ESTIMATING LONG TERM EARNINGS MOBILITY IN ARGENTINA WITH PSEUDO-PANEL DATA*

MEDICION DE LA MOVILIDAD DE INGRESOS DE LARGO PLAZO EN ARGENTINA USANDO PSEUDO-PANELES

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Abstract

Applying a dynamic pseudo-panel to the earnings data in Argentina, the present paper estimates the long-term earnings mobility in the period 1985-2004. The results obtained herein show some earnings mobility over the long term in Argentina for male occupied workers. The results also suggest that the labor market in Argentina does not substantially contribute to the acceleration of the individual' earnings level recovery after a negative shock.

Keywords: *Argentina, dynamic pseudo-panel, earnings mobility, measurement error.*

JEL Classification: *O12, D31, C81.*

Resumen

Aplicando un pseudo-panel dinámico a la información de ingresos en Argentina, el presente estudio estima la movilidad de ingresos a largo plazo en el período 1985-2004. Los resultados aquí obtenidos muestran cierta movilidad de ingresos a largo plazo en Argentina para los trabajadores varones empleados. Los resultados también sugieren que el mercado laboral en Argentina no contribuye sustancialmente a acelerar la velocidad del nivel de recuperación de ingresos individuales después de un shock negativo.

Palabras Clave: *Argentina, pseudo-panel dinámico, movilidad, ingresos, errores de medición.*

Clasificación JEL: *O12, D31, C81.*

I.   INTRODUCTION

Recent empirical literature provides sound evidence of the distressing growth in the levels of inequality and poverty in Latin American countries[1]. By using 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 this literature evaluates inequality in a static context, it fails to reveal whether it is the same individual who remains poor or rich throughout the period under analysis. It is quite clear that if there is mobility, neither the individual position in the distribution of income nor the degree of the individual well-being, which depends on the expected evolution of his position in the income ladder, may remain the same along 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. In particular, it appears to be relevant for some countries, as Argentina, which once stood out in Latin America for offering eminent opportunities of progress to its people[2], but lately shows growing inequality.

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 or rich over time. Hence, longitudinal data sets have been broadly used in the literature to estimate the degree of the individuals' earnings, incomes, or wealth mobility in developed countries (*e.g.*, Hart, 1976; Schiller, 1977; Lillard and Willis, 1978; Jianakoplos and

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[1]   See Gasparini *et al*. (2007).
[2]   See Gasparini *et al*. (2005, 2001).

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 estimating mobility using panels. One of these issues is the length of the panel available. As long as many 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 weak when the period of analysis is extended more. From this perspective using a long panel would be 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). The other issue about using panel data relates to the 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; this is a well known consequence of the measurement errors of 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 Menéndez, 2007) base their estimations on a predicted measure of permanent earnings. That 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). Unfortunately, this procedure is restricted to the estimation of unconditional mobility only (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 for studying income mobility; that is, groups of individuals selected through random sampling from different surveys. Based on the cohorts they build pseudo-panels or synthetic cohorts that allow track down specific groups of individuals through their randomly selected representatives in consecutive years. Excepting Calónico, 2006 and Cuesta, Ñopo, and Pizzolitto (2007), this methodology has rarely been used in the study of the intertemporal dynamic of income for each individual.

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.

There are enough valuable reasons to be interested in studying long term mobility in Argentina. In the first place, there is the fact that 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. Likewise, the enlargement of the earnings gap between the individuals at the top of the earnings distribution and those at the bottom in the last two decades is a well documented fact (Gasparini, Marchionni, and Sosa Escudero, 2001). Moreover, during those years, two notorious macroeconomic crises hit the economy and strongly reduced the real incomes of the individuals. 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. 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 suggesting that the income distribution worsened in Argentina in the last quarter of the twentieth century. 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. Moreover, it is particularly interesting to analyze the degree of mobility in Argentina since the country underwent deep institutional transformations and sharp rules changes 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 offers a valuable scenario for analyzing whether under more flexible rules the labor market enlarged the opportunities of economic progress for the workers.

Herein, 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 a consistent estimation of mobility by avoiding the problem of measurement error. Moreover, since mobility is essentially a long term phenomenon, it is apparent that estimating it over a period of twenty years makes it possible to capture underlying structural mobility that affects the possibilities of people's economic progress. Hence, the length of the period considered here is a major contribution of the paper to the literature. Furthermore, 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.

Given that earnings mobility is still a nascent area of research in Latin American countries, there are few studies regarding 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 individuals 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. 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 the 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. Second, Cuesta *et al.* (2007) used per capita household's incomes for the study, whereas the estimations conducted in the present study uses the individuals' labor earnings. All in all, both the earlier studies found a lower degree of income mobility with regard to the results obtained in the present paper.

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, 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 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 3, describes the data and brings forth an analysis of the mean labor earnings conducted by the cohort technique during the studied period. Section 4 contains the foremost results of the present paper. Section 5 concludes the analyses conducted in the present study.

II. MOBILITY AND COHORT METHODOLOGY

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:

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

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 to either an individual or a household. The relevant parameter to measure economic (im) to 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 β < 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), panel data is considered the ideal data structure. Nevertheless, as Ashenfelter *et al*. (1986) and Antman and McKenzie (2007) point out, panel data are not free from the difficulties that can distort the measurement of mobility. Firstly, the panel length may cause problems in developing countries' estimations as long panels are not commonly available; and if they are, they surely suffer from the usual problem of attrition. Therefore, 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:

$$Y^*_{i,t} = \alpha + \beta Y^*_{i,t-1} + u_{i,t}, \tag{2}$$

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

$$Y_{i,t} = Y^*_{i,t} + \varepsilon_{i,t} \tag{3}$$

Further, substituting (3) in (2), provides the following equation in terms of the observed earnings:

$$Y_{i,t} = \alpha + \beta Y_{i,t-1} + \eta_{i,t} \tag{4}$$

$$\eta_{i,t} = u_{i,t} + \varepsilon_{i,t} - \beta \varepsilon_{i,t-1} \tag{5}$$

Under standard assumptions, applying the method of least squares to the previous model, gives a β coefficient that is asymptotically biased because of both classical and nonclassical measurement errors (Antman and McKenzie, 2007)[3]. 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,

$$\beta^{OLS} \xrightarrow{p} \beta \left(1 - \frac{Var\left(\varepsilon_{i,t-1}\right)}{Var\left(Y_{i,t-1}\right)} \right) \tag{6}$$

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.

2.2. Cohort Approach

To avoid the occurrence of the above mentioned drawbacks in using true panel data in the measurement of mobility, the parameter of mobility can alternatively be identified from the repeated cross-section data (RCS). This RCS data is 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 of 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, 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

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

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.

Adopting cohort methodology entails several advantages for the estimation of mobility. In first place, provided the cohorts are long enough, the averaging process involved in the construction of the synthetic cohorts may eliminate the measurement error that occurs on an individual-level. Even though it entails assuming there is no cohort-level component to measurement error and that a law of large numbers applies within a cohort, it does not impose severe restrictions over the forms of measurement error at the individual level. That is, the individual-level measurement error can be autocorrelated and it is also admitted that it correlates with true earnings and/or with the individual shock. In contrast, true panel estimator gives biased estimations under these distributions of the error term (Antman and McKenzie, 2007). 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 panel estimations (Mazumder, 2005). Moreover, replacing the declared earnings by the predicted ones, based on time invariant characteristics, does not solve the problem completely. Even though this procedure allows the estimation of the unconditional mobility, it is not well suited to estimate conditional mobility. Predicted earnings approximate longer-term earnings but not the initial ones. Therefore, the conditional equation would have no clear interpretation. In addition, 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).

As synthetic cohorts technique removes the individual measurement error, the summary statistics of the cohort earnings distribution will be more accurate than the ones corresponding to the individuals' data generated from true panels. This entails –as is standard in much of the panel data literature– assuming cross-sectional independence since pseudo-panels techniques do not solve the bias that may arise because of measurement error correlation across individuals, like the enumerator bias or the correlation that exist across households within an area. So, Antman and McKenzie's estimator will be consistent if there is weak spatial correlation between observations.

In second place, since with cross-section data each individual or each household is interviewed only once, the measurement errors observed in different moments of time does not correspond to the same unit. 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. Furthermore, pseudo-panels technique facilitates 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.

As expected, the cohort methodology also presents several limitations. In the one hand, 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 similar sense Antman and McKenzie (2007, pp. 138) recognize that pseudo-panels facilitate 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".

On the other hand, the length of the cohort is critical to obtain an unbiased estimator using a dynamic pseudo-panel technique. Using RCS data, the observed individuals in each cross-section are not the same, pseudo-panel's estimation could cause an additional measurement error. This will cause a downward bias unless cohorts are long enough and the occurrence of events like migration or deaths do not alter the representativeness of the sample, in order to expect that sample means are close to the population mean (McKenzie, 2004; Fields *et al*., 2007a). Changes between the different samples that occur from events like migration, deaths, and household dissolution is particularly a problem for older cohorts where for example the probability of dying between consecutive samples is bigger for poorer individuals than for richer individuals. This is also a problem for very young cohorts which may be changing its composition because of the formation of new households. For these reasons, pseudo-panels are less appropriate for estimating mobility at early or late stages of life. In addition, when consecutive samples are taken over longer time periods both problems become more severe.

Moreover, regarding genuine panels, the standard errors from pseudo-panel estimation will be larger. This is a consequence of that the speed of convergence depends on the number of individuals per cohort, rather than on the total number of individuals in the sample (Antman and McKenzie, 2007). Consequently, without measurement errors panel data would be preferred.

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

Unlike dynamic panels in which the lagged dependant variable is observable, in the RCS data it is unobservable. 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 estimating consistently the RCS data. In addition, Verbeek and Nijman (1992), Moffitt (1993), Collado (1997), Girma (2000), McKenzie (2004), and Verbeek and Vella (2005) discuss the conditions required to obtain consistent estimates in a variety of dynamic linear models by using pseudo-panels when the dependant lagged variable is not observable. Essentially, the model proposed by each of these authors is first order autoregressive, comprised of 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:

$$Y_{i(t),t} = \alpha + \beta Y_{i(t),t-1} + X'_{i(t),t} \delta + u_{i(t),t} \qquad i = 1,\ldots,N \qquad t = 2,\ldots,T, \quad (7)$$

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; $X'_{i(t),t}$ is a vector of exogenous explanatory variables.

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 $u_{i(t)t}$ 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 be unrelated to the exogenous regressors. Whereas the first assumption may be defended under the usual IV assumptions, this excludes any possibility 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. In Girma (2000), the author uses noise approximations to the lagged value of incomes –an arbitrarily selected observation from the cohort– and to the other instruments. Nevertheless, although it is possible to obtain consistent estimators using this approach –provided each cohort is long enough– Verbeek and Vella (2005) point out that there does not seem to be any gain in using such an approach.

The estimation procedure adopted by McKenzie (2004) and Antman and McKenzie (2007) consists of obtaining the cohort average from equation (4) over the n_c individuals in cohort c observed at time t. The authors do not use the IV methods since its validity requires 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 (4) across the n_c observed individuals from cohort c in time t, gives the following:

$$\overline{Y}_{c(t),t} = \alpha + \beta \overline{Y}_{c(t),t-1} + \overline{u}_{c(t),t} + \overline{\varepsilon}_{c(t),t} - \beta \overline{\varepsilon}_{c(t),t-1} \qquad (8)$$

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:

$$\overline{Y}_{c(t),t} = \alpha + \beta\overline{Y}_{c(t-1),t-1} + \overline{u}_{c(t),t} + \overline{\varepsilon}_{c(t),t} - \beta\overline{\varepsilon}_{c(t),t-1} + \lambda_{c(t),t},\tag{9}$$

where,

$$\lambda_{c(t),t} = \beta\left(\overline{Y}_{c(t),t-1} - \overline{Y}_{c(t-1),t-1}\right).\tag{10}$$

When the number of individuals in the sample n_c becomes large (100/200 individuals according to Verbeek and Nijman, 1992), and provided the occurrence of events like migration or deaths do not alter the representativeness of the sample, $\overline{Y}_{c(t),t-1}$ and $\overline{Y}_{c(t-1),t-1}$ may come close to the population mean for the cohort c in time t–1. Therefore, $\lambda_{c(t),t}$ –the measurement error term added by observing different individuals in each moment– would converge to zero (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 $\varepsilon_{c(t),t}$,

$$\varepsilon_{c(t),t} = \frac{1}{n_c}\sum_{i=1}^{n_c}\varepsilon_{i(t),t} \xrightarrow{p} E\left(\varepsilon_{i(t),t}\right) = 0,\tag{11}$$

therefore, the measurement error problem in the data collection is also avoided.

McKenzie (2004) considers least squares and instrumental variables estimators, and multidimensional limits as the cross-sections and temporal dimensions of the data pass to infinity, allowing for stationary and nonstationary case. The consistency of estimators considered in McKenzie (2004) depends on the relative asymptotic magnitude of T and n_c. Having a fixed value of T and the value of n_c only going to infinity, OLS and IV are both consistent estimators and have asymptotically normal distributions, provided individual errors do not show cohort effects or temporal effects once controlled by cohort fixed effects and the temporal aggregated trend. That is, it is necessary to assume that in the individual error term $u_{i(t)t} = v_{cj}+\eta_{i(t),j}$, $\sigma^2_v = 0$. In addition, Verbeek and Vella (2005) emphasize that using the averages of the sample cohort and applying OLS to (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 (9) is a within cohort average of individual error terms that is asymptotically zero. It is already possible to allow cohort-specific effects in equation (9); since from the data-generating process, u_{it} includes an individual fixed effect, the corresponding

relationship at the cohort level will also include a fixed effect but now at the cohort level. If this is the case, it is needed to assume that there is no time-varying cohort-level component to measurement errors (Antman and McKenzie, 2007). When n_c is large and T is moderate, the sequential and diagonal path asymptotics show that both the OLS and IV estimators will be consistent. The simulations show that, in both fixed and moderate T, IV estimators are notably more variable than the OLS estimators, especially in small cross-sectional samples; hence the author concludes that in practice the OLS estimator is likely to be preferred.

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:

$$\overline{Y}_{c(t),t} = \alpha + \beta\overline{Y}_{c(t-1),t-1} + \omega_{c(t),t} \tag{12}$$

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:

$$\overline{Y}_{c(t),t} = \alpha_c + \beta\overline{Y}_{c(t-1),t-1} + \omega_{c(t),t} \tag{13}$$

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.

III. 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 is an urban survey; carried out in cities larger than 100.000 inhabitants who represent 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, it is now 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. Unfortunately, the other cities in the country have to be excluded from this study since they were incorporated late into the survey and 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 has historically concentrated almost 55 percent of the country's entire urban population. Notwithstanding, as the labor market is not homogeneous across the country, incorporating them would have enriched the analysis.

The analyzed period includes the years 1985-2004. Although the data is available for Great Buenos Aires since 1974, 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 already existent empirical literature (Calónico, 2006; Cuesta *et al*., 2007; Fields and Sánchez Puerta, 2006; 2008). That way, the literature tries to avoid confusions that might arise between true income mobility and the fluctuations corresponding to first time entries to the labor force and retirements. 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 to allow the middle point of the band to define 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, these pseudo-panels 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 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.

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 to 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 labor 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.

Although the hourly earnings variable is missing in the surveys of the fourth trimester of the years 2003 and 2004, 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

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

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

TABLE 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	3,865	4,159	3,289	2,794	2,614															
2	4,55	4,331	3,717	3,241	2,645	2,262	2,736	3,734	3,885	3,425										
3	5,068	5,221	4,338	3,939	3,483	2,849	3,969	4,203	4,109	4,556	3,376	3,482	3,574	3,965	3,088					
4	5,574	6,533	4,99	3,789	3,434	2,967	3,557	5,275	4,704	4,769	4,559	4,174	4,155	4,599	3,977	3,006	3,324	2,679	2,636	2,984
5	5,649	5,812	4,492	4,096	3,635	3,477	4,072	4,851	5,354	4,67	4,678	4,932	4,138	4,896	4,182	4,082	4,157	3,02	3,091	3,157
6	5,228	5,868	4,432	3,662	3,535	3,373	4,017	4,804	4,976	5,428	5,441	5,355	4,967	5,3	5,032	4,822	5,39	3,33	3,903	3,647
7	5,557	4,724	4,304	3,774	3,57	3,339	3,849	4,885	5,007	4,944	5,604	5,125	5,705	6,72	5,231	5,537	5,153	3,068	3,659	3,647
8	6,592	7,65	4,329	4,101	3,216	3,065	3,823	4,453	3,94	5,677	5,468	5,632	5,477	5,869	5,531	5,09	5,532	4,051	4,261	3,74
9					4,659	3,103	4,109	3,758	4,205	4,784	5,607	4,977	5,834	5,457	5,278	5,132	5,494	4,584	4,358	5,582
10										5,14	5,265	5,261	5,95	5,015	5,433	6,034	6,18	4,533	3,977	4,703
11															5,661	5,809	5,835	5,225	5,127	3,732

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

TABLE 3

DATA DESCRIPTIVE STATISTICS

	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 4

INDIVIDUAL MOBILITY MEASURED WITH SHORT PANELS

Real Individual Earnings (Log)	1991/92	1992/93	1993/94	1994/95	1995/96	1996/97	1997/98	1998/99	1999/00	2000/01	2001/02
Two Year Panel											
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
Two Year Pseudo–Panel											
Annually Lag of Individual Earnings (Log)	0.70** (0.157)	0.35* (0.184)	0.59** (0.190)	0.77** (0.149)	0.91** (0.119)	0.90** (0.149)	0.80** (0.167)	0.62** (0.141)	0.84** (0.127)	0.94** (0.086)	0.82** (0.259)
Cohort–annual observations	16	16	16	16	16	16	16	16	16	16	16

** $p \leq 0.05$
*$0.05 < p < 0.10$

Note: Panel estimations correspond to the 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. For pseudo-panel estimations all cohort-period observations are averages based on at least 100 individual observations.
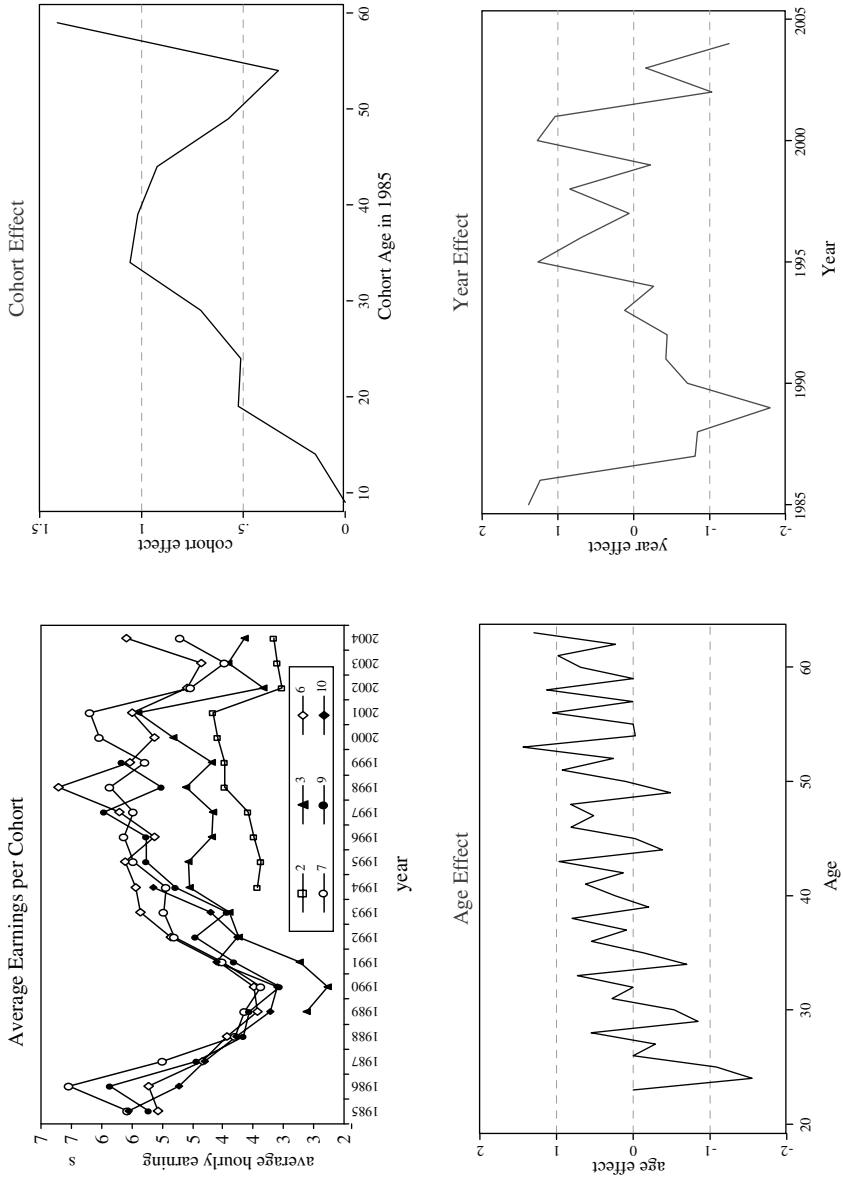*Source:* Own calculations based on *EPH*.

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 forward 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.

3.1. Macroeconomic Instability and Cohorts' Earnings Path

The average earnings profiles of several cohorts are shown in the top left-hand panel of the Figure 1. On a wide outline these profiles show a common macroeconomic pattern for all cohorts. 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. As a result of that extreme macroeconomic instability, for example, those born in 1956 (cohort number five) at age 39 had average earnings that were two percent below the earnings at the same age of the cohort born ten years earlier (cohort number seven); then at age 44 they earned fifty one percent more than the earnings obtained by the ten years older cohort at the same age; but when the former were 48 years old the difference reversed against them up to twenty four percent.

The three remaining panels plot the decomposition of the earnings averages of the cohorts into cohort, age, and year dummies following Deaton (1997). The top right-hand panel of the Figure 1 show cohort effects in cohort earnings regarding the youngest cohort in the sample (cohort one); it shows that except for the individuals belonging to cohorts that have between thirty four and forty nine years old in 1985 (cohorts number six to number nine), the picture depicts close to steady earnings decline from cohort to cohort. Hence, only those cohorts that entered the labor market between the end of the fifties and the middle of the seventies improved their earning path regarding their antecessors. For the rest of them, successive cohorts entering the labor market faced a lower path of earnings than their predecessors. The bottom left-hand panel of the Figure 1 shows a rather weak life-cycle profile for the earnings.

FIGURE 1

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

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

As a result, not only are the younger cohorts of male workers in Argentina worse-off than their predecessors, but they have also experienced much more rapid decline in earnings. In addition, the bottom right-hand panel of the Figure 1 shows a noticeable volatile macroeconomic pattern for all cohorts.

IV. ESTIMATION RESULTS

In order to bring a preliminary overview of the pseudo-panel estimation method regarding true panel method, Table 4 presents the estimates of the degree of earnings mobility by employing the Arellano-Bond dynamic panel data estimator (Arellano and Bond, 1991) and the Antman-McKenzie pseudo-panel estimator (Antman and McKenzie, 2007). The former estimations are obtained from a set of ten short panels covering the years 1991-2002. Due to the six-month rotating structure of the *EPH* data all the intervals correspond to four *EPH* waves included between the months of May of the first year and the month of October of the second year. The later estimations correspond to a set of ten biannual pseudo-panels where cohorts are built as explained in the data description above. The first row provides the panel data instrumental variables estimates; in all of these short panels 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, the results obtained by using true panels could be biased toward zero due to the presence of the measurement error[4]. The second row provides the pseudo-panel β estimates which ranges from a value of 0.35 to a value of 0.94[5]. Comparing these results with those in row one, it is seen that true panel estimates suggest much larger mobility than the pseudo-panel estimates.

The annual mobility estimations were obtained by using the twenty-year pseudo-panel data shown in Table 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 percent level. Similar to the results given by Antman and McKenzie with the Mexican data, the pseudo-panel estimate is larger than the one obtained by using the Arellano-Bond IV method (shown in Table 4). 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, if an individuals labor earnings per hour in a year exceed 10 percent, the mean value of the labor market would be only 6.63 percent above average a year later. This result reveals a high degree of mobility relative to the results derived by Calónico and Cuesta. By including the fixed effects per cohort in the second model the value of coefficient β is

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[4]   The presence of attrition could also bias the result but, according to Albornoz and Menéndez (2007), since the time span is only one year, these panel data present small non-systematic differences between the October waves, so the attrition bias would not be such that it would invalidate the panel data estimates.

[5]   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.

lightly decreased, making it 0.614, that is, statistically significant at the 1 percent level. Despite the fact that the results derived by Calónico reveal less degree of mobility, 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.

TABLE 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.

The third model in Table 5 adds two usual controls (age and square age) and the size of the cohort; the later to capture the effect on earnings of compete with many more workers in the market. Adding those controls besides the dependant variable in Model 3, gives a value of β coefficient equal to 0.629, which continues to be statistically significant at the 1 percent level. The obtained value is significantly below one, as the confidence interval of 95 percent 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.

Table 6 shows the results obtained by the estimation of the models in Table 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. 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. It also helps in reducing potential bias by tracking a consistent group of individuals. This is particularly helpful for the older cohorts since, as Table 1 shows vividly, cohort shrinks through time because of age effects. 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 to the 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.

TABLE 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.

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 mobility from 1990. The corresponding results are shown in Table 7. The results showed in Table 7 correspond to the sub sample of men aged 23 to 49 years old.

The absolute and conditional estimations for the two-year period show 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. The conditional results are similar to those provided by Antman and McKenzie (2007) for 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. Nevertheless, the drop of the absolute mobility coefficient over different time lags obtained herein contrasts with Antman and McKenzie's results. Finding more absolute mobility when the exercise is estimated using 5-year intervals vis-a-vis two-year intervals, may be also related to the period of recovery after the convertibility reform rather than or only because of an increase in the length of the period considered. This may be particularly the case for those who had the better chance to excel in a recovery market as survived employed the crisis.

TABLE 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.

Given that significant macroeconomic instability and changing rules characterized the analyzed twenty year period, it is possible that the value of earnings mobility may not be uniform during the entire period. Figure 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 8, the inclusion of the sub-period interacting dummies diminishes the value of the β coefficient throughout the period under study. This result would suggest that despite the fact that inequality grew during the 1990s, a more market oriented economy favored earnings mobility. However, since those who remained unemployed or moved out of the labor market during those decades were left out of the present analysis, this enlargement of the earnings mobility has to be taken with caution. Table 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. On one hand, the deep macroeconomic crisis that Argentina underwent in those years would certainly require us to analyze a larger period than the one we analyzed. On the other hand, the policies adopted during those years and in the subsequent years –not considered in the present study– involved a return to a more intervened economy.

TABLE 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.

V.   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. A word of caution is necessary at this point because the results mainly correspond to prime age male occupied workers throughout the period, which undoubtedly constitutes an interesting group in itself but its trends should not be confused with labor mobility trends. A more comprehensive exercise, including the unemployed and those in and out the labor market; non-labor incomes; females; would be necessary to convincingly elaborate on labor mobility, more so if attempting to relate them with inequality trends. 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 accelerating the speed of the individual' earnings level recovery after a negative shock. This suggests 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 remarkable growth in mobility as the temporal framework becomes longer as well. Thus, the individual earnings convergence with the mean earnings is faster when the mobility is studied during a two-year period and it shows reversal signs as the period studied becomes longer. The results show that the earnings mobility increase through time, also, 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 reveal more earnings 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 be considered with some caution because the authors added labor earnings over the household members for their estimations, therefore, their definition of earnings and their sample scope is wider than the one used herein.

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