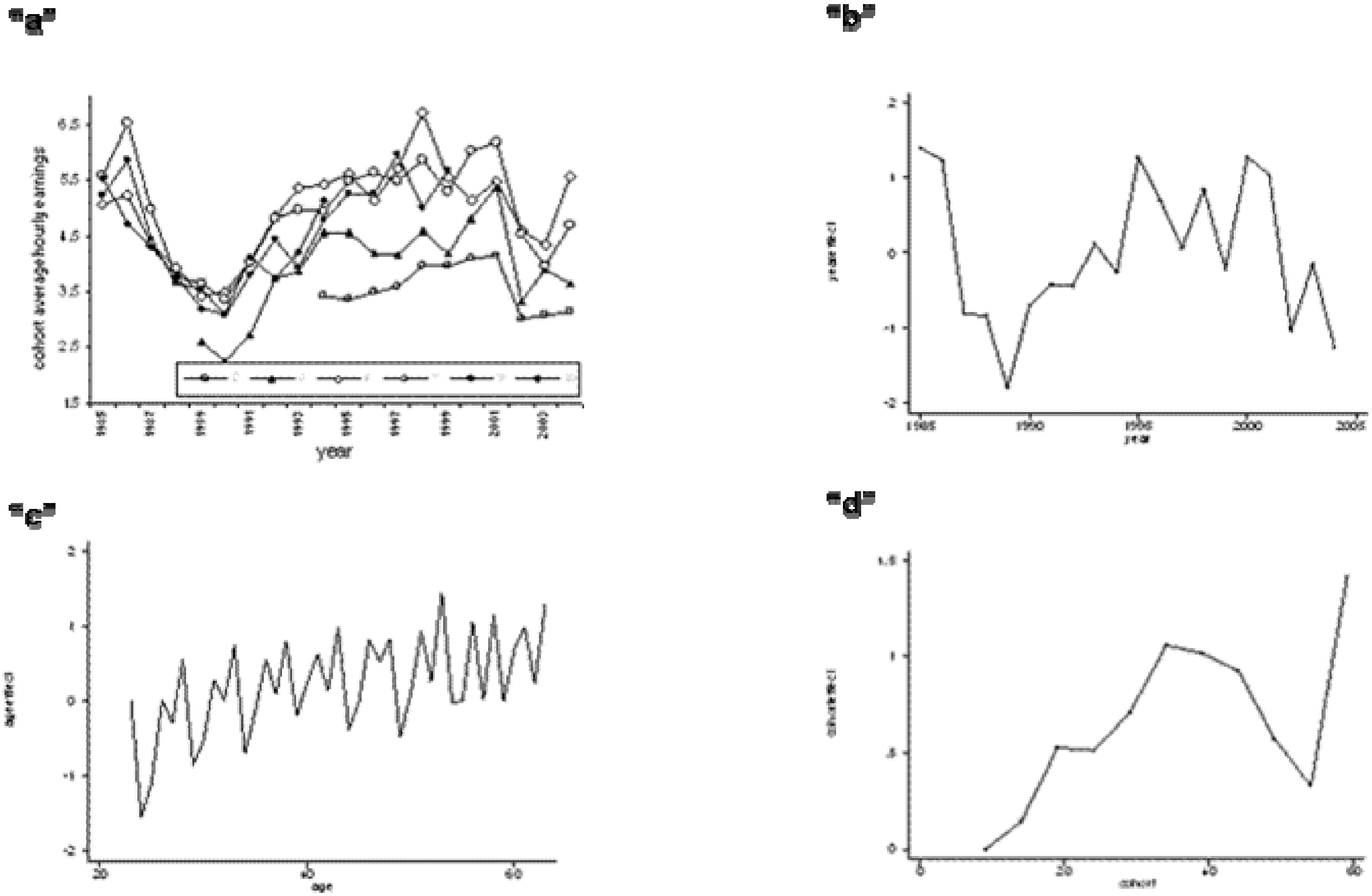
Real Individual Earnings (Log)	Model
Annually Lag of Individual Earnings (Log)	0.741**
	(0.0612)
Interact ALIE Period 1991-2001	-0.180**
	(0.0900)
Interact ALIE Period 2002-2004	-0.745**
	(0.1103)
Period 1991-2001	0.384**
	(0.1090)
Period 2002-2004	0.754**
	(0.1221)
Constant	0.198**
	(0.0723)
Cohort-annual observations:	152
Adjusted R squared:	0.758
** p<0.05	
* 0.05<p<0.10	

Note. All cohort-period observations are averages based on at least 100 individual observations. The number in parentheses is the homoskedastic standard error.

Source. Own calculations based on *EPH*, October waves.

FIGURE 1.1

COHORTS' EARNINGS. DECOMPOSITION INTO YEAR, AGE AND COHORT EFFECTS



Source. Own calculations based on *EPH,* October waves.

[i] See Gasparini et al. (2007).

[ii] See Gasparini et al. (2004, 2001).

[iii] Antman and McKenzie (2007) provide a detailed analysis of the many sources of bias.

[iv] Given that the enter age of a cohort into the sample is 23 years old and that it abandons it at the age of 63, the pseudo-panel built is necessarily unbalanced.

[v] The results showed in Table 1.6 correspond to the sub sample of men aged 23 to 49 years old.

Chapter II

Uncovering Mobility Patterns in Argentina using Quantile Regression

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First version: November, 2006

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Abstract

The present paper adopts the quantile regression methodology to estimate intra-generational earnings mobility models in Argentina. This methodology facilitates the detection of differences in the earnings' dependence across the conditional distribution of earnings.

The most consistent result obtained is that the earnings of individuals in the past are a more important explanatory variable to ascertain the individual's current earnings at the middle of the conditional earnings distribution and around it than at the top or at the very bottom of the distribution. It is also found that including the education level in the analysis diminishes the link that exists between the past and present earnings, thus suggesting that education plays a significant role in explaining the dependence of earnings.

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2.1 Introduction

Empirical studies conducted on earnings mobility flourished in Latin American countries in the last few years, as Fields et al. (2007a) show in their very detailed review of the literature. Most of these works were motivated by the high macroeconomic instability that characterized Latin America, and by the fact that not only is Latin America one of the most unequal regions of the world (Bourguignon, Ferreira, and Leite 2002; De Ferranti et al. 2004), but also because its unequal earnings distribution become worse in the last two decades (Gasparini, Gutiérrez, and Tornarolli 2005). These quite uncomfortable facts triggered much academic interest in assessing how permanent is the loss of individual well-being. Nowadays, the general consensus is that the measures of earnings inequalities, in the absence of measures of the degree of earnings mobility enlighten very little about the welfare of a particular society. However, as larger level of inequality usually entail lower opportunities to climb the earnings ladder for the poor (Conconi et al. 2007), the assessment of mean mobility may not be enough to judge social fairness. Hence, the evaluation of the poor specific mobility as well as mean mobility constitutes a critical dimension in the appraisal of social justness. Moreover, Bénabou and Ok (2001) argue that the tolerance for inequality is highly related to the earnings mobility in the sense of Hirschman's (1973) famous tunnel allegory: stalled motorists can be patient if they see movements in the other line of cars, because that way they get a signal that eventually they will move too; however, this allegory fails if there is a mean mobility but the poor are stuck in their initial economic position.

Since the research conducted on earnings mobility is still a new interest as per academic work in Latin America, just a few studies are conducted up till for each country specifically or for a group of them. In the context of Argentina and of the intra-generational side of the mobility studies, the works of Albornoz and Menéndez (2007), Fields and Sánchez Puerta (2007a), Fields et al. (2007b), Calónico (2006), Navarro (2006) and Cuesta J. et al. (2007) should be mentioned, which assess the degree of earnings mobility as time dependence in Fields' words. Despite the different methods that these authors utilized to cope with the limitations in the data and the methodological issues related to the measurement of the degree of mobility, basically short panels in the first three works mentioned above and synthetic cohorts in the last three, and, with the exception of Calónico and Cuesta, all the authors agree to the presence of some convergence of earnings through the results or at least, as Fields et al. (2007b) show, that there is no divergent mobility in Argentina. Regarding the two works that find a lower degree of mobility for Argentina, it is possible that the region-pooled estimates average out different country specific patterns of earnings mobility, thus, a higher degree of mobility is found across countries when they are studied separately than when they are pooled regionally (Cuesta et al. 2007).

The approach adopted throughout the present paper differs from the studies carried out earlier because the main focus herein is to explore the heterogeneity in the transmission of the economic status over the individuals' lifetime. Hence, the approach does not impose the restriction that all individuals in the sample would regress to the mean by the same speed (that is, the 'homogeneous assumption' given by Giovagnoli 2007). This approach allows that the inter-temporal linkage in the individual earnings differs depending on the position each individual holds in the conditional earnings distribution ('heterogeneous assumption' given by Giovagnoli 2007).

The methodological approaches adopted by the studies mentioned above constituted the techniques of ordinary least squares (OLS) and/or instrumental variables (IV), thus they estimated the dynamic persistence of earnings at the mean conditional earnings, by assuming that mobility is identical across the conditional earnings distribution. However, it is possible that the inter-temporal linkage that existed in the incomes of individuals differ depending on the position each individual holds in the conditional income distribution. This would happen if there was an unobserved, individual-specific, component that is heterogeneously distributed (Eide and Showalter 1999). Consider the effect of the income level obtained in the past for individuals with the same observed characteristics. If the level of income the individual generates in the past does not depend on his or her non-observables characteristics in the determination of the current income, hence, acquiring higher incomes in the past imply just a pure location shift of the conditional distribution of incomes. However, given the role played by unobservable heterogeneity in generating current incomes, it is possible that the variables of past incomes interact with the factors not included in the model in a non-obvious way. It could be asserted that any unobservable heterogeneity would be already embodied in the level of the individual's observed past earnings or any other observable trait of the individual, like his/her educational level. This certainly would be the case for the unobservable ability, or certain cognitive skills, but there are non-cognitive traits of personality that may not affect the past earnings level of the individuals and determine its current position. For example, the level of past income might influence the current incomes of more ambitious individuals differently. Therefore, while a low income level in the past may motivate the ambitious to work hard in order to improve it, it may produce a rather mild effect in the less ambitious. In this case, the mean income mobility would not represent just anybody in particular in the population: it underestimates mobility for the ambitious, and overestimates mobility for the conformist.

Considering the possibility of different degree of earnings persistence, it becomes apparent that OLS techniques are not enough to describe them. Their mean approach does not allow taking into account the varied behavior of the earnings dynamic at different parts of the distribution. Therefore, if mobility is not uniform across the earnings distribution, studying just the parameter of mean persistence would not provide a complete picture of the degree of earnings mobility. Hence, it becomes interesting to study it across the entire earnings distribution to gain a better idea of the individuals that are progressing and those who are stuck at their initial earnings position.

There are several different approaches that can capture the mobility differences that arise across the earnings distribution[i]. Among them, the Markov-chain approach has been widely adopted by the authors because it brings a measure of earnings persistence as well shows who moves where (e.g., Corak and Heisz 1999; Fertig 2003; Fields and Sánchez Puerta. 2007a). However, the method of transition matrices is complicated by the occurrence of the phenomenon of so-called floor-ceiling effects: upward mobility is not possible for those at the top or falling down for those at the bottom of the earnings distribution. Hence, due to the way the transition matrices are constructed, it is not possible to ascertain whether the high earnings persistence found at the very top and bottom of the conditional distribution are by design (Keswell 2004). However, a more flexible estimation framework than OLS can be obtained and the limitation of transition matrices can be overcome by using semi-parametric techniques, such as, Koenker's quantile regression. To estimate the relationship that exists between a covariate x and any conditional centile of the dependant variable y, Koenker and Basset (1978) develop the quantile regressions technique. Applying quantile regressions involves computing several different regression curves corresponding to the various percentage points of the distribution. Hence, this methodology makes it possible to measure the effect of the explanatory variables at any point in the conditional distribution of the response variable.

According to Koenker and Hallock (2001), mobility is a natural field for the utilization of the quantile regression technique since its flexibility to look across the distribution allows examining the differences that exist between the individuals at the top of the earnings conditional distribution and those at the bottom. Nevertheless, there are a few empirical works that apply quantile techniques to study the degree of mobility. Some authors like Eide and Showalter (1999), Fertig (2003), Grawe (2004), and Bratberg et al. (2005), apply the quantile method for studying intergenerational income mobility. Their findings broadly show that mobility is lower or higher at the bottom of the income distribution than at the upper end. Others, like Corak and Heisz (1999), turn to nonparametric techniques to explore heterogeneities or non-linearities. There are yet fewer works that deal with the intra-generational earnings mobility by using either nonparametric techniques or quantile regression models. A remarkably valuable exception constitutes Morillo (2000), who estimates nonparametric conditional quantile curves describing the transition dynamics of earnings by using the data obtained from the U.S. and Germany. In addition, by using the nonparametric quantile techniques, Trede (1998) proposes a graphical device to easily understand the mobility process. Using data from the U.S and Germany he finds that differences existed not just between countries but also between different quantiles lines. Keswell (2004) apply the non-parametric smoothing technique of locally weighted (or nearest neighborhood) regression to estimate the inter-temporal earnings elasticity in South

Africa. The author finds that persistence is especially high over the middle range of the earnings distribution whereas the tails exhibit considerable regression to the mean. Although the above mentioned papers adopt different techniques, yet the results of all of them broadly suggest there are differences in the degree of mobility across the conditional income distribution. This is also the key finding of the present paper.

The central theme of the present paper is that the estimation of the average earnings mobility is not enough to provide a complete picture of the degree of earnings convergence when mobility is not uniform across the conditional earnings distribution. The purpose of this study is to investigate the pattern of intra-generational earnings mobility in Argentina. It uses the method of quantile regression to detect differences in the explanatory power of the past earnings across the conditional distribution of the present ones. First, it tries to establish if the individuals located throughout the conditional distribution of earnings show different degrees of earnings mobility. Secondly, it examines the effect of the level of education on the documented earnings correlation. Moreover, considering that education and ability interact separately in a non-trivial way in the generation of human capital (Arias et al. 2001), thus, quantile techniques allow to freely characterize the effect of education on the entire conditional distribution of earnings. Ability and education could be complements or substitutes in the generation of human capital, and consequently, marginal returns to the accumulation of human capital would increase or decrease in ability. If both the determinants of human capital were complementary to each other, education would contribute more for individuals of superior ability (those located at the upper end of the conditional earnings distribution), but if both these determinants were substitutes of each other, education would contribute relatively more to individuals of a low ability. Third, it assesses if the differences that exist in the degree of mobility across the conditional earnings distribution change through time. The study further compares the patterns of earnings mobility between the years of economic boom and those in which there was a downturn, to observe if the pattern of the earnings mobility changes when the economy declines. Since the short length of the panel and the possibility that earnings' volatility and not true mobility is measured, the present paper implements additional estimations in order to check the volatility hypothesis. The analysis is based on the data acquired from the Argentinean survey *Encuesta Permanente de Hogares (EPH)*, collected by Argentina's National Statistical Agency, *INDEC*.

The results of the present paper suggest that the past earnings of an individual are a more important explanatory variable to reflect his/her current earnings at the middle of the conditional earnings distribution and around it than at the top. In particular, it reveals that the inter-temporal earnings dependence of the individuals is heterogeneous for the upper tail of the conditional distribution as well as for the very bottom. These findings denote that the degree of mobility is not uniform across the earnings distribution; consequently, the estimation of the average earnings mobility is not enough to provide a complete picture of the degree of earnings convergence in Argentina. It is also found that including the education level in the study diminishes the existent link between the past and present earnings, thus suggesting that education plays a significant role in explaining the inter-temporal dependence of earnings.

The remainder of the present paper is structured as follows: Section 2.2 explains the methodology used for estimation and the advantages of the quantile technique. Section 2.3 describes the data. Section 2.4 includes the major results of the paper and the next section, Section 2.5, analyses the volatility hypothesis. Finally, Section 2.6 concludes the study.

2.2 Methodology

The measurement of earnings mobility as time dependence entails the estimation of an autoregressive model, which in its simplest version involves a dynamic linear model linking the current earnings to the immediate past and some observable determinants like the following:

$$y_{it} = \beta y_{it-1} + X'_{it}\delta + \varepsilon_{it}, \qquad (2.1)$$

where $y_{i,t}$ is the endogenous variable of interest (that is, earnings), $y_{i,t-1}$ is the lagged value of the endogenous variable, $X_{i,t}$ is a vector of exogenous explanatory variables, and $\varepsilon_{i,t}$ is the error term. In this simple model, β is the relevant parameter; a value of β close to one indicates high temporal dependence in earnings and consequently low economic mobility; whereas, a value of $\beta < 1$ reflects a low temporal dependence, suggesting that the individuals do not remain in the same place within the earnings distribution through time. By applying ordinary least squares (OLS) or instrumental variables (IV) to (1), it is possible to estimate the inter-temporal persistence of the individual earnings[ii] at the mean value of the conditional earnings distribution, assuming herein, that the effects of the explanatory variables are identical over the entire distribution of the dependent variable.

As noted in the introduction, there are reasons to expect differences across the conditional earnings distribution in the inter-temporal linkage in individual earnings. That is, the value of β may depend on the earnings' centile of the individual. The technique of quantile regression is well suited to explore those potential differences since the estimation of several quantiles makes the exploration of the mean of the conditional distribution as well as its shape possible. Complementing the exclusive focus of classical least squares regression on the conditional mean, quantile regression methodology quantifies the effects of covariates at different points in the conditional distribution of the dependent variable, for example, the median, the 95th percentile, the 5th percentile, and so on. Quantile regression has many advantages. According to Buchinsky (1998), the quantile regression model assumes that the covariates may not only shift the location or the scale of the conditional distribution, but could also affect the shape of the distribution. At the same time, as the objective function of quantile regression is a weighted sum of the absolute deviations, it gives a robust measure of location, so that the estimated coefficient vector is not sensitive to outlier observations on the dependent variable. Besides, when the error term is non-normal, quantile regression estimators may be more efficient than least square estimators. When random variables are known to be normal, the value of the least square estimator, β, is efficient and unbiased; but unfortunately this estimator is highly sensitive to outlier contamination, even if it is low, making it a very poor estimator in many non-normal, especially long-tailed situations (Koenker and Basset 1978).

Replacing the process of ordering and sorting the sample observations by the process of optimizing, Koenker and Bassett (1978) obtain quantiles from a simple optimization problem and defines the conditional quantiles in the same way as the least squares regression explains the conditional expectation function E(Y|x). Applying quantile regression to the linear autoregressive model in (2.1), involves expressing the τth conditional quantile function of the response y_{it} as a linear function of the lagged values of the response, and can be written as,

$$Q_{Yit}(\tau|F_{t-1}) = \beta_0 + \beta_1(\tau)y_{it-1}, \qquad (2.2)$$

where y_{it} is the individual's current earnings, τ is the quantile to be estimated, and y_{it-1} is the lagged value of the dependent variable. The measure of quantile regressions for different values of τ produce estimates of the whole family of earnings correlation. Adding controls, the standard version can be expressed as,

$$Q_{Yit}(\tau | y_{t-1,} x_{it}) = \beta_0 + \beta_1(\tau) y_{it-1} + x'_{it}\gamma(\tau) , \tag{2.3}$$

where x_{it} is the k by 1 vector of covariates and the coefficients will differ depending on the particular quantile being estimated. By applying the standard Koenker and Bassett (1978) estimator, the following is solved as:

$$\hat{\beta}(\tau) = \arg\min \sum_{i=1}^{n} \rho_\tau\left(y_i - x_i' b(\tau)\right),$$

where the loss function ρ_τ (·) is the piece-wise linear function that weigh asymmetrically absolute residuals, it is possible to estimate the coefficients of the model for several quantiles.

Koenker and Xiao (2002) develop the statistical inference necessary to test the location and scale shift hypotheses. The "location shift" hypothesis is a model that depicts a pure location change, which corresponds to the classical homoskedastic linear regression model. This hypothesis implies that the quantile regression slopes are constant and independent of the value of τ, implying only a change in the mean value of the distribution without altering its shape. The "location-scale" hypothesis implies a particular form of heterogeneity that allows the variables to shift the conditional distribution while altering its scale in a simple `heteroskedastic' fashion. The latter is an interesting hypothesis that arises when the values of the "regression quantiles", the β(τ) or γ(τ) coefficients, differ systematically across the value of τ, suggesting that the earnings correlation or the marginal effect of any particular explanatory variable is heterogeneous across different quantiles of the conditional earnings distribution.

Quantile methods for panel data are far from being considered a settled technique. Koenker (2005) points out that longitudinal data is challenging to be used for quantile regression methods, particularly, since the large amount of the technical tricks developed for Gaussian random effects models are no longer directly applicable in the context of quantile regression. Koenker (2005) proposes to estimate a vector of the individual effects directly by applying a penalty term to shrink the vector of individual effects, and a tuning parameter λ to control the degree of shrinkage. Lamarche (2006) investigates a class of penalized quantile regression estimators for panel data that offers a robust alternative for λ selection. Nevertheless, since in dynamic panel models, the random effect standard assumption of strict exogeneity never holds, Koenker's and Lamarche's developments may be not well suited to study the individual earnings persistence. Lamarche (2006) performs the method of quantile regressions by using the weighted and unweighted fixed effects methods, however, in the dynamic contexts, the exogeneity assumption required for the pooled OLS technique is also violated (Wooldridge 2002). Based on these methodological considerations, and due to the explorative oriented look of this paper, quantile regressions are used herein, abstracting away from the panel structure of the data. By applying the pooled OLS, biased estimators would be produced. Notwithstanding, the bias that arises by not applying the panel data estimation method will not produce a serious problem in this paper. To do so, the bias has to affect the shape of the conditional function. The bias that arises by using pooled OLS moves the function upward or downward but it does not change the shape of the distribution function. Since the focus of the present paper is about exploring the existence of a heterogeneous rate of earnings convergence, that is, to say a different degree of earnings persistence across the conditional earnings function, a bias that changes the height of the function does not affect the distributive result.

The present paper applies quantile regression to the estimation of several empirical specifications of the intra-generational earnings mobility model. The analysis is performed for each of the seven annual panels that can be built over the studied time span. The technique of conditional quantile regression is also performed by pooling the annual panels in order to gain an additional degree of freedom. In each empirical model, the differences that existed in the values of the $\beta(\tau)$ coefficients are evaluated by performing the bootstrap tests of equality of the quantile slopes coefficients. Those tests are based on the asymptotic normality of the estimated parameters (Koenker and Bassett 1982). A standard Wald test is formed by using a bootstrapped estimate of the covariance matrix given by Koenker and Bassett (1982). The actual estimation was conducted by means of the sqreg procedure of STATA Version 9.

2.3 Data

The data used in the present study was obtained from the *Encuesta Permanente de Hogares (EPH)* conducted by Argentina's National Statistical Agency, *INDEC*. The survey is a six-month rotating panel in which 25 percent of the households rotate every semester so that each of them can be followed for four periods. It is collected in cities comprising over 100.000 inhabitants who represent 71 percent of the urban areas of the country and, approximately 62 percent of the entire population of the country. The survey includes detailed information regarding the characteristics of employment, earnings, and demographic of the analyzed households. From the year 1973 up to 2002, the *EPH* was collected twice a year ("May wave" and "October wave") in the main cities of the country. However, the year 2003 onward, some modifications were introduced in the questionnaire and in the frequency of conducting the survey; nowadays, it is carried out every three months.

The first set of data used here corresponds to the one obtained from Greater Buenos Aires (GBA Sample). This area represents approximately 55 percent of the sample of the entire country and, according to *INDEC*, reveals the best percentage of matching data required to build the annual panels. Besides, several cities that nowadays are under the perimeter of the survey were progressively incorporated during the period under analysis, thus, including them herein would produce different sub-samples in each annual panel. Therefore, in order to maintain comparability across the period under analysis, the first set of estimations is carried out by using only the data obtained from Greater Buenos Aires (GBA Sample). The analyzed period includes the years 1995–2003. Nevertheless, discarding a wider data set is not costless at all. By using the entire sample the estimations can be improved from a higher degree of freedom. Given that, the second set of data used is the whole data set available for each year (Whole Sample).

INSERT TABLE 2.1 ABOUT HERE

INSERT TABLE 2.2 ABOUT HERE

For the purpose of the present paper, it is taken the micro-data for two consecutive years including the observations of the four waves to build the annual panels. Seven balanced annual panels are built for the following years: 1996–1997, 1997–1998, 1998–1999, 1999–2000, 2000–2001, 2001–2002, and 2002–2003. To increase the size of the sample, the annual panels are pooled into two groups that correspond to the years of economic growth (1996–1997, 1997–1998, 2002–2003), and the years of economic decline (1998–1999, 1999–2000, 2000–2001, 2001–2002) in Argentina[iii]. To alleviate the measurement error commonly present in the registered earnings, and the downward bias that the classical measurement error produces, the earnings were estimated as values of yearly average at the individual level. Calculating the average earnings also mitigates transitory shocks. Unfortunately, the short length of the rotating design of the *EPH* panel does not allow the estimation of average earnings for numerous years, which would have provided a better measure of the permanent earnings (e.g., Corak and Heisz 1999; Eide and Showalter 1999; and Fertig 2003). An alternative approach entails using a measure of the predicted earnings. However, using the predicted earnings is also not advisable here since multicollinearity would probably appear as long as many of the variables used to predict earnings will be included as covariates when carrying out the multiple regressions (Fields et al. 2007b).

Due to the rotating nature of the *EPH* survey, it would be expected that each annual panel would contain around 25 percent of the first sample observations. Given that this percentage is actually around 10 percent, non-random attrition could bias mobility estimations. However, as Fields and Sánchez Puerta (2005) mention, several authors have established that attrition in the *EPH* panel is not such a serious problem[iv].

The unit of analysis considered herein is males of age group 23 to 65 years, who were employed and possessed positive earnings during the four studied waves. The reason for choosing only men in the study is justified by the literature based on the differences that exist between the status of men and women in the labor market. It is habitual in the literature to focus on a prime-aged male sample to mitigate the impact of changes in the participation of the female labor force. The age range is restricted in order to avoid confusing the degree of earnings mobility with the fluctuations that occur due to the first time entries to the labor force and to the retirement group (Fields and Sánchez Puerta 2007a). The restriction of being employed in each wave of the panel is considered in the present paper, since the focus is to assess the opportunities of progress that the labor market provides to the individuals who are permanently attached to it. In the present paper, individuals and not households are taken as the unit of analysis. This is due to the fact that households could improve their position in the earnings distribution by adding extra workers to the labor market, but this frequently entails a well-being loss for its members and a limitation for the future progress for those who reach the labor market before obtaining enough human capital (Paz 2007).

The dependent variable used herein the log hourly earnings that the individuals obtain in their main occupation. Further, those individuals who had no earnings or earnings not declared in any wave are not included. Non-labor sources of earnings are also not considered herein. In this way, the focus of the earnings mobility is precisely binding to the opportunities of progress in the labor market. As usual, the earnings were deflated by the consumer's price index. The main covariate for the mobility estimation is the dependent variable lagged by one period. This is the average individual's hourly labor earnings in the first year of the panel. Other covariates—age, square age, and education— used as standard controls. The parameter of age considered herein corresponds to the age noted in the October wave of the first year of each panel. Education is defined by the highest level acquired by the individual as defined in the first October wave of the panel. The purpose of including this characteristic in the regression analysis is to measure the extent to which education accounts for the observed inter-temporal correlation in the earnings. As the *EPH* survey does not register the number of years of the education of the individuals, rather asks about the highest level of education achieved by him or her, the education variable is categorical. Seven levels of education are defined herein. A summary of the variables is included in Table 2.1 for both sets of data.

2.4 Estimations Results

2.4.1 GBA Sample

Tables 2.2 through 2.5 present the results given by the OLS and the quantile regression techniques for each annual panel, by studying the GBA Sample. As discussed earlier in the paper, the dependent variable is the log hourly earnings that the individual obtained in his/her main occupation. The results for the simplest specification (without controls) are shown in Table 2.2 for each of the seven annual panels. The estimated OLS (mean) coefficients varies from 0.74 for the first annual panel to 0.88 for the last one, with all estimates being highly statistically significant. These results suggest that there has been some degree of annual earnings mobility in the analyzed period, though mobility appears to diminish with time.

INSERT TABLE 2.2 ABOUT HERE

The above moderate mobility picture changes when the analysis is broadened by estimating the quantile regressions. At the 50th quantile, the median regressions show that the degree of mobility is lower than that of mean mobility in all the seven annual panels, and in the first and the seventh panel it can not be rejected that the value of the coefficient equals to one. The median coefficients are also more homogeneous across time with regard to the mean (OLS) results. In the light of these results, the value of looking beyond the median to other quantiles to gain a better picture of the earnings mobility becomes evident. For the seven annual panels, the estimated values of $\beta(\tau)$ always diminish for the upper quantiles, with the 0.99 quantile in the panel of 1999–2000 with the lowest point estimate of 0.37, indicating that some 63% of the future earnings are explained by factors other than previous earnings. It is also remarkable to note that although for some panels the $\beta(\tau)$ estimates at the bottom quantiles are low with regard to the middle and even the upper ones, for other panels, notably the two last panel, they become higher. In every panel, the estimated coefficients are statistically different from zero at the 1% significance level. These results broadly suggest that earnings are less dependent on the past values for individuals located at the upper end of the conditional earnings distribution. This is because the quantiles are points along the current individual earnings distribution conditional on their past earnings; these findings imply that the high earners do not depend as much on their past earnings, whether high or low. On the contrary, for those individuals that lie at the middle of the conditional earnings distribution, it seems that their earnings experiment less inter-temporal mobility. For those at the bottom, the pattern does not appear completely defined.

To test the location-scale hypothesis, that is to say, if the above observed differences are statistically significant across quantiles, formal tests are conducted. For six of the seven annual panels, the test rejects the hypothesis of equality of coefficients at the 1% significance level.

The characteristics of education level, age, and square age of the individuals were added as controls in the second specification which is showed in Table 2.3. By adding the controls, the values of the mean (OLS) mobility estimates become low as was revealed by comparing the OLS estimates given in Table 2.2 and Table 2.3. For the quantile regression estimation, accounting for the controls causes the earnings coefficients to drop, further, the degree of fall was noted to be quite large at the higher quantiles than the decline at the lower and central quantiles. Nevertheless, in this specification neither education nor age nor square age is found to be statistically significant in any of the seven estimated annual panels. Furthermore, the tests conducted for the equality of the slope rejects the null only in three of the seven annual panels.

INSERT TABLE 2.3 ABOUT HERE

To improve the degrees of freedom by building a larger sample, the annual panels are pooling in two groups corresponding to the years of economic growth (1996–1997, 1997–1998, 2002–2003) and years of economic decline (1998–1999, 1999–2000, 2000–2001, 2001–2002) in Argentina[iv]. The obtained results are showed in Table 2.4a. The value of mean (OLS) mobility, without controls, is found to be moderate and it diminishes during the recession years. Accounting for education level, age, and square age, drops the value of the earnings OLS coefficient by 18.2% in the positive growth years and by 8.5% in negative growth years. As neither the age coefficient nor its square happens to be statistically or economically significant, the observed contraction in the OLS result suggests that education is certainly a considerable component in explaining intra-generational earnings linkage, although it still leaves the majority of the inter-temporal earnings correlation to unobserved individual characteristics. Note, however, that education influence over mobility diminishes when the economy is going through a recession.

With regard to quantile estimates, it is found that the lowest values for the earnings coefficient correspond to the upper tail and as the value of the quantile decreased, the estimates become higher. All the coefficients are statistically significant at the 1% level. All values of the earnings coefficients decrease when the controls are added, however, the decline at the higher quantiles was noted to be larger than at the lower quantiles; this pattern is more evident for the flourishing years. The pattern followed by the values of estimated earnings coefficient obtained by adding the controls is, in general, quite similar to the previous specifications, but it seems to be more defined herein. Further, a striking decrease was still noted in the values of the earnings coefficient for the high quantiles. The estimated values of $\beta(\tau)$ for the upper tail of the conditional earnings distribution are always found to be below the median coefficient, but for the bottom tail only the value of the lowest quantile coefficient lay below the median one. Formal tests of the null hypothesis of equality of earnings coefficients are rejected in both periods with p-values close to zero (less than 0.004). These results confirm that, although the education level of individuals is an evident mechanism of intra-generational earnings correlation, yet there is still another unobservable individual factor that explains the earnings position of the individuals.

INSERT TABLE 2.4a ABOUT HERE

Figure 2.1a and b plot the quantile regression mobility estimates for both pooled period specifications, separately. The point estimates of the coefficients for the 5^{th} to 95^{th} quantiles are plotted in increments of 0.05. Both plots control the characteristics of education level, age, and square age. The 95% confidence bounds are also plotted herein. Both figures show that the values of $\beta(\tau)$ diminishes for higher quantiles suggesting a heterogeneous pattern of earnings dependence at the right tail of the conditional earnings distribution. The pattern is more notorious for the flourishing years, where the slope at the upper tail is steeper than for the bad times. Both figures also show quite homogeneous mobility pattern for quantiles which lie below the middle. The complete picture illustrates a mobility pattern of less earnings dependence for the right tail (more mobility) of the earnings distribution, meanwhile, its middle and lower parts present a homogeneous pattern of small earnings mobility.

INSERT FIGURE 2.1a ABOUT HERE

INSERT FIGURE 2.1b ABOUT HERE

To test if the observed differences in the estimated mobility coefficients are statistically significant across the quantiles, formal tests are conducted to evaluate the null hypothesis of equality of the earnings coefficients. Table 2.5a reports the results of this test for both periods. The tests broadly confirm the visual impression.

INSERT TABLE 2.5a ABOUT HERE

The tests of equality of mobility conducted between the middle and higher quantiles reject the hypothesis of homogeneous coefficients at a 5% significance level. For example, a statistically significant difference is found to exist between the earnings mobility at the 0.50 and 0.95 quantiles in both the periods (Prob > F = 0.0002). Besides, the differences that exist between the lower and middle quantiles are not significant and are consistent with the flattening out of Figure 1b below the middle and the flattening out showed by Figure 1a between the quantiles 0.15 and 0.35.

The estimates for the education level coefficient are showed in the second row of the specification with controls in both periods and plotted in Figure 2.2. The examination of the coefficients shows that they are not homogeneous, and that the return of education is higher both for individuals located at the very bottom or at the upper end of the earnings distribution, in comparison with those at the middle. These results imply that reaching a higher level of education is more valuable for individuals located at the lower or the upper tail of the conditional earnings distribution but not for those at the middle. These findings also imply that schooling acts as substituting the individual ability at the lower end of the conditional earnings distribution, while, at the upper end, the effect of a higher educative level enhances the earnings position of individuals with a superior ability.

INSERT FIGURE 2.2 ABOUT HERE

The age coefficient does not present the expected positive sign in keeping with the life-cycle hypothesis and it is statistically and economically not significant; the same is seen for its squared coefficient.

2.4.2 Whole Sample

This section repeats the analysis of sections 2.4.2 using herein the entire sample. The estimated coefficients that correspond with the pooled annual panels by using the Whole Sample (WS) are presented in Table 2.4b[v]. As expected, due to the larger number of observations in the WS with regard to the GBA Sample (GBAS), the new results obtained here are found to be more accurate. Although the WS estimates are noted to be broadly similar to those given in Table 4a, that are based on GBAS, yet the new estimates show a slightly more degree of mobility for the lowest quantiles, but less mobility for the rest of them.

By using this larger sample for analysis, both the OLS estimates, with and without controls, are found to be slightly greater in the downturn years, with regard to the results for the regressions based on the GBAS; for the flourishing years, the WS results show a less degree of mean mobility than the GBAS results when the values of controls are added and a slightly more degree of mobility without them. It is evident that adding controls reduces the estimated correlation between the earnings for both the pooled annual panels, but it is worth noticing that by using this sample for analysis the amount that diminished—9.05 percent—is the same for the growth as well as the recession years. By using this larger sample with regard to the smaller one, a look at each of the control variables reveals that the education return is quite small in the flourishing years.

For the quantiles results, both specifications—with and the without controls—for the downturn years bring estimates that are quite similar to the ones obtained by the analysis of the GBAS data. However, there is a noticeable difference in the values obtained for the flourishing years at the lower end of the conditional earnings distribution. By using the WS data for the analysis, the very low quantiles show a greater degree of mobility than the estimates obtained by analyzing the GBAS data. For instance, the estimated coefficient (without controls) for the 0.05 quantile herein is 0.55 with a standard error of 0.06, and with the previous data set, it was 0.80 with a standard error of 0.13. From up to the 0.5 quantile, the values of $\beta(\tau)$ raises up to 0.86 and thereafter diminish for the upper quantiles. This pattern demonstrates a degree of similarity with the inverted V-shape pattern find by Corak and Heisz (1999) and Keswell (2004). By adding the standard controls the right tail coefficients diminish more than the middle and the left tail coefficients, but the pattern still demonstrates the same shape. This concave shape illustrates the following story: neither extreme earnings poverty nor earnings wealth persists across an individual's life time. On the contrary, for the large mass of individuals placed between these extremes positions, the values of their current earnings are highly correlated with the past ones.

INSERT TABLE 2.4b ABOUT HERE

Figure 2.3a and b plot the quantile regression mobility estimates obtained for both the pooled period specifications, showing the values of $\beta(\tau)$ for the 5^{th} to 95^{th} quantiles in increments of 0.05. Both the plots controls for the characteristics of education level, age, and square age. The 95% confidence bounds are also reported in the figures. The concave shape pattern described above is easily seen in both figures. By comparing the quantile pattern found in the two samples; the existent differences between the flourishing and the downturn years reveal a trend of fading away with the largest sample.

INSERT FIGURE 2.3a ABOUT HERE

INSERT FIGURE 2.3b ABOUT HERE

Table 2.5b reports the results of the formal tests of equality of the earnings coefficients for both periods. As with the analysis of the GBAS data, the tests broadly confirm the visual impression.

INSERT TABLE 2.5b ABOUT HERE

The estimates for the education level coefficient are showed in the second row of the specification with controls in both periods and plotted in Figure 2.4. Although the pattern herein is broadly similar to the one found with the analysis of the GBAS data, yet with this larger sample the return for education appears to be smaller than the other one. Besides, for the growing years, the effect of education on the current earnings seems to rise across the entire conditional earnings distribution, but it is not statistically significant for its lower end.

INSERT FIGURE 2.4 ABOUT HERE

The examination of the coefficients reveals that they are not homogeneous, and that the return of education is higher for individuals located at the upper end of the earnings distribution in comparison with the rest of them. The age coefficient is not statistically or economically significant nor its squared coefficient. These results suggest that once the past earnings are taken into account; the estimated effect of age on the short-term transition dynamics is small. According to Morillo (1999), a possible explanation for this is that as age progresses gradually, the past earnings embody most of the information provided by the covariate age.

Based on the quantiles pattern found for the two samples that were used to estimate quantile mobility, it appears that the differences between the flourishing and the downturn years faded away with the largest sample.

2.5 Mobility or volatility?

Since both the samples used so far comprised annual short panels, the results obtained could be more a reflex of the short term earnings volatility than the true earnings mobility. Mobility and volatility are quite different phenomena. Mobility captures the earnings variation over time, which is not quickly reversed. Volatility measures the extent of the short-term changes that occur around the current earnings level. Whether a given change reflects mobility or volatility depends on the time window the earnings' path are observed. It is expected that as the time window shortens, the results reflect volatility instead of mobility. In this case, the concave pattern found here might change by using the data that allows more volatility than the annually averaged ones.

To check this "volatility hypothesis", quantile regressions are estimated by using the individual earnings corresponding to the May wave instead of the yearly averaged earnings. The results for the growing years by analyzing the Whole Sample are shown in Table 2.4c and 2.5c.

INSERT TABLE 2.4c ABOUT HERE

INSERT TABLE 2.5c ABOUT HERE

In Figure 2.4c, the quantile regression mobility ("volatility") estimates obtained with this data are plotted. Although it is noticed that the estimates of earnings mobility ("volatility") are below the mobility estimates in analyzing the yearly averaged earnings, yet the same concave pattern of the previous estimations was also noticed, which reveals a higher degree of mobility for the tails of the conditional earnings distribution than for the middle and around it. Hence, as expected, without calculating the average of the earnings, the degree of estimated mobility is higher, probably as a consequence of the measurement errors; however, it seems that the concave pattern shown by the quantile regression analysis with the average data does not change.

INSERT FIGURE 2.5 ABOUT HERE

2.6 Concluding Comments

In the present paper, the intra-generational earnings mobility is estimated for Argentina for the period of 1996–2003 in order to assess if the inter-temporal dependence of the earnings differ across the conditional earnings distribution. The autoregressive quantile regressions and the data for employed men are utilized herein to estimate the inter-temporal link that exists between the earnings at different quantiles of the conditional distribution of hourly earnings.

The most consistent result generated by this paper is that the individuals' past earnings is a more important explanatory variable for their current earnings at the middle of the conditional earnings distribution and around it than at the top. In particular, the paper reveals that the individuals' inter-temporal earnings dependence is heterogeneous for the upper tail of the conditional distribution, in addition, for the extremely low quantiles, the degree of mobility is heterogeneous, too. The results suggest that the degree of mobility is not uniform across the earnings distribution and consequently estimating just the average earnings mobility is was not enough to gain a complete perspective of the degree of earnings convergence in Argentina. It is also found that including the education level of the individuals in the analysis diminishes the existent link between the past and the present earnings, suggesting that education plays a significant role in explaining the inter-temporal dependence of earnings. It is also noteworthy that the influence of education on the mobility diminishes when the economy undergoes a phase of recession. In addition, the quantile estimations show that a fall in the individuals' earnings intertemporal dependence appears to be more at higher quantiles than at the lower ones. This result also denotes that achieving a higher level of education influences the degree of mobility of those located at the right tail of the conditional earnings distribution differently with regard to those that are located at the bottom.

Broadly speaking, the results of the present study indicate that the intra-generational earnings mobility is better explained at the middle of the conditional earnings distribution and around it, than at the very bottom or at the top. That is, a combination of the characteristics of past earnings and the education level explain the earnings dynamics for the mass of employed men, but there is another factor that explains the individual's earnings at the very end and at the top of the conditional earnings distribution.

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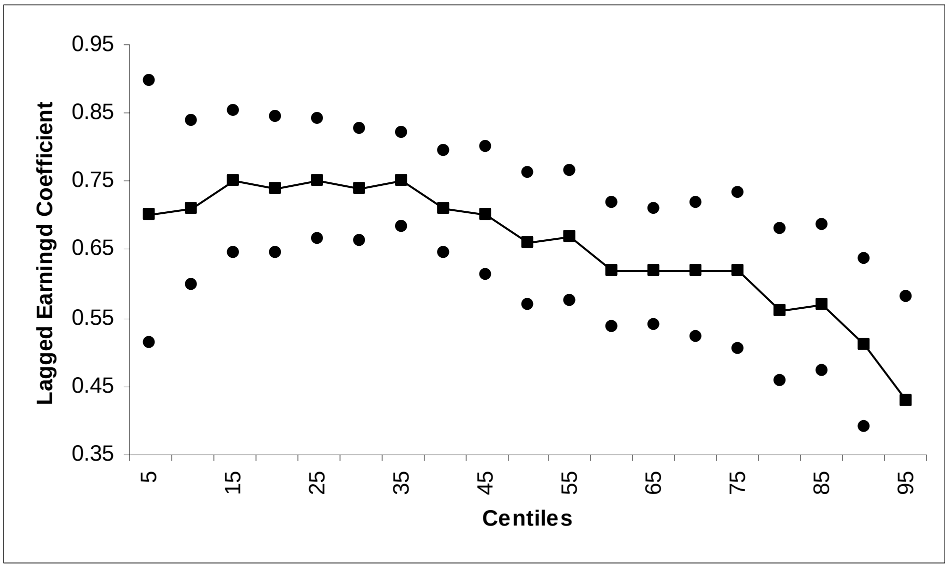
FIGURE 2.1a

EARNINGS DEPENDENCE. POOLED GROWTH YEARS. GBA SAMPLE.

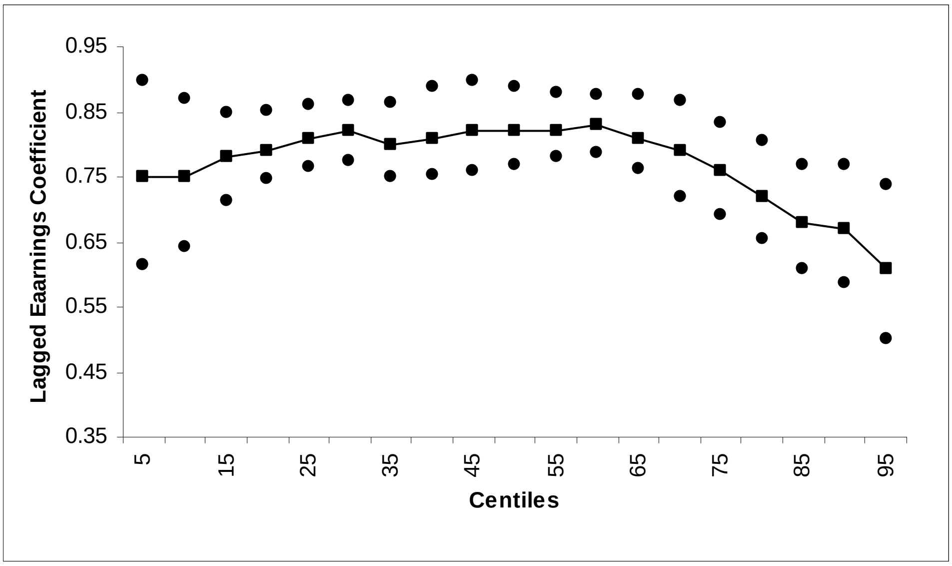


Note. The beta coefficients correspond to the estimations including as controls: individual education level, age and square age. Confidence bounds at 95%.

Source. Own calculations based on *EPH*.

FIGURE 2.1b

EARNINGS DEPENDENCE. POOLED RECESSION YEARS. GBA SAMPLE.

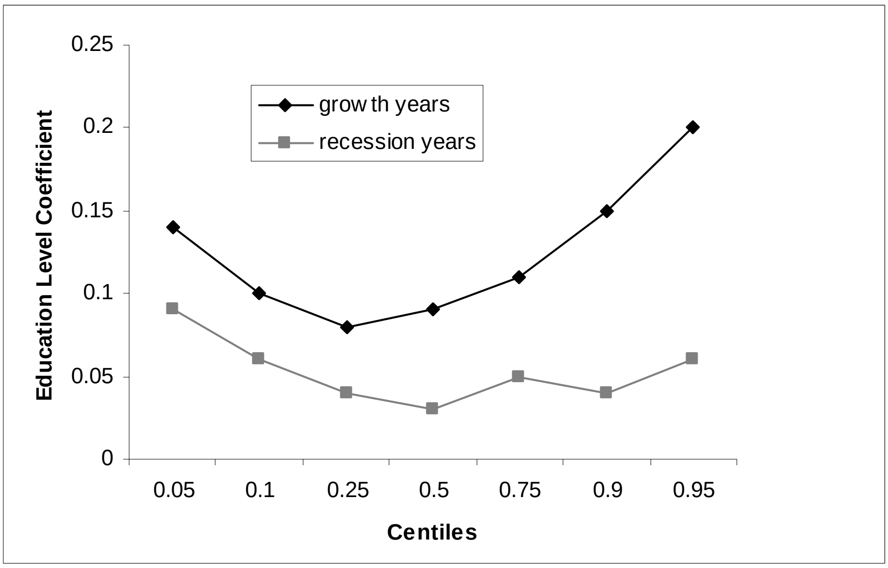


Note. The beta coefficients correspond to the estimations including as controls: individual education level, age and square age. Confidence bounds at 95%.

Source. Own calculations based on *EPH*.

FIGURE 2.2

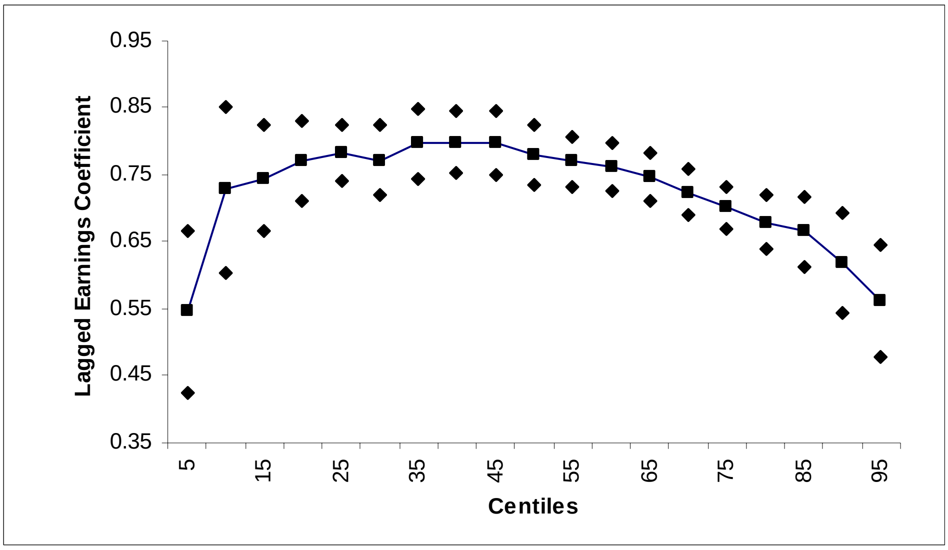
RETURNS TO EDUCATION LEVEL. POOLED GROWTH AND RECESSION YEARS. GBA SAMPLE.



Source. Own calculations based on *EPH*.

FIGURE 2.3a

EARNINGS DEPENDENCE. POOLED GROWTH YEARS. WHOLE SAMPLE.

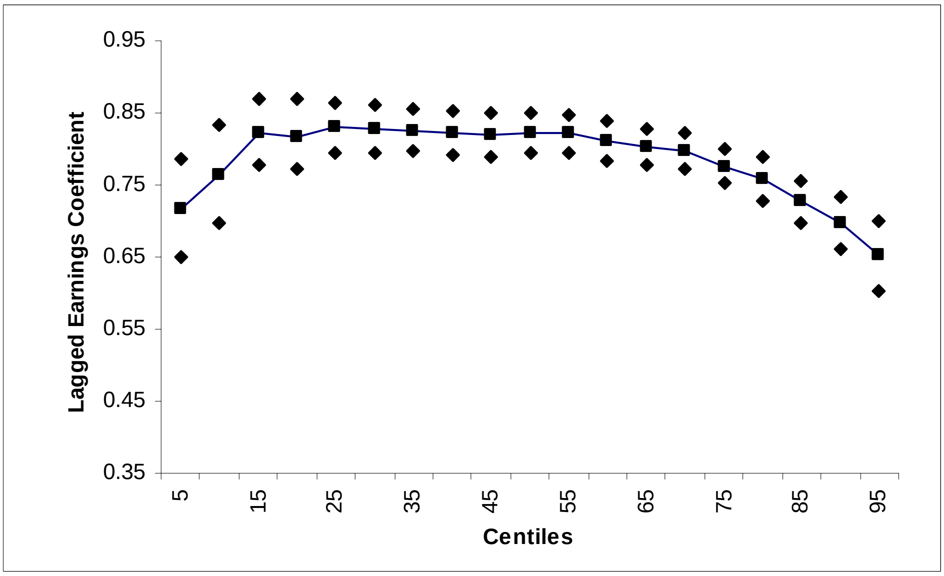


Note. The beta coefficients correspond to the estimations including as controls: individual education level, age and square age. Confidence bounds at 95%.

Source. Own calculations based on *EPH*.

FIGURE 2.3b

EARNINGS DEPENDENCE. POOLED RECESSION YEARS. WHOLE SAMPLE.

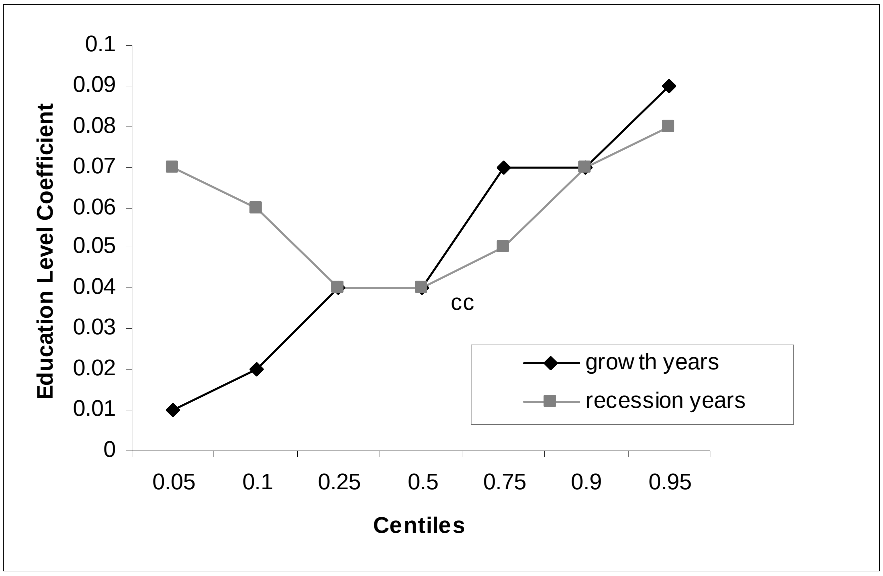


Note. The estimates include controls for education level, age and square age. Confidence bounds at 95%.

Source. Own calculations based on *EPH*.

FIGURE 2.4

RETURNS TO EDUCATION LEVEL. POOLED GROWTH AND RECESSION YEARS. WHOLE SAMPLE.

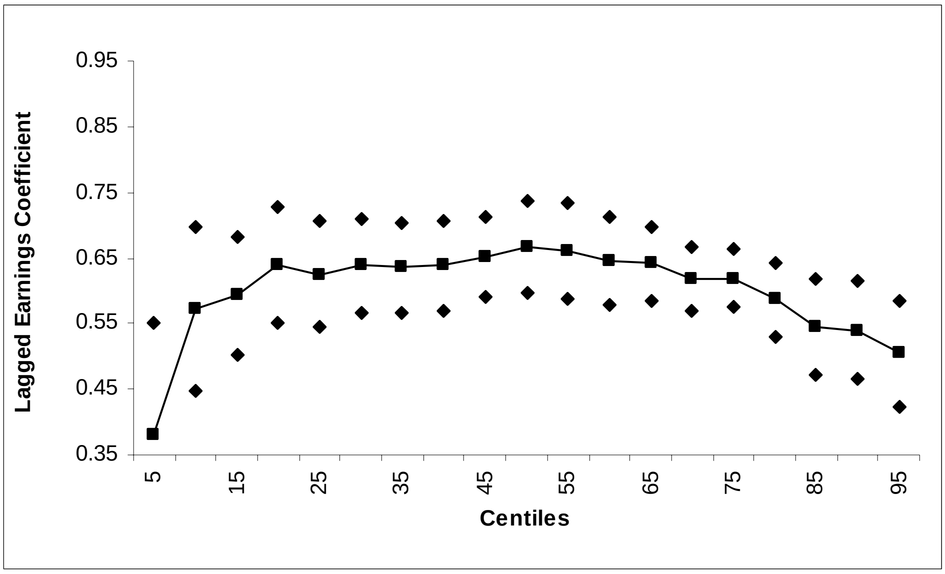


Source. Own calculations based on EPH.

FIGURE 2.5

EARNINGS DEPENDENCE. POOLED GROWTH YEARS. WHOLE SAMPLE.

MAY EARNINGS.



Note. The beta coefficients correspond to the estimations including as controls: individual education level, age and square age. Confidence bounds at 95%.

Source. Own calculations based on *EPH*.

TABLE 2.1a

GBA SAMPLE SUMMARY STATISTICS

	Pooled Growth Years					Pooled Recession Years				
	Mean	Standard Deviation	Median	Min	Max	Mean	Standard Deviation	Median	Min	Max
Log. Hourly Earnings	1.41	0.68	1.34	-1.13	3.83	1.35	0.71	1.30	-0.91	3.65
Lagged Log. Hourly Earnings	1.22	0.66	1.18	-1.03	3.58	1.37	0.72	1.30	-0.78	3.96
Education Level	3.37	1.50	3.00	0.00	6.00	3.44	1.52	3.00	0.00	6.00
Age	41.09	10.89	40.00	23.00	63.00	41.14	10.36	41.00	23.00	64.00

Note: pooled growth sample contains 571 observations including the annual panels 1996- 1997, 1997-1998 and 2002-2003; pooled recession sample contains 744 observations and includes annual panels 1998-1999, 1999-2000, 2000-2001 and 2001-2002.

Source. Own calculations based on *EPH*.

TABLE 2.1b

WHOLE SAMPLE SUMMARY STATISTICS

	Pooled Growth Years					Pooled Recession Years				
	Mean	Standard Deviation	Median	Min	Max	Mean	Standard Deviation	Median	Min	Max
Log. Hourly Earnings	1.02	0.66	0.98	-1.54	4.14	0.95	0.71	0.91	-1.92	3.64
Lagged Log. Hourly Earnings	1.02	0.64	0.97	-1.27	3.97	1.03	0.69	0.98	-1.72	4.39
Education Level	3.21	1.52	3.00	0.00	6.00	3.29	1.48	3.00	0.00	6.00
Age	40.61	10.12	40.00	23.00	64.00	40.51	10.20	40.00	23.00	64.00

Note: pooled growth sample contains 1,937 observations including the annual panels 1996-1997, 1997-1998 and 2002-2003; pooled recession sample contains 3,714 observations and includes annual panels 1998-1999, 1999-2000, 2000-2001 and 2001-2002.

Source. Own calculations based on *EPH*.

TABLE 2.2

OLS AND QUANTILE REGRESSION RESULTS. ANNUAL PANELS.

GBA SAMPLE.

Dependent Variable: Annually Lag of Individual Earnings (Log)	OLS	Quantile 0.01	0.05	0.1	0.25	0.5	0.75	0.9	0.95	0.99
Panel 1997-1996	0.74	0.41	0.49	0.73	0.86	0.89	0.78	0.69	0.60	0.60
{1.69}ns	(0.05)	(0.20)	(0.18)	(0.14)	(0.06)	(0.18)	(0.05)	(0.12)	(0.12)	(0.09)
Cohort-annual observations:	132									
R squared:	0.56									
Panel 1998-1997	0.81	0.52	0.94	0.90	0.91	0.88	0.81	0.78	0.79	0.61
{3.85}**	(0.04)	(0.21)	(0.10)	(0.06)	(0.06)	(0.03)	(0.04)	(0.06)	(0.09)	(0.25)
Cohort-annual observations:	231									
R squared:	0.61									
Panel 1999-1998	0.82	0.63	0.66	0.72	0.84	0.90	0.84	0.81	0.85	0.68
{2.95}**	(0.03)	(0.08)	(0.08)	(0.08)	(0.05)	(0.02)	(0.03)	(0.04)	(0.08)	(0.13)
Cohort-annual observations:	244									
R squared:	0.68									
Panel 2000-1999	0.80	0.78	0.76	0.80	0.88	0.91	0.81	0.62	0.54	0.37
{5.67}**	(0.03)	(0.17)	(0.06)	(0.08)	(0.04)	(0.02)	(0.04)	(0.06)	(0.12)	(0.11)
Cohort-annual observations:	222									
R squared:	0.68									
Panel 2001-2000	0.82	0.38	0.92	0.89	0.83	0.82	0.79	0.70	0.72	0.84
{2.40}**	(0.03)	(0.19)	(0.08)	(0.03)	(0.03)	(0.02)	(0.05)	(0.05)	(0.09)	(0.16)
Cohort-annual observations:	194									
R squared:	0.74									
Panel 2002-2001	0.88	1.70	1.06	1.05	0.95	0.88	0.86	0.85	0.58	0.50
{4.52}**	(0.06)	(0.43)	(0.26)	(0.11)	(0.07)	(0.03)	(0.07)	(0.13)	(0.16)	(0.15)
Cohort-annual observations:	84									
R squared:	0.62									
Panel 2003-2002	0.88	1.26	0.92	0.94	0.92	0.90	0.83	0.76	0.73	1.19
{2.64}**	(0.04)	(0.30)	(0.22)	(0.10)	(0.03)	(0.06)	(0.05)	(0.05)	(0.08)	(0.17)
Cohort-annual observations:	208									
R squared:	0.62									
** p<0.05										
* 0.05<p<0.10										
ns p>0.10										

Note: The number in curly brackets is the F statistic testing the equality of the quantile slope coefficients. In the OLS regression column, the number in parentheses is the heteroskedasticity-robust standard error. In the quantile columns, the number in parentheses is the bootstrapped standard error.

Source. Own calculations based on *EPH*.

TABLE 2.3

OLS AND QUANTILE MULTIPLE REGRESSION RESULTS. ANNUAL PANELS. GBA SAMPLE.

		Quantile								
Dependent Variable	OLS	0.01	0.05	0.1	0.25	0.5	0.75	0.9	0.95	0.99
					Panel 1997-1996 {0.82}[ns]					
Annually Lag of Individual Earnings (Log)	0.63 (0.06)	0.59 (0.28)	0.72 (0.19)	0.73 (0.19)	0.76 (0.10)	0.73 (0.11)	0.55 (0.13)	0.57 (0.14)	0.46 (0.15)	0.64 (0.15
Education Level	0.10 (0.02)	0.10 (0.13)	0.02 (0.09)	0.08 (0.08)	0.08 (0.03)	0.05 (0.02)	0.09 (0.04)	0.07 (0.05)	0.10 (0.07)	0.13 (0.08)
Age	0.01 (0.02)	-016 (0.08)	-0.06 (0.06)	-0.02 (0.04)	0.00 (0.02)	0.02 (0.01)	0.04 (0.02)	-0.01 (0.04)	0.05 (0.06)	0.04 (0.08)
Square Age	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Number of observations:	132									
R squared:	0.62									
					Panel 1998-1997 {0.74}[ns]					
Annually Lag of Individual Earnings (Log)	0.68 (0.05)	0.53 (0.25)	0.80 (0.13)	0.71 (0.11)	0.80 (0.07)	0.77 (0.05)	0.67 (0.09)	0.71 (0.11	0.56 (0.21)	0.47 (0.29)
Education Level	0.08 (0.02)	0.02 (0.06)	0.08 (0.04)	0.10 (0.03)	0.06 (0.01)	0.05 (0.01)	0.10 (0.03)	0.05 (0.05)	0.12 (0.09)	0.11 (0.13)
Age	0.03 (0.01)	0.15 (0.08)	0.06 (0.04)	0.03 (0.03)	0.00 (0.03)	0.01 (0.01)	0.04 (0.02)	0.06 (0.04)	0.08 (0.05)	0.12 (0.10)
Square Age	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Number of observations:	231									
R squared:	0.64									
					Panel 1999-1998 {2.37}**					
Annually Lag of Individual Earnings (Log)	0.74 (0.04)	0.52 (0.10)	0.59 (0.09)	0.64 (0.07)	0.79 (0.07)	0.87 (0.04)	0.78 (0.06)	0.69 (0.08)	0.60 (0.10)	0.37 (0.24)
Education Level	0.05 (0.01)	0.07 (0.03)	0.06 (0.04)	0.05 (0.04)	0.03 (0.02)	0.02 (0.02)	0.03 (0.03)	0.09 (0.04)	0.13 (0.04)	0.20 (0.08)
Age	0.00 (0.00)	-0.06 (0.06)	-0.01 (0.06)	-0.01 (0.04)	0.01 (0.02)	0.00 (0.02)	-0.00 (0.01)	0.01 (0.02)	0.04 (0.02)	0.07 (0.04)
Square Age	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Number of observations:	244									
R squared:	0.70									

TABLE 2.3 (CONT)

	Panel 2000-1999 {1.72}*									
Annually Lag of Individual	0.74	0.76	0.77	0.76	0.84	0.86	0.77	0.67	0.49	0.34
Earnings (Log)	(0.04)	(0.13)	(0.09)	(0.05)	(0.04)	(0.06)	(0.06)	(0.08)	(0.11)	(0.14)
	0.04	0.12	0.06	0.05	0.06	0.03	0.02	-0.00	0.04	0.00
Education Level	(0.02)	(0.05)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.05)	(0.09)
	0.01	-0.00	-0.01	0.00	0.01	0.00	-0.00	0.05	0.04	0.06
Age	(0.01)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.04)	(0.04)	(0.05)
	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	0.00	-0.00	-0.00	-0.00
Square Age	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of observations:	222									
R squared:	0.69									
	Panel 2001-2000 {2.18}**									
Annually Lag of Individual	0.76	0.25	0.89	0.90	0.80	0.80	0.68	0.67	0.66	0.45
Earnings (Log)	(0.04)	(0.31)	(0.12)	(0.07)	(0.05)	(0.03)	(0.08)	(0.07)	(0.10)	(0.14)
	0.04	0.13	-0.01	0.01	0.04	0.02	0.07	0.01	0.11	0.16
Education Level	(0.02)	(0.14)	(0.07)	(0.04)	(0.02)	(0.02)	(0.04)	(0.04)	(0.07)	(0.06)
	-0.01	-0.11	0.01	0.00	-0.02	-0.02	-0.04	-0.07	-0.04	-0.12
Age	(0.01)	(0.13)	(0.06)	(0.04)	(0.02)	(0.02)	(0.03)	(0.04)	(0.05)	(0.08)
	0.00	0.00	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00
Square Age	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of observations:	194									
R squared:	0.75									
	Panel 2002-2001 {1.58}^{ns}									
Annually Lag of Individual	0.73	0.66	0.64	0.85	0.79	0.79	0.74	0.57	0.33	0.36
Earnings (Log)	(0.07)	(0.21)	(0.13)	(0.09)	(0.08)	(0.07)	(0.12)	(0.21)	(0.18)	(0.15)
	0.12	0.43	0.16	0.13	0.14	0.05	0.08	0.18	0.20	0.19
Education Level	(0.03)	(0.16)	(0.10)	(0.04)	(0.04)	(0.03)	(0.06)	(0.09)	(0.08)	(0.07)
	-0.02	-0.16	-0.09	-0.03	-0.05	-0.02	0.02	0.02	0.00	0.03
Age	(0.03)	(0.13)	(0.08)	(0.06)	(0.04)	(0.03)	(0.04)	(0.06)	(0.06)	(0.07)
	0.00	0.00	0.00	0.00	0.00	0.00	-0.00	-0.00	0.00	-0.00
Square Age	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of observations:	84									
R squared:	0.74									
	Panel 2003-2002 {2.43}**									
Annually Lag of Individual	0.70	0.70	0.59	0.72	0.85	0.74	0.60	0.50	0.59	0.42
Earnings (Log)	(0.61)	(0.14)	(0.10)	(0.09)	(0.09)	(0.06)	(0.08)	(0.13)	(0.11)	(0.11)
	0.10	0.34	0.27	0.16	0.09	0.10	0.13	0.17	0.13	0.22
Education Level	(0.02)	(0.04)	(0.06)	(0.03)	(0.03)	(0.02)	(0.03)	(0.07)	(0.05)	(0.05)
	-0.03	0.08	-0.05	-0.05	-0.07	-0.04	-0.03	-0.03	-0.02	-0.05
Age	(0.02)	(0.12)	(0.07)	(0.04)	(0.02)	(0.02)	(0.03)	(0.05)	(0.05)	(0.04)
	0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Square Age	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of observations:	208									
R squared:	0.66									

** $p<0.05$
* $0.05<p<0.10$
ns $p>0.10$

Note: The number in curly brackets is the F statistic testing the equality of the quantile slope coefficients. In the OLS regression column, the number in parentheses is the heteroskedasticity-robust standard error. In the quantile columns, the number in parentheses is the bootstrapped standard error.

Source. Own calculations based on *EPH*.

TABLE 2.4a

OLS AND QUANTILE REGRESSION RESULTS. POOLED ANNUAL PANELS. GBA SAMPLE.

		Quantile								
Dependent Variable	OLS	0.01	0.05	0.1	0.25	0.5	0.75	0.9	0.95	0.99
Specification without controls	Positive Growth {1.39}[ns]									
Annually Lag of Individual Earnings (Log)	0.77 (0.03)	0.65 (0.21)	0.80 (0.13)	0.83 (0.06)	0.84 (0.03)	0.82 (0.02)	0.77 (0.03)	0.76 (0.05)	0.71 (0.04)	0.56 (0.18)
Number of observations:	571									
R squared:	0.57									
Specification with controls	Positive Growth {2.45}**									
Annually Lag of Individual Earnings (Log)	0.63 (0.03)	0.40 (0.14)	0.70 (0.09)	0.71 (0.06)	0.75 (0.04)	0.66 (0.04)	0.62 (0.05)	0.51 (0.10)	0.43 (0.07)	0.39 (0.15)
Education Level	0.11 (0.01)	0.19 (0.05)	0.14 (0.05)	0.10 (0.02)	0.08 (0.01)	0.09 (0.02)	0.11 (0.02)	0.15 (0.03)	0.20 (0.04)	0.14 (0.06)
Age	-0.01 (0.01)	0.05 (0.08)	-0.02 (0.03)	-0.01 (0.02)	-0.01 (0.01)	0.02 (0.01)	-0.02 (0.01)	-0.02 (0.03)	-0.11 (0.03)	-0.02 (0.05)
Square Age	0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Number of observations:	571									
R squared:	0.62									
Specification without controls	Negative Growth {4.70}**									
Annually Lag of Individual Earnings (Log)	0.82 (0.01)	0.63 (0.09)	0.72 (0.07)	0.83 (0.03)	0.85 (0.01)	0.88 (0.02)	0.84 (0.02)	0.74 (0.02)	0.63 (0.07)	0.59 (0.10)
Number of observations:	744									
R squared:	0.68									
Specification with controls	Negative Growth {2.98}**									
Annually Lag of Individual Earnings (Log)	0.75 (0.02)	0.57 (0.09)	0.75 (0.07)	0.75 (0.05)	0.81 (0.02)	0.82 (0.03)	0.76 (0.03)	0.67 (0.04)	0.61 (0.06)	0.53 (0.11)
Education Level	0.05 (0.01)	0.11 (0.05)	0.09 (0.03)	0.06 (0.02)	0.04 (0.01)	0.03 (0.01)	0.05 (0.01)	0.04 (0.02)	0.06 (0.03)	0.06 (0.05)
Age	-0.00 (0.01)	-0.05 (0.04)	-0.05 (0.03)	-0.01 (0.01)	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.02)	-0.00 (0.02)	0.05 (0.05)
Square Age	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)
Number of observations:	744									
R squared:	0.69									

** p<0.05

* 0.05<p<0.10

ns p>0.10

Note: The number in curly brackets is the F statistic testing the equality of the quantile slope coefficients. In the OLS regression column, the number in parentheses is the heteroskedasticity-robust standard error. In the quantile columns, the number in parentheses is the bootstrapped standard error.

Source. Own calculations based on *EPH*.

TABLE 2.4b

OLS AND QUANTILE REGRESSION RESULTS. POOLED ANNUAL PANELS. WHOLE SAMPLE.

		Quantile								
Dependent Variable	OLS	0.01	0.05	0.1	0.25	0.5	0.75	0.9	0.95	0.99
Specification without controls					Positive Growth {8.53}**					
Annually Lag of Individual Earnings (Log)	0.74 (0.02)	0.18 (0.12)	0.55 (0.06)	0.74 (0.06)	0.82 (0.02)	0.86 (0.01)	0.80 (0.01)	0.74 (0.02)	0.70 (0.03)	0.62 (0.05)
Number of observations:	1937									
R squared:	0.52									
Specification with controls					Positive Growth {7.12}**					
Annually Lag of Individual Earnings (Log)	0.67 (0.02)	0.28 (0.18)	0.54 (0.06)	0.72 (0.06)	0.78 (0.02)	0.77 (0.02)	0.70 (0.01)	0.61 (0.03)	0.56 (0.04)	0.53 (0.60)
Education Level	0.05 (0.00)	-0.06 (0.06)	0.01 (0.02)	0.02 (0.02)	0.04 (0.00)	0.04 (0.00)	0.07 (0.00)	0.07 (0.01)	0.09 (0.02)	0.08 (0.03)
Age	0.02 (0.00)	0.09 (0.09)	0.01 (0.03)	0.01 (0.01)	0.00 (0.00)	0.00 (0.00)	0.02 (0.00)	0.01 (0.01)	0.01 (0.01)	0.06 (0.04)
Square Age	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Number of observations:	1937									
R squared:	0.53									
Specification without controls					Negative Growth {7.01}**					
Annually Lag of Individual Earnings (Log)	0.84 (0.01)	0.70 (0.08)	0.79 (0.03)	0.85 (0.02)	0.88 (0.01)	0.88 (0.01)	0.85 (0.01)	0.79 (0.01)	0.76 (0.02)	0.73 (0.04)
Number of observations:	3714									
R squared:	0.66									
Specification with controls					Negative Growth {8.87}**					
Annually Lag of Individual Earnings (Log)	0.76 (0.01)	0.65 (0.08)	0.71 (0.03)	0.76 (0.03)	0.81 (0.02)	0.82 (0.01)	0.77 (0.01)	0.69 (0.01)	0.65 (0.02)	0.56 (0.04)
Education Level	0.05 (0.00)	0.05 (0.03)	0.07 (0.01)	0.06 (0.01)	0.04 (0.00)	0.04 (0.00)	0.05 (0.00)	0.07 (0.00)	0.08 (0.01)	0.11 (0.02)
Age	0.01 (0.00)	0.00 (0.02)	0.03 (0.01)	0.00 (0.01)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.01)	0.00 (0.01)	0.03 (0.02)
Square Age	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Number of observations:	3714									
R squared:	0.67									
** p<0.05										
* 0.05<p<0.10										
ns p>0.10										

Note: The number in curly brackets is the F statistic testing the equality of the quantile slope coefficients. In the OLS regression column, the number in parentheses is the heteroskedasticity-robust standard error. In the quantile columns, the number in parentheses is the bootstrapped standard error.

Source. Own calculations based on *EPH*.

TABLE 2.4C

OLS AND QUANTILE REGRESSION RESULTS. POOLED ANNUAL PANELS. WHOLE SAMPLE. MAY EARNINGS.

		Quantile								
Dependent Variable	OLS	0.01	0.05	0.1	0.25	0.5	0.75	0.9	0.95	0.99
Specification without controls					Positive Growth {7.48}**					
Annually Lag of Individual Earnings (Log)	0.64 (0.02)	0.15 (0.14)	0.47 (0.06)	0.60 (0.04)	0.70 (0.03)	0.75 (0.02)	0.71 (0.01)	0.64 (0.02)	0.59 (0.02)	0.53 (0.05)
Number of observations:	2046									
R squared:	0.46									
Specification with controls					Positive Growth {3.69}**					
Annually Lag of Individual Earnings (Log)	0.56 (0.03)	0.26 (0.17)	0.38 (0.08)	0.57 (0.06)	0.62 (0.04)	0.66 (0.03)	0.61 (0.02)	0.53 (0.03)	0.50 (0.04)	0.41 (0.09)
Education Level	0.07 (0.01)	-0.07 (0.06)	0.00 (0.03)	0.01 (0.01)	0.05 (0.01)	0.06 (0.01)	0.09 (0.01)	0.12 (0.02)	0.13 (0.01)	0.14 (0.05)
Age	0.03 (0.01)	0.03 (0.10)	0.02 (0.03)	0.01 (0.02)	0.02 (0.01)	0.02 (0.01)	0.02 (0.01)	0.02 (0.01)	0.02 (0.02)	0.03 (0.04)
Square Age	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Number of observations:	1509									
R squared:	0.47									
** p<0.05										
* 0.05<p<0.10										
ns p>0.10										

Note: The number in curly brackets is the F statistic testing the equality of the quantile slope coefficients. In the OLS regression column, the number in parentheses is the heteroskedasticity-robust standard error. In the quantile columns, the number in parentheses is the bootstrapped standard error.

Source. Own calculations based on *EPH*.

TABLE 2.5a

TEST OF EQUALITY OF EARNINGS COEFFICIENTS FOR QUANTILE REGRESSION ESTIMATES. GBA SAMPLE.

Quantiles		Pooled Growth Years Prob > F	Pooled Recession Years Prob > F
0.05	0.10	0.843	0.9888
0.05	0.25	0.5701	0.3359
0.05	0.50	0.6907	0.2612
0.05	0.75	0.4053	0.9279
0.05	0.90	0.0714	0.2814
0.05	0.95	**0.0369**	0.1099
0.10	0.15	0.3925	0.5246
0.10	0.20	0.5690	0.3329
0.10	0.25	0.5122	0.2037
0.10	0.30	0.6409	0.2207
0.10	0.35	0.5364	0.3633
0.10	0.40	0.9937	0.2808
0.10	0.45	0.8547	0.2050
0.10	0.50	0.4215	0.1857
0.10	0.75	0.1600	0.9094
0.10	0.90	**0.0066**	0.2702
0.10	0.95	**0.0005**	**0.0901**
0.25	0.50	**0.0198**	0.5620
0.25	0.75	**0.0049**	0.1793
0.25	090	**0.0000**	**0.0099**
0.25	0.95	**0.0000**	**0.0012**
0.35	0.40	0.1802	0.4982
0.35	0.45	0.1660	0.3176
0.35	0.50	**0.0278**	0.3423
0.50	0.55	0.8090	0.8972
0.50	0.60	0.1374	0.8720
0.50	0.65	0.1705	0.7331
0.50	0.75	0.2549	0.0519
0.50	0.90	**0.0045**	**0.0019**
0.50	0.95	**0.0002**	**0.0002**
0.75	0.90	**0.0317**	0.0656
0.75	0.95	**0.0049**	**0.0145**
0.90	0.95	0.1575	0.2521

Note: Tests correspond to estimates plotted on FIGURE 2.1a and FIGURE 2.1b

Source. Own calculations based on *EPH*.

TABLE 2.5b

TEST OF EQUALITY OF EARNINGS COEFFICIENTS FOR QUANTILE REGRESSION ESTIMATES. WHOLE SAMPLE.

Quantiles		Pooled Growth Years Prob > F	Pooled Recession Years Prob > F
0.05	0.10	**0.0001**	**0.0477**
0.05	0.25	**0.0002**	**0.0000**
0.05	0.50	**0.0004**	**0.0000**
0.05	0.75	**0.0247**	**0.0202**
0.05	0.90	0.3370	0.4778
0.05	0.95	0.8478	0.0836
0.10	0.15	0.6172	**0.0022**
0.10	0.20	0.3222	**0.0228**
0.10	0.25	0.2597	**0.0067**
0.10	0.30	0.3725	**0.0146**
0.10	0.35	0.1657	**0.0186**
0.10	0.40	0.1523	**0.0286**
0.10	0.45	0.1808	**0.0406**
0.10	0.50	0.3234	**0.0359**
0.10	0.75	0.6301	0.6968
0.10	0.90	0.0868	**0.0474**
0.10	0.95	**0.0145**	**0.0086**
0.25	0.50	0.8253	0.5628
0.25	0.75	**0.0002**	**0.0004**
0.25	090	**0.0000**	**0.0000**
0.25	0.95	**0.0000**	**0.0000**
0.35	0.40	0.8628	0.6366
0.35	0.45	0.9661	0.4534
0.35	0.50	0.3051	0.7087
0.50	0.55	0.3551	0.8780
0.50	0.60	0.1686	0.1912
0.50	0.65	**0.0386**	0.0581
0.50	0.75	**0.0001**	**0.0000**
0.50	0.90	**0.0000**	**0.0000**
0.50	0.95	**0.0000**	**0.0000**
0.75	0.90	**0.0055**	**0.0000**
0.75	0.95	**0.0002**	**0.0000**
0.90	0.95	**0.0393**	**0.0000**

Note: Tests correspond to estimates plotted on FIGURE 2.2a and FIGURE 2.2b

Source. Own calculations based on *EPH*.

TABLE 2.5C

TEST OF EQUALITY OF EARNINGS COEFFICIENTS FOR QUANTILE REGRESSION ESTIMATES. WHOLE SAMPLE.

Quantiles		Pooled Growth Years (volatility) Prob > F
0.05	0.10	**0.0009**
0.05	0.25	**0.0012**
0.05	0.50	**0.0004**
0.05	0.75	**0.0037**
0.05	0.90	0.0736
0.05	0.95	0.1570
0.10	0.15	0.5534
0.10	0.20	0.1479
0.10	0.25	0.2870
0.10	0.30	0.1985
0.10	0.35	0.2459
0.10	0.40	0.2110
0.10	0.45	0.1564
0.10	0.50	0.0986
0.10	0.75	0.4435
0.10	0.90	0.6305
0.10	0.95	0.3159
0.25	0.50	0.1787
0.25	0.75	0.8439
0.25	090	0.0779
0.25	0.95	**0.0113**
0.35	0.40	0.7759
0.35	0.45	0.4092
0.35	0.50	0.1609
0.50	0.55	0.6209
0.50	0.60	0.2627
0.50	0.65	0.2252
0.50	0.75	0.0775
0.50	0.90	**0.0033**
0.50	0.95	**0.0003**
0.75	0.90	**0.0071**
0.75	0.95	**0.0002**
0.90	0.95	0.2394

Note: Tests correspond to estimates plotted on FIGURE 2.4.

Source. Own calculations based on *EPH*.

[i] See Keswell (2004) for the inefficiencies or inconsistencies that arise by using standard approaches to dealing with non-linearities like adding higher order terms of $y_{i,t-1}$ or by partitioning the sample along various dimensions.

[ii] Though problems of measurement errors involves some extra technical considerations to avoid biases in the estimated coefficients, there are not mentioned here to keep focus on the main differences between quantile methodology and mean techniques. For a thoroughly analysis of this subject, see Fields et al. (2006a).

[iii] Fields and Sánchez Puerta (2005) groups annual panels in the same way to compare mobility between growth and recession years.

[iv] Among others, Gasparini and Sosa Escudero (1999).

[v] Results corresponding to annual panels do not differ with GBA Sample, but they are more precise. They are available from the author upon request.

Chapter III

Exploring Intergenerational Social Mobility in Argentina

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Abstract

This paper aims to estimate the degree of intergenerational mobility in Argentina, focusing on the mobility differences between teenagers and young adults. Based on a new data base, the Survey of Employment and Education of Youth *(CEDLAS-INDEC)* non-biased mobility estimations for children older than teenagers is obtained. The estimations reveal a rather lower degree of intergenerational mobility for young adults than teenagers, a result that is robust for several specifications of the model. It also observed that young adult immobility is not uniform across parents' education level. Further, gender differences affect mobility.

[*] I would like to thank to CEDLAS an particularly to Mariana Marchionni for giving me the data base corresponding to the Survey of Employment and Education of Youth and to Ana Pacheco for kindly help me understanding some aspects of it. I am also grateful for the helpful suggestions of Walter Sosa Escudero and Guillermo Cruces; and to the Universidad Austral for its financial support.

3.1 Introduction

To pass sound judgment of social fairness entails knowing not only the degree of income inequality and its evolution over time, but also an accurate measure of social mobility. With a high mobility degree, the progress prospect for the less favored depends on a combination of effort, ability and luck; and indeed the poor are not severely hampered by their initial conditions of life. Hence, regardless of the income inequality of a society, the latter would not be unfair as it would offer equal opportunities to all. Specifically, with the availability of equal opportunity between the haves and the have-nots, family background like parents' education and households' income will not be relevant in determining a child's future socioeconomic level. In Roemer's view, childhood circumstances will not impinge upon their success in later life.

Although there is a vast empirical evidence indicating that Latin America is still one of the most unequal regions of the world (IPES 2008, Perry et al. 2005; De Ferranti et al. 2004; Bourguignon, Ferreira and Leite 2002), systematic quantitative analysis in social mobility across generations is rather meager here. The vast data requirement of those estimations is, undoubtedly, a major drawback for the researchers. To overcome the lack of appropriate longitudinal data, some researchers have attempted to measure intergenerational mobility in Latin American countries using cross-sectional surveys (e.g., Behrman, Birdsall and Székely 1998; Dahan and Gaviria 2001; Andersen 2001 and Conconi et al. 2007). Focusing on young children who still live with their parents, their strategy consists on estimating the degree to which family background determines the schooling outcomes of children. This methodology is advantageous as it allows for comparisons on social mobility among the Latin American countries, because it uses standardized data sets from household surveys; it is assured that the differences in mobility between countries will not reflect differences in data structures, measurement or statistical approach. All in all, the strategy of those papers strongly focuses on teenagers' school attainment, revealing practically nothing about young adults' mobility, for which the proportion of individuals that live on their own greatly increases. In terms of social mobility, it appears safe to state that young adults, who leave home relatively early, may differ significantly from those who leave home later. The papers mentioned above focus on young children, to avoid potential bias associated with including young adults who still live with their parents (Andersen 2001). However, if family background affects differently the marginal decisions of education of young people beyond adolescence, stopping to look at schooling achievements around 20 years old, tells only part of the intergenerational mobility story. Hence, those results have a caveat as they apply only to young people.

The aim of this paper is to investigate the degree of social mobility in Argentina, exploring differences in the estimations when using different databases, including young adults, besides teenagers. The Survey of Employment and Education of Youth (*Encuesta de Educación y Empleo de los Jóvenes*, *EEEJ*) collected by the *Instituto Nacional de Estadística y Censos (INDEC)* and the *Centro de Estudios Distributivos, Laborales y Sociales (CEDLAS)* of Argentina was used for this purpose. This is a new and original source of information on labor and educational issues. The *(EEEJ)* was carried out in the Greater Buenos Aires area, Argentina, on young men and women between 15 and 30 years of age, who have earlier been interviewed by the Permanent Household Survey *(Encuesta Permanente de Hogares, EPH)*. This paper contributes to the ongoing discussion on the suitable data to measure social mobility in developing countries, where the absence of long panel data that would allow to link data across generations, prevents the researcher from studying intergenerational income mobility in a straight way. The paper exploits the information provided by this new survey, which includes several retrospective recall questions that provide information on individual family background. Hence, although it is a cross-section sample, this new survey allows exploring measurement differences in social mobility between teenagers and young adults, avoiding the common bias that arises when using household surveys. Besides, given that for Argentina there are very few research studies studying intergenerational mobility (see Fernandez 2006 and FIEL 2008), this paper contributes to the analyses and evaluation of the equality of opportunity in Argentina.

The rest of the paper is organized as follows: Section 3.2 describes the methodology used to estimate social mobility. Section 3.3 describes the data used for this project. Section 3.4 summarizes the main results. Section 3.5 explores mobility patterns for young adults and, section 3.6 concludes.

3.2 Methodology

3.2.1 Schooling and social mobility

The intergenerational transmission of social status is a complex process that involves many links among family incomes, home investments in children's human capital, family tastes, children abilities, schooling attainment and future incomes of children in later life (Becker and Tomes 1979, 1986; Behrman, Birdsall and Székely 1998; Han and Mulligan 2001; Bowles and Gintis 2002). In the context of perfect capital markets, without unobserved differences between low- and high-income households, there would be no differences in schooling investments associated with income after controlling for any observed differences in household characteristics. In this scenario, educational accomplishment of children would be independent of their households' socioeconomic characteristics. Therefore, intergenerational mobility would be high. Instead, if household income and the unobserved innate ability of the children were positively correlated, associations would appear between household income and investments in schooling. The causal role of household income on child's schooling appears with imperfect capital markets as well.

Following Behrman, Gaviria and Székely (2001), measuring social mobility entails the estimation of a dynamic linear model linking a relevant socioeconomic indicator for entity i in period t (S_{it}) with the value of that indicator in the preceding period (S_{it-1}) and a stochastic term (w_{it}) that is independent of the prior period indicator and that is independently distributed across individuals and across periods:

$$S_{it} = \alpha + \beta S_{it-1} + w_{it}, \qquad (3.1)$$

Applying the linear model in equation (3.1) to the transmission of schooling from parents to children, S_{it} refers to the educational children achievement and S_{it-1} to the educational attainment of each parent or the education level of the most educated parent. The standard interpretation of β suggests a very limited intergenerational mobility whenever β is close to unity, while the estimates of β close to zero suggest that schooling outcomes are not closely related across the generations. In this simple model, β is interpreted as a measure of the degree to which family background affects children's socioeconomic outcomes, and thus as a measure of (in)equality of opportunities. However, considering equality of opportunities as synonymous with a zero intergenerational correlation could be misleading, particularly when taking public policies into account to enhance fairness (Corak 2006). Parents influence children not only through the genetic transmission of ability, but also through their social connections, culture, beliefs and motivation. β value close to zero would imply that all these sources of inheritance are irrelevant. As Roemer (2004) points out, this is "a view that only a fraction of those, who consider the issue would, upon reflection, endorse" (Roemer, 2004, p. 49).

3.2.2 Data requirements

The estimation of intergenerational mobility is a challenging task due to the detailed data requirements it necessitates. Actually, ideal data sets for intergenerational studies rarely exist even in developed countries (Corak 2006). This is because analyzing the linkage of earnings or incomes across generations requires a longstanding longitudinal survey that follows people from their early years when living in their parental home to their adulthood. The survey needs also to be based upon a representative sample of individuals. Parental incomes need to reflect a measure of their permanent income, not merely the annual income for a limited number of years. In developing countries, these requirements largely surpass the longitudinal existent data. Not only are sample sizes often too small but also the temporal length of the surveys. Besides, frequently, household panel studies did not follow people who moved out of their original households or after the family split up. So the samples are not truly representative (Jenkins and Siedler 2007). Therefore, very little information is available on how much family background affects the socioeconomic outcomes in Latin America, or the extent of inequality of opportunities in the region as a whole and in particular countries.

Behrman, Birdsall and Székely (1998), Dahan and Gaviria (2001) and Andersen (2001) offer an alternative approach to measure social mobility. They use standard household surveys information on parental and children's schooling. The authors focus on young children still co-residing with their parents, thus overcoming the lack of appropriated longitudinal data. Two basic assumptions underlie their strategy. The first is that schooling and future opportunities are highly correlated for young people. The second is that equality of opportunity is a good indicator of social mobility.

This approach defines children's schooling gap as "the disparity between the years of education that a teenager or young adult would have completed had she entered school at normal school starting age and advanced one grade each year, on the one hand, and the actual years of education, on the other hand" (Andersen 2001, p.8). This concept is a very simple indicator of future opportunities, principally very well suited to study social mobility for teenagers or young adults. For example, a 17 year-old teenager who has completed 9 years of schooling will register a schooling gap of (17-9-6) = 2 years, if he lives in a country where children begin schooling only at the age of 6 years. Hence, schooling gap is defined as the average years of missing schooling time. Following Andersen (2001), the schooling gap has several advantages as compared with measures based on earnings or years of education. First, income measures are notoriously inaccurate, highly dependent on the season for large groups of the population, and generally difficult to compare across countries. Besides, a measurement error bias arises when using reported data on incomes. Secondly, using the number of years of education has not proved to be a good measure of educational attainment for young people, as many of them are still in school. The differences in school quality, however, are not considered and that appears to be the main drawback of the schooling gap concept.

However, there is a limitation under this approach because although it allows for estimating intergenerational school mobility for teenagers still living in parental households, there still remains a very large group of children who are young adults and could not be included in the analysis. Studying mobility for young adults using the standard household surveys would involve substantial loss of information and probably bias, as long as those who leave home relatively early, may differ significantly from those who leave home later, in terms of social mobility (Behrman, Gaviria, and Székely 2001). Hence, restricting the sample to teenagers still co-residing with their parents solves the data problem in estimating social mobility, but it could be telling only part of the story. Using cross-section data would involve losing information on any important change in the link between family background and socioeconomic performance beyond adolescence.

Cross-sectional surveys containing retrospective questions on parental background are an alternative approach to overcome data restriction. In retrospective surveys, individuals are typically interviewed only once and they provide retrospective information using recall. Parental income information from such a source evidently will not be highly accurate. However, retrospective information on parental education and occupation can be very precisely obtained. It is thus possible to estimate mobility for young children and also for young adults as according to Behrman, Gaviria and Székely (2001). This is also the strategy followed by FIEL (2008), which designed and collected a specific survey on the socioeconomic life conditions and family background in the Greater Buenos Aires area. Retrospective surveys has the advantage not only of enlarging the sample, but also in allowing the researcher to detect the potentially different links between children's schooling and parental background across the successive educational levels achieved by the former. Educational persistence can be low for children at the secondary level when secondary schooling has been expanded or when it becomes mandatory. In both cases, many children whose parents themselves had barely completed their primary studies, will achieve secondary studies. But, since tertiary or university studies did not expand, educational persistence could be large for individuals deciding to pursue their studies beyond secondary schooling. This advantage is more valuable given the close link between educational attainment and later incomes, and the fact that demand in the labor market for high-skilled workers has been steadily growing. Including young adults, allows the inspection of the intergenerational link for those who have reached or would have reached tertiary studies or university.

This paper is based on the concept that when parents' education and household income are both important determinants of the offspring's opportunities, social mobility would be low. Conversely, when the opportunities children encounter are not strongly determined by family background, their social mobility would be high. Thus, this methodology recognizes a strong relationship between incomes and schooling. This is a sound hypothesis for Argentina where empirical evidence reveals that returns to education increases with the schooling level, and that the overall rate of return to an additional year of schooling is above the average for middle income countries (López Bóo 2007)[i]. Hence, with convex returns to schooling, stopping to look at educational mobility for children under the age for university studies could produce a misleading measurement of the real intergenerational mobility.

To overcome the lack of longitudinal data sets in Argentina, and to counter the limitation that arises by using cross-section data, the strategy used here involves exploring intergenerational links using a survey collected from young men and women between 15 and 30 years of age, earlier interviewed by the Permanent Household Survey, which provide some covariates regarding family background. The survey included retrospective questions on parental socioeconomic characteristics. Using this data set it is possible to measure the effects of family background schooling success of teenagers co-residing with their parents. It is also possible to study the intergenerational link for young adults who still reside with their parents or have already left, revealing differences, if any, among the age groups. To compare teenagers' mobility with the older groups, Andersen's definition of schooling gap is used to define children's schooling performance.

3.3 Data

Data for this study comes from the Survey of Employment and Education of Youth *(Encuesta de Educación y Empleo de los Jóvenes)(EEEJ*) collected in June 2005 by *Instituto Nacional de Estadística y Censos (INDEC) and Centro de Estudios Distributivos, Laborales y Sociales (CEDLAS)* of Argentina *(INDEC-CEDLAS).* This is a new and original source of information that focuses on labor and educational issues in young people. This sample has never been used in any study before, apart from Marchionni, Bet and Pacheco (2007) who present the basic information contained in the survey, and some potentially valuable uses of the sample to estimate models on youngsters' inclusion in the labor market. The survey was designed to collect more complete and relevant information to study labor participation and labor experience of the youth. It provides additional data on the educational performance of the youth and the characteristics of the school -whether private or public, single or double shift type- that they have attended or are currently attending. It also offers information on early job experiences of the youth and their social environment and family background. The present work is particularly interested in the respondents' response in the survey, on their parents' educational level. This is highly valuable, as the household survey regularly collected in Argentina omits any question on the respondents' family background. The *EEEJ* was carried out in the Greater Buenos Aires, Argentina, on 807 young men and women between 15 and 30 years of age, from 526 households, , who had been earlier interviewed by the Permanent Household Survey *(Encuesta Permanente de Hogares, EPH)*. This strategy links both surveys, substantially improving the Survey of Employment and Education of Youth by including the demographic, socioeconomic, and labor information of all household's members. Unfortunately, at the time of this study, there was no way to link both surveys as the code necessary to accomplish the matching purposes had not been provided by *INDEC* (Marchionni, Bet and Pacheco 2007). However, the *INDEC* has already added several households' variables in the *EEEJ* data base.

Table 3.1 shows that the three age groups are quite similar in size and a little less in gender composition. It also reveals that about 95% of all teenagers live in the parental home. However, for young adults, the percentage of co-residing children drops to 73% for those between 20-25 years of age, and to 61% for the older group.

INSERT TABLE 3.1 ABOUT HERE

School gap, as defined in Andersen (2001), requires first calculating the number of schooling years per individual. In the survey, the respondent declares the highest level of schooling (e.g., primary, secondary)[vi] that he is currently in or has been in, whether he has completed it or not, and the last grade he passed. This information makes it possible to calculate each individual's years of schooling. In cases where some questions are left unanswered, the variable years of schooling cannot be defined. However, in cases where children did not respond about the last grade they had passed but did declare that the highest level of education achieved was primary or secondary, it was possible to calculate their years of schooling. For example, if a child declares having completed secondary studies, she would have attended 7 years of primary plus 5 of secondary; thus having had 12 years of schooling. In the rest of the educational levels, it was not possible to calculate the years of schooling as the duration of the tertiary or university education studies is not fixed. Similarly, it was not possible to calculate the schooling years for those children for whom *Educación General Básica* (*EGB*) was the highest level achieved. This level includes 9 years of basic education composed of 3 consecutive levels, which are not distinguishable in the data[ii]. In addition, although the last year of preschool was not mandatory until 1993, attending one year of kindergarten was quite the norm earlier. Therefore, here it is assumed that all children had attended it. Hence, in the above scenario, the entire span of schooling attainment would amount to 13 years. Hence, schooling gap is computed as the age at the time of the interview minus the years of schooling, minus the normal school starting age, where the last set at five years corresponded to a child entering school to attend one year of kindergarten. For example, for a 15 year-old boy who has achieved eight grades of education, 9 years of schooling are computed; thus assuming 5 years of age as mandatory to attend preschool implies one year of schooling gap. For people above 25, the maximum number of schooling years they may have achieved is assumed to be 17. This would mean assuming that the duration of university studies on an average is not more than four years. This assumption avoids spurious schooling gap based on the respondent's age.

Considering parents' education, the survey computes the highest education level that they have really achieved (e.g., none, primary, secondary), but does not specify how many years of education they have completed. This is a limitation of the *EEEJ* and does potentially affect the regression coefficients. Hertz et al. (2007) found that regression coefficients were sensitive to these coding decisions. However, this paper aims to measure the social mobility differences between teenagers and young adults, and not to establish its overall degree. Thus, it appears that this deficit would not seriously affect the main purpose of the study. There are 74 records that do not recall their parents' education level, and 14 declared that either parent had no education at all. Here, those zero values are treated as the true value, although a few could have acquired some informal education. The survey also questions if this parental' level of education had been completed at the time the respondent was attending secondary school. Restricting the sample to those respondents whose fathers had completed their education level by the time the child was at school, diminishes the sample in 40% or in 36% when considering the mothers. The survey does not consider whether parents ended their studies after that. As mentioned earlier, *INDEC* added some information to the *EEEJ* data base. Several definitions of household income are included. The per capita household income was included in the estimation of conditional education mobility. However, those income variables correspond to parents' home only for children who still co-reside with them. For those living on their own, those magnitudes are their own contemporaneous incomes. Fortunately, the *EEEJ* includes a set of qualitative questions pertaining to which school the children attended or are still attending (e.g., whether it is public or private, single or double shift, teaching foreign languages or not). Those characteristics were analyzed to select the best proxy to the household's income level at the time the children attending primary school.

The survey includes a question on the age at which the individuals began their first job. The data reveals that in many cases this happened during the child's school age. This early entrance to the labor market could undoubtedly be significant in explaining schooling gaps. Therefore, two additional controls were added. One of them is a dummy to detect whether the individual was previously employed or not. The other control is a variable that registers the age of her first employment.

INSERT TABLE 3.2 ABOUT HERE

Table 3.2 shows that on average, the group of young adults (20-25 years of age) has achieved more schooling, while the teenage group presents a much lower schooling gap. For the latter, the average schooling gap is 1.08 grades, indicating that on the average a 16 year-old who should have completed 11 grades of schooling, assuming he had begun at age 5 (preschool level) and advanced one grade each subsequent year, in reality has completed a little less than 10 grades. Meanwhile, on average, a 20-year-old who could have completed 15 grades of schooling, in fact has also completed a little less than 10 grades. These data suggest that the average schooling gap is substantial for young adults. By gender, on average, females have a little higher education level than males, and exhibit less disparity between the expected and actual years of education. Regarding the educational level of parents, Table 3.2 reveals that mothers possess a higher educational level than the fathers. The average educational level of the parents is around 3.5, indicating that they have achieved an education level between the primary and secondary levels. Although it is not possible to precisely compare the number of years of education between the parents and children, it appears that education level does not differ too much between the two generations. However, the effective schooling level of parents would in reality fall below the level showed in Table 3.2. Respondents declared that 36-40% of both parents had not completed the education level computed in the survey when their children were attending school, or at least the children could not recall. Restricting the sample to those parents whose children could recall for certain that they had completed their education level (e.g., completed primary, completed secondary) reveals average education levels that are practically the same as those obtained with the full sample of parents. The Table also reveals that the percentage of children who attended primary private schools ranges between 24% to almost 30%, indicating the major role of the private schools in Argentina's educational system.

3.4 Estimation Results

3.4.1 Educational mobility

In this section the results of applying the linear model in equation are reported (3.1). Several different specifications are estimated and the results are shown in Tables 3.3 through 3.7. To detect differences in social mobility between teenagers and young adults, the model is estimated for each group separately, besides for the whole sample. Estimations are shown to be robust to specification changes of the basic model, and the sign and the significance of the coefficients do not change when adding progressively the explicative variables.

Table 3.3a shows the results of estimating model (3.1) using schooling gap as the independent variable, and the parents' maximum educational level as the covariate. This exercise reveals the unconditional mobility (Fields et al. 2007), documenting the degree of generational convergence on educational level. This is relevant because children's convergence on educational achievement is an indicator of equality of opportunity in the economy. The results show that mobility is large for teenagers (β_{15-19}= -0.24) but not for young adults (β_{20-25}= -0.73 and β_{26-30}= -0.91), all the coefficients being statistically significant at a 5%. For example, for young adults older than 25 years, the findings indicate that an improvement of one education level for their most educated parent (e.g., from primary to secondary level) results in a drop of almost a year in their schooling gap; for the youngest group, a one level improvement of their most educated parent amounts to a meager decrease of their schooling gap. Even so, as the schooling gap is quite different between teenagers and young adults, these differences in the absolute magnitudes of β do not necessarily indicate the relative differences in the family educational background influence over both groups. Considering that the schooling gap for teenagers is about one year, and about 5 years for young adults (25-30), their respective β coefficient entails about a 20% decrease in the average educational gap. Considering both these results together, it is evident that the parents' education level is quite decisive on the generational transmission of social status for the young adults who take marginal decisions on education but not for those for whom education is at the compulsory stage. It is also evident that parents' educational influence is proportionally the same for both groups, the average delay of their cohort taken into account.

It is possible that as many parents had not completed their educational level at the time the child attended school, the results obtained here are affected. To check the robustness of the results obtained above, Table 3.3b shows the results of estimating unconditional educational persistence using a smaller sub-sample of those records for which the children recall that both parents had completed their educational level by the time the children were at school. Despite the large drop in the sample size, the results are quite similar to those seen in Table 3.3a, corresponding to the full sample. Similar results are obtained with the whole sample, when assigning a lower education level to those parents whose children do not recall whether they had completed the educational level they had attended or not. The results are shown in Table 3.3c.

INSERT TABLE 3.3 ABOUT HERE

Considering conditional mobility, Table 3.4 shows the results of estimating a model (Model 1) with the same independent variable but using both parents' educational level as covariates, and the deciles of per capita household income, as family background. Standard controls like sex and age are also included. When the whole sample is considered, the educational link between parents and children indicates high intergenerational mobility. Both coefficients are quite below 0.5, being statistically significant at the 1% level. The results also indicate that the schooling gap tends to diminish as the family income rises higher, being the coefficient statistically significant at the 1% level. The age coefficient is positive and statistically significant at the 1% level, indicating an increase in the years of missing education as the youth get older. The gender dummy has a negative and significant effect in the mean schooling gap, suggesting that the expected performance of boys is higher than that of girls. Table 3.4 also shows the results for each group of children estimated separately. The estimates of the intergenerational link on education for both parents grow markedly from teenagers to young adults (26-30 years of age). The father's coefficient is neither statistically nor economically noted to be significant for teenagers.

INSERT TABLE 3.4 ABOUT HERE

Following Behrman's approach, Table 3.5 shows the results of applying the linear model in equation (3.1) to the transmission of schooling from the parents to children, where S_{it-1} refers to the educational attainment of the most educated parent and the rest of explanatory variables are the same as in Table 3.4. The results in Table 3.5 are broadly similar to those found in Table 3.4, showing that the estimations are robust to changing the definition of the main independent variable. Here again differences are detected between the groups in the absolute magnitude of the intergenerational link, but the relative influence of parents' education level over each group of young ones is similar. For the whole sample, the gender dummy shows a negative and significant effect in the mean schooling gap. For each sample sub-group separately, the effect of being a male is still advantageous but it is not statistically significant for teenagers.

INSERT TABLE 3.5 ABOUT HERE

Regarding the effect of household incomes on children's schooling performance, these results suggest that this is more the older the youth group. But, that income is a variable largely prone to measurement error is evident, and due to the lack of a long panel it is not possible to estimate permanent incomes by averaging household income across several years, as is usual in the empirical literature (e.g., Eide and Showalter 1999). Besides, and more importantly for the purpose of this study, for those who are no longer living with their parents, the income variable included by INDEC in the EEEJ data base refers to their own income, not to their parents' income. Hence, for young adults who do not co-reside any longer with their family, the income variable does not reveal the family background at all. For all these reasons, it seems helpful to select a variable that better reflects the family's financial capacity to educate their children.

The survey poses several questions regarding the type of primary school the students had attended, which reveals the socio-economic level of the family during children's early schooling age. Specifically, it focuses on whether the primary school they had attended was public or private, single or double shift, gender-exclusive or not, and bilingual or not. All these features also reveal the quality of the school. But in this study analysis is done with respect to the differential cost that each pair of possibilities entails, such as public, one shift, not gender-exclusive, not bilingual primary school, which is free. A substantial difference does exist between the public free primary school and private primary school, because in Argentina's education system, the former is rarely other than single shift, all gender, and monolingual. Thus the type of primary school (public or private) selected becomes an indicator of parents' income level and the results of the estimations including it are shown in Table 3.6 (Model 3).

INSERT TABLE 3.6 ABOUT HERE

The negative sign for the estimated coefficient on "private primary school" implies that better family's economic background has a diminishing effect on schooling gap. The results show that this indicator of family background is strongly associated with the schooling gap of the young, suggesting that having attended a private primary school reduces about one year the average schooling gap of the whole sample. But considerable variation occurs across the age groups. For the older group (26-30) Table 3.6 shows that the estimated coefficient on "private primary school" amounts to more than one year and a half. This estimate largely doubles for the teenagers, denoting that the economic position of the family affects the schooling gap of those individuals beyond the age of educative compulsory level, much more. Besides, in Table 3.6 (Model3) replacing incomes by a dummy for private school enlarges the intergenerational transmission of schooling for the whole sample, revealing more pronounced the differences between teenagers' social mobility for young adults. All those coefficients are still statistically significant at the 1% level. The gender effect is negative but it is statistically significant only for the whole sample and the young adults (20-25) group.

Marchionni, Bet and Pacheco (2007) point out that, according to the students surveyed on the *EEEJ*, the choice between continuing to study or starting to work is the main reason for dropping out of secondary school or never attending it. According to the authors, more than 80% of the sample declared being employed. All of them were 18 years or younger by the time they landed their first job. Table 3.7 shows the negative impact of this early entrance into the labor market, which enlarged the schooling gap. The effect on the schooling gap of having had to work at an early age is more pronouncedly evident in young adults.

INSERT TABLE 3.7 ABOUT HERE

3.4.2 Gender differences

Tables 3.4 -3.7 had consistently revealed that being a boy showed a drop in the schooling gap of the child. Considering that girls on average showed better educational performance than boys, seen both in the attained years of schooling and in the schooling gap, it is interesting to study gender differences more thoroughly. Tables 3.8a -3.9b show the estimated results of former Model 3.3 and Model 3.4, by gender.

Table 3.8a-3.8b shows that the parents' education level has a greater influence on males than on females irrespective of whether they were teenagers or young adults. However, the family's economic background has the greatest significance to explain schooling gap in females. Attending private primary school reduces about a year and a half of schooling gap for females. However, for young adult men (26-30) primary private school coefficient is greater than for females.

INSERT TABLE 3.8 ABOUT HERE

Table 3.9a-3.9b shows the strong negative effect on the schooling gap for young adult males who have had to seek employment early in life; the results indicate an enlargement of the gap, in about 7 years. For females, the employment coefficient is statistically significant only for teenagers, at a significance level greater than 5%.

INSERT TABLE 3.9 ABOUT HERE

3.5 Intergenerational immobility patterns

The results obtained above broadly suggest that, in absolute magnitude, the transmission of educational level between parents and children is higher for young adults than for teenagers. The intergenerational persistence of education level between parents and their adult offspring possibly varies with the parents' education level. To add to the understanding of the young adults' low mobility, transition matrices are estimated to determine who moves where, within a generation. To construct those matrices, schooling years for young adults were grouped in three levels, and similarly, the former educational level for each parent was grouped in three levels too.

Table 3.10 presents non-conditional transition matrices for young adults (20-30 years of age) for the whole sample and also differentiating it by gender. Each element p_{kj} of the matrix provides an estimate of a child's non-conditional probability of being in educational level k, given that his parents' maximum educational level achieved was j. For example, the top left-hand element of the first matrix indicates that a child, whose father or mother has achieved only primary schooling, has 24.8% probability of ending up with a similar low level of education. The diagonal elements of each matrix represent the non-conditional probability of a child remaining at the same schooling level as that of their parents.

INSERT TABLE 3.10 ABOUT HERE

The results show diminishing mobility from low to high school level, and reveal that for children older than teenagers the educational marginal decision depends largely on the education level achieved by their parents. Elements in the lower triangle of the matrix represent the probabilities of a child achieving a higher education level than their parents. In the three matrices studied, it is evident that children raised in households where parents have, at most, achieved primary school, have a higher probability of attending secondary school, but a very low probability attending university or tertiary studies. For those children whose family educational background is at the secondary level, the probability of attaining the same educational level as their parents is already the same as that of achieving university level. The elements in the upper triangle represent the non-conditional probabilities of a child achieving a lower education level than their parents. Those probabilities are quite low in all the matrices.

The transition matrices for sons and daughters show different patterns of intergenerational persistence, suggesting that different mechanisms of intergenerational education transmission exist, by gender. Mobility seems quite large for daughters whose parents have achieved a low education level. Conversely, it appears that having parents with low education levels largely indicates that their sons achieve a low education level as well. However, a female child whose parents' maximum education level is at the secondary school level also has a greater probability of getting a university degree than a male one. But, intergenerational persistence is higher for daughters over sons, when the parents have achieved a university or tertiary degree.

Table 3.11 shows the results obtained by employing the multinomial probit model to assess the conditional probabilities of transition from the maximum parents' educational level to the child's. It is shown that, both child age and private primary school diminish the intergenerational educative persistence for low educational level (primary or less). This drop of the intergenerational link at the lowest educational level suggests that the family's income plays a significant role in explaining the persistence of this low educative level.

INSERT TABLE 3.11 ABOUT HERE

Differentiating by children's gender, it appears that this effect is substantial for daughters but rather low for sons. Besides, conditioning on families' economic background markedly increases the probability of obtaining a secondary degree for daughters from poorly educated families. These results suggest that girls from poor families would have less opportunities of climbing the social ladder than boys. Conditioning reveals another interesting result. For those parents who had achieved the maximum education level, a decline of persistence was evident when adding the controls. Although the effect here is quite small, this goes in the same direction, suggesting that family background, specifically their income levels, plays a role in explaining intergenerational mobility. These results are quite different by gender. For male children, conditioning on family's income slightly increases the intergenerational persistence of attaining a university degree; for females, the intergenerational persistence diminishes, largely showing that the family income background indeed plays an important role on the daughter's highest educative level of success.

3.6 Concluding Comments

In this chapter, exploring the differences in the degree of intergenerational mobility in Argentina between teenagers and young adults is a major contribution. A new data base, the Survey of Employment and Education of Youth *(Encuesta de Educación y Empleo de los Jóvenes,)* helps to obtain the unbiased mobility estimations for young people older than teenagers. Applying several models of Behrman et al. like the dynamic linear model, the degree to which family background determines schooling outcomes of children was estimated.

The estimations unveil quite low intergenerational mobility for young adults relative to teenagers, a result that is robust for several specifications of the model. These findings suggest that when deciding whether to continue studying or not beyond compulsory schooling, the young are strongly influenced by their parents' educative background. The results also reveal that generational convergence of young adults and teenagers is quite similar when considering the average schooling gap of each group. This means, belonging to a family where the highest education level achieved by the parents' increases by one level (for example from primary to secondary), the education delay of any child drops by around 20%. However, while for teenagers this implies a very short delay, for young adults it involves more than a year. Discriminating by gender, the influence of the parents' education level seems greater on males than on females, irrespective of whether they were teenagers or young adults. However, it is evident that the family's economic background has the utmost importance on the schooling gap of females. It was also found that young adult immobility is not uniform across parents' educative level. Specifically, it appears that immobility is quite large at the higher (university and tertiary) educative levels. Besides, the findings show different patterns of intergenerational mobility by gender.

This result also cautions against studying intergenerational mobility solely by using only cross-section data, which allows estimating the mobility for teenagers, though not for young adults. In light of these findings it appears necessary to complement the diagnosis obtained from regular household surveys with other surveys that include retrospective information on parental background, to overcome the limitations imposed by the former data.

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TABLE 3.1

DATA DESCRIPTIVE STATISTICS

Age Group	Total	% of Male	% of Female	% Still Living at Home
15-19	278	51	49	95
20-25	296	47	53	73
26-30	233	45	55	61
Total Observations	807	375	432	587

Note. This data come from the Survey of Employment and Education of Youth (Encuesta de Educación y Empleo de los Jóvenes) (EEEJ) collected by the Instituto Nacional de Estadística y Censos (INDEC) and Centro de Estudios Distributivos, Laborales y Sociales (CEDLAS) of Argentina (INDEC-CEDLAS) in june 2005.

Source. Own calculations based on EEEJ.

TABLE 3.2

MEAN ON PARENTAL AND RESPONDENTS' SCHOOLING CHARACTERISTICS

Respondent	Average Schooling	Average Schooling Gap	Father Average Education Level	Mother Average Education Level	Household's Average Income Decile	% Private Primary
Whole Sample	11.60	3.66	3.40	3.55	5.61	27.70
15-19	10.79	1.08	3.31	3.50	5.19	29.50
20-25	12.31	5.09	3.58	3.70	5.99	28.72
26-30	11.74	5.25	3.31	3.42	5.67	23.46
Male	11.37	3.81	3.52	3.66	5.68	25.80
Female	11.80	3.52	3.31	3.46	5.55	29.30

Note. This data come from the Survey of Employment and Education of Youth (Encuesta de Educación y Empleo de los Jóvenes) (EEEJ) collected by the Instituto Nacional de Estadística y Censos (INDEC) and Centro de Estudios Distributivos, Laborales y Sociales (CEDLAS) of Argentina (INDEC-CEDLAS) in june 2005. Average schooling includes 1 grade of preschool. In the survey parent's education is collected by attainment level. An Average Education Level = 3 means parents have achieved around 9-10 years of school. Average schooling gap for respondents older than 25 is computed assuming 17 years of education as a top. Parent's education level is achieved assuming that all of them have completed the level.

Source. Own calculations based on *EEEJ.*

TABLE 3.3

EDUCATIONAL MOBILITY

PANEL A: ALL INDIVIDUALS

SchoolingGap				
	Whole Sample	Teen-Agers	Young Adults(20-25)	Young Adults(26-30)
Maxschoolparents	-0.634**	-0.236**	-0.728**	-0.907**
	(0.0650)	(0.0610)	(0.0955)	(0.1091)
Cohort-annual observations:	682	251	247	184
Adjusted R squared:	0.121	0.052	0.188	0.271

Note. Education level for parents is achieved assuming that all of them have completed the level.
** p<0.05
* 0.05<p<0.10

PANEL B: INDIVIDUAL WHO'S PARENTS COMPLETED SOME EDUCATIONAL LEVEL

SchoolingGap				
	Whole Sample	Teen-Agers	Young Adults(20-25)	Young Adults(26-30)
Maxschoolparents	-0.581**	-0.239**	-0.676**	-1.030**
	(0.0897)	(0.0767)	(0.1238)	(0.1711)
Cohort-annual observations:	294	99	119	76
Adjusted R squared:	0.122	0.081	0.196	0.319

Note. The sample includes only the records for wich educative level for parents was achieved before children attend media school.
** p<0.05
* 0.05<p<0.10

PANEL C: ALL INDIVIDUAL WHITH PARENTS' EDUCATIONAL LEVEL REESTIMATED

SchoolingGap				
	Whole Sample	Teen-Agers	Young Adults(20-25)	Young Adults(26-30)
Maxschoolparents	-0.599**	-0.230**	-0.720**	-0.907**
	(0.0643)	(0.0596)	(0.0927)	(0.1112)
Cohort-annual observations:	682	251	247	184
Adjusted R squared:	0.112	0.052	0.297	0.263

Note. Education level for parents whose children do not recall if they had completed the level they attended is reduced one level.
** p<0.05
* 0.05<p<0.10

Source. Own calculations based on *EEEJ.*

TABLE 3.4

INTERGENERATIONAL MOBILITY BY PARENT'S LEVEL OF EDUCATION

SchoolingGap	Model 1			
	Whole Sample	Teen-Agers	Young Adults(20-25)	Young Adults(26-30)
Father Schooling Level	-0.207**	0.007	-0.266*	-0.489**
	(0.0898)	(0.0882)	(0.1518)	(0.1752)
Mother Schooling Level	-0.262**	-0.278**	-0.173	-0.315
	(0.0916)	(0.0887)	(0.1492)	(0.1903)
Sex	-0.638**	-0.062	-1.018**	-0.927*
	(0.2391)	(0.2248)	(0.4113)	(0.4745)
Age	0.455**	0.351**	0.914**	0.329*
	(0.0263)	(0.0814)	(0.1148)	(0.1671)
Household Income Decile	-0.199**	-0.022	-0.341**	-0.384**
	(0.0506)	(0.0538)	(0.0863)	(0.0895)
Cohort-annual observations:	492	190	172	130
Adjusted R squared:	0.444	0.151	0.399	0.377

Note. Education level for parents is achieved assuming that all of them have completed the level.
** p<0.05
* 0.05<p<0.10

Source. Own calculations based on *EEEJ.*

TABLE 3.5

INTERGENERATIONAL MOBILITY BY PARENT'S MAXIMUM LEVEL OF EDUCATION

SchoolingGap	Model 2			
	Whole Sample	Teen-Agers	Young Adults(20-25)	Young Adults(26-30)
Maxschoolparents	-0.387**	-0.221**	-0.322**	-0.692**
	(0.0742)	(0.0775)	(0.1318)	(0.1287)
Sex	-0.623**	-0.0514	-1.082**	-0.858*
	(0.2365)	(0.2268)	(0.4101)	(0.4607)
Age	0.453**	0.379**	0.888**	0.303*
	(0.0260)	(0.0820)	(0.1150)	(0.1622)
Household Income Decile	-0.213**	-0.053	-0.349**	-0.410**
	(0.0489)	(0.0519)	(0.0863)	(0.0849)
Cohort-annual observations:	499	193	173	133
Adjusted R squared:	0.447	0.148	0.394	0.395

Note. Education level for parents is achieved assuming that all of them have completed the level.
** p<0.05
* 0.05<p<0.10

Source. Own calculations based on *EEEJ.*

TABLE 3.6

ECONOMIC FAMILY BACKGROUND AND MOBILITY

SchoolingGap	Model 3			
	Whole Sample	Teen-Agers	Young Adults(20-25)	Young Adults(26-30)
Maxschoolparents	-0.488**	-0.169**	-0.687**	-0.779**
	(0.0546)	(0.0618)	(0.0839)	(0.1127)
Sex	-0.541**	-0.165	-1.032**	-0.436
	(0.1958)	(0.1984)	(0.3244)	(0.4052)
Age	0.402**	0.376	0.814**	0.254*
	(0.0211)	(0.0708)	(0.0911)	(0.1396)
Private Primary School	-0.928**	-0.683**	-0.976**	-1.639**
	(0.2279)	(0.2300)	(0.3636)	(0.5068)
Cohort-annual observations:	682	251	247	184
Adjusted R squared:	0.442	0.174	0.415	0.323

Note. Education level for parents is achieved assuming that all of them have completed the level.

** p<0.05

* 0.05<p<0.10

Source. Own calculations based on *EEEJ.*

TABLE 3.7

INTERGENERATIONAL MOBILITY AND EARLY ENTRANCE IN LABOR MARKET

SchoolingGap	Model 4			
	Whole Sample	Teen-Agers	Young Adults(20-25)	Young Adults(26-30)
Maxschoolparents	-0.425**	-0.147**	-0.624**	-0.620**
	(0.0552)	(0.0622)	(0.0845)	(0.1119)
Sex	-0.371*	-0.078	-0.866**	-0.179
	(0.1964)	(0.1996)	(0.3280)	(0.3904)
Age	0.419**	0.394	0.868**	0.281**
	(0.0240)	(0.0793)	(0.0907)	(0.1338)
Private Primary School	-0.835**	-0.667**	-0.889**	-1.330**
	(0.2248)	(0.2278)	(0.3575)	(0.4863)
Employment	3.260**	2.349**	3.262**	3.453**
	(0.6703)	(0.9155)	(1.297)	(1.5329)
Age First Employment	-0.189**	-0.139**	-0.224**	-0.277**
	(0.0381)	(0.0601)	(0.0665)	(0.0581)
Cohort-annual observations:	682	251	247	184
Adjusted R squared:	0.460	0.178	0.440	0.396

Note. Education level for parents is achieved assuming that all of them have completed the level.

** p<0.05

* 0.05<p<0.10

Source. Own calculations based on *EEEJ.*

TABLE 3.8

INTERGENERATIONAL MOBILITY BY GENDER

PANEL A: MALES

SchoolingGap	Model 3			
	Whole Sample	Teen-Agers	Young Adults(20-25)	Young Adults(26-30)
Maxschoolparents	-0.530**	-0.292**	-0.757**	-0.707**
	(0.0794)	(0.914)	(0.1278)	(0.1569)
Age	0.416**	0.345**	0.716**	0.078
	(0.0321)	(0.1043)	(0.1463)	(0.1906)
Private Primary School	-0.448	0.444	-0.523	-1.726**
	(0.3491)	(0.3348)	(0.5763)	(0.8288)
Cohort-annual observations:	317	117	118	82
Adjusted R squared:	0.421	0.165	0.323	0.316

Note. Education level for parents is achieved assuming that all of them have completed the level.
** p<0.05
* 0.05<p<0.10

Source. Own calculations based on *EEEJ*.

PANEL B: FEMALES

SchoolingGap	Model 3			
	Whole Sample	Teen-Agers	Young Adults(20-25)	Young Adults(26-30)
Maxschoolparents	-0.439**	-0.060	-0.557**	-0.872**
	(0.0758)	(0.0840)	(0.1103)	(0.1627)
Age	0.396**	0.417**	0.915**	0.434**
	(0.0282)	(0.0965)	(0.1109)	(0.2032)
Private Primary School	-1.336**	-0.913**	-1.549**	-1.557**
	(0.3011)	(0.3157)	(0.4580)	(0.6511)
Cohort-annual observations:	365	134	129	102
Adjusted R squared:	0.461	0.168	0.515	0.327

Note. Education level for parents is achieved assuming that all of them have completed the level.
** p<0.05
* 0.05<p<0.10

Source. Own calculations based on *EEEJ*.

TABLE 3.9

INTERGENERATIONAL MOBILITY AND EARLY ENTRANCE IN LABOR MARKET BY GENDER

PANEL A: MALES

SchoolingGap	Model 4			
	Whole Sample	Teen-Agers	Young Adults(20-25)	Young Adults(26-30)
Maxschoolparents	-0.439**	-0.259**	-0.622**	-0.556**
	(0.0803)	(0.0942)	(0.1293)	(0.1438)
Age	0.402**	0.341**	0.663**	0.023
	(0.0362)	(0.1158)	(0.1433)	(0.1705)
Private Primary School	-0.383	-0.462	-0.202	-1.510**
	(0.3416)	(0.3340)	(0.5614)	(0.7412)
Employment	4.486**	2.162*	7.564**	-
	(1.0424)	(1.2113)	(2.2979)	-
Age First Employment	-0.223**	-0.127	0.348**	-0.389
	(0.0605)	(0.0808)	(0.1110)	(0.0850)
Cohort-annual observations:	317	117	118	82
Adjusted R squared:	0.450	0.175	0.374	0.455

Note. Education level for parents is achieved assuming that all of them have completed the level.

** p<0.05

* 0.05<p<0.10

Source. Own calculations based on *EEEJ.*

PANEL B: FEMALES

SchoolingGap	Model 4			
	Whole Sample	Teen-Agers	Young Adults(20-25)	Young Adults(26-30)
Maxschoolparents	-0.391**	-0.048	-0.517**	-0.700**
	(0.0764)	(0.0841)	(0.1089)	(0.1682)
Age	0.435**	0.463**	1.008**	0.510**
	(0.0.323)	(0.1116)	(0.1126)	(0.2015)
Private Primary School	-1.271**	-0.867**	-1.577**	-1.263*
	(0.2989)	(0.3153)	(0.4438)	(0.6460)
Employment	2.234	2.550*	1.472	2.337
	(0.8699)	(1.4319)	(1.4967)	(1.8475)
Age First Employment	-0.155**	-0.155*	-0.164**	-0.223**
	(0.0490)	(0.0927)	(0.0787)	(0.0794)
Cohort-annual observations:	365	134	129	102
Adjusted R squared:	0.474	0.176	0.547	0.372

Note. Education level for parents is achieved assuming that all of them have completed the level.

** p<0.05

* 0.05<p<0.10

Source. Own calculations based on *EEEJ.*

TABLE 3.10

TRANSITION MATRICES (YOUNG ADULTS 20-30 YEARS OLD)

NON CONDITIONAL PROBABILITIES OF CHILD'S SCHOOLING LEVEL

GIVEN PARENTS SCHOOLING LEVEL

Children	Parents		
	Primary	Secondary	University
Primary	24.8	5.0	0.0
Secondary	57.0	47.5	17.2
University	18.2	47.5	82.8
	100.0	100.0	100.0

Male Children	Parents		
	Primary	Secondary	University
Primary	58.6	5.6	0.0
Secondary	56.0	54.9	18.7
University	15.4	39.4	81.3
	100.0	100.0	100.0

Female Children	Parents		
	Primary	Secondary	University
Primary	22.0	4.5	0.0
Secondary	57.7	41.6	15.7
University	20.3	53.9	84.3
	100.0	100.0	100.0

Note. Primary includes preschool, primary and *EGB*; Secondary includes secondary and *polimodal*; university includes tertiary, university and post grades.

Source. Own calculations based on *EEEJ.*

TABLE 3.11

TRANSITION MATRICES (YOUNG ADULTS 20-30 YEARS OLD)

CONDITIONAL PROBABILITIES OF CHILD'S SCHOOLING LEVEL GIVEN PARENTS SCHOOLING LEVEL

Children	Parents		
	Primary	Secondary	University
Primary	14.0	3.0	0.0
Secondary	64.5	52.8	19.6
University	21.5	44.0	80.3
	100.0	100.0	100.0

Male Children	Parents		
	Primary	Secondary	University
Primary	55.1	17.9	0.0
Secondary	27.9	39.4	10.8
University	16.9	42.6	89.1
	100.0	100.0	100.0

Female Children	Parents		
	Primary	Secondary	University
Primary	1.4	2.7	0.0
Secondary	84.3	47.3	33.1
University	14.3	50.0	66.8
	100.0	100.0	100.0

Note. Primary includes preschool, primary and *EGB*; Secondary includes secondary and *polimodal*; university includes tertiary, university and post grades.

Source. Own calculations based on *EEEJ.*