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Earnings Mobility in Times of Growth and Decline

Argentina from 1996 to 2003

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Abstract

In recent years, the economy of Argentina has experienced both rapid economic growth and severe economic decline. In this paper, we use a series of one-year long panels to study who gained the most in pesos when the economy grew and who lost the most in pesos when the economy contracted. To answer these questions, we test two hypotheses both unconditionally and conditionally. The 'divergence of earnings' hypothesis holds that in any given year, the highest earning individuals are those who experienced the largest earnings gains or the smallest earnings losses in pesos. The 'symmetry of gains and losses' hypothesis holds that those groups that gained the most in pesos when the economy grew are those that lost the most in pesos when the economy contracted. Both hypotheses are decisively rejected in the data. …/

Keywords: finance, growth, inequality, Argentina, survey, gains, losses

JEL classification: O16, D14, I31, D63

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Rather, we find that it is the *lowest income* individuals and groups who gain the most in pesos, whether in good times or in bad. Thus, the panel data analysis performed in this paper presents a picture of economic growth that is much more pro-poor than one gets from cross sectional inequality comparisons.

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Tables and figures appear at the end of this paper.

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1 Introduction

The Argentine economy has experienced extraordinary macroeconomic variability (Figure 1). Having pegged its exchange rate to the dollar under a currency board type arrangement in 1991, Argentina had succeeded in ending hyperinflation, reducing inflation rates to single digit levels, which led the country to be seen as a model of successful economic policymaking. Greater economic stability attracted foreign investment inflows, contributing to an acceleration of economic growth; indeed, even as lenders withdrew their financing from East Asia in 1997, capital inflows continued to Argentina. Then, Argentina entered into a prolonged recession. The combination of the hard peg of the local currency to the US$ and excessive borrowing led to an unsustainable fiscal situation and, ultimately, to the collapse of the economy at the end of 2001. The gross domestic product fell by 13.5 per cent in one year, and the share of the population in poverty reached 58 per cent in October 2002 as compared with 38 per cent a year earlier. The economy then recovered and has grown consistently since.[1]

This paper addresses earnings mobility in urban Argentina during these tumultuous years.[2] Looking at the same individuals from one year to the next, we ask: Who benefited the most from Argentine economic growth? Who lost the most in economic decline? Are those groups that gained the most in good times the ones that lost the most in bad times? Are the answers to these questions the same for all measures of economic advantage?

What is novel about this analysis compared with most of the previous work on changing income distribution in Argentina is that it is based on a series of panels of individuals. For each one-year period from 1996–1997 through 2002–2003, we examine the *change* in labour market earnings for the *same individuals* from May of one year to May of the next. For the most part, researchers who have studied distributional change in Argentina have looked at *anonymous* individuals and households: those in the poorest 20 per cent of the income distribution versus others, men versus women, and so on. The advantage of using panel data to study distributional change is that we are able to measure the extent to which those individuals who initially were at various points on the income ladder moved up or down during different macroeconomic conditions.

To learn about earnings changes for identified individuals during positive and negative growth years, we construct seven one-year long panels covering workers in twenty-eight cities in Argentina. For a sample of women and men aged twenty-five to sixty, we analyse earnings changes both unconditionally in a univariate framework and conditionally using multiple regressions. We test whether the initially advantaged individuals gain the most in pesos in any given year; this is the ‘divergent mobility hypothesis’. We also test whether the groups that gain the most in pesos in positive growth years are the ones that lose the most in pesos in negative growth years; this is the ‘symmetry of mobility hypothesis’.

1 GDP numbers are from INDEC, poverty numbers from Gasparini (2004). The poverty numbers are for the official moderate poverty line, which is based on the cost of a basic food basket and non-food consumption bundle whose combined values are just sufficient to allow a typical household to achieve a minimum level of material welfare.

2 The analysis is limited to urban Argentina for reasons of data availability.

The rest of the paper is laid out as follows. Section 2 reviews previous literature pertinent to our questions. Section 3 presents the theoretical foundations for the hypotheses concerning divergence of earnings and symmetry of mobility. Section 4 describes the data and Section 5 the hypotheses and the methodologies for testing them. The results for the five hypothesis tests are presented in Section 6, Section 7 concludes.

2 Literature review

Mobility studies are of two types. *Micromobility studies*, of which this paper is one, relate the change in a measure of economic well-being to a number of explanatory variables. In this study, the measure of economic well-being is the labour market earnings of an individual, and the dependent variable in our analysis is the one-year change in labour market earnings for each individual.[3] The explanatory variables used here include base year income and other time varying and time invariant characteristics. By contrast, *macromobility studies* gauge how much mobility of a certain type there is in an economy as a whole, often comparing differences in aggregate mobility over time or for different groups.[4] Being an aggregate measure, macromobility is like macrogrowth (how much economic growth an economy has in aggregate), macro-unemployment (how much unemployment an economy has in aggregate), macroinequality (how much inequality an economy has in aggregate), and macropoverty (how much poverty an economy has in aggregate.)

The study of earnings and income micromobility has a long tradition in economics; for a survey of empirical studies, see Atkinson et al. (1992). However, due to the lack of panel data surveys, the study of mobility patterns in developing countries' labour markets is still a fresh area of research where much remains to be learned; for reviews of the developing country literature, see Baulch and Hoddinott (2000) and Fields (2001). To the best of our knowledge, with the exception of the as yet unpublished work on Venezuela by Freije (2001) and on Argentina by Albornoz and Menéndez (2004), no previous developing country study offers a comparison of various panels over time, which is required for analysing changing earnings dynamics in positive and negative growth years.

In the case of Latin America, to the extent that earnings gains and losses of different income groups have been studied for periods of macroeconomic growth and decline, the answers are based on data from comparable cross sections (IDB, 1999, 2004; Lustig and Székely, 1999; de Ferranti et al., 2004; Bourguignon et al., 2004). The same is true for the specific case of Argentina; see Gasparini (2004) and Sánchez Puerta (2005) for recent reviews.

Past studies of Argentina have shown that inequality has been rising, sometimes slowly and sometimes rapidly, over a long period of time. This increase appears clearly in Figure 2, which displays the evolution of inequality of household per capita incomes since 1980.

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3 Other measures of economic well-being in other mobility studies include changes in total income, log-income, or consumption on a household, per-capita, or adult-equivalent basis as well as changes in economic position (such as decile or quintile).

4 See Fields (2001) for a description of the different types of mobility.

The reader is cautioned not to draw the wrong inference from rising inequality. First of all, in no way does rising inequality provide evidence that absolute economic conditions have worsened for the poor. The poor could have been getting richer but at a slower rate than others. Second, rising inequality indicates that the dispersion of income has widened, but implies nothing about the movement of specific individuals within that distribution. If a sufficiently large number of poor and non-poor individuals swap incomes, the initially poor will gain more on average than the initially non-poor, even as the distribution of income grows more unequal.

Given the availability of panel data for Argentina, it is not surprising that economic mobility is receiving considerable attention in the literature. The highlights of previous economic mobility studies for Argentina are briefly reviewed here.

Wodon (2001) analysed income – wages and self-employment – macromobility and risk over the business cycle in Argentina and Mexico. He used a new measure of mobility, namely the Gini index of mobility, which is a function of ranks of individuals in the distribution of income, and found that mobility is higher during recessions and lower during growth in Argentina compared to Mexico. Even though the author focused on the different patterns of mobility in periods of growth and recession, he did not analyse the relationship between earnings changes and initial earnings or other measures of initial advantage of the individuals as explanatory variables of income dynamics in either country.

Gutierrez (2004) studied labour force mobility and time independence in urban Argentina for the period 1998–2002. He constructed panels for all individuals including the economically inactive, with which he studied the determinants of wage mobility and the determinants of finding or losing a job. He found that low earnings individuals have more wage volatility and more movements into and out of employment. Also men, the least educated, and younger individuals show more instability. His results are incompatible with ours because he does not look at directional income movements as we do.

The Inter-American Development Bank (2004) used panel data from Argentina to look at six-month labour market transitions during the period 1993–2001. They found that about 3.5 per cent of the population between ages 15 and 64 transited from unemployment to employment or from employment to unemployment. Furthermore, within the employed group, in a six-month period, about 12 per cent transited between formal sector jobs and informal sector jobs. Not examined were which workers were more apt to make these transitions, how these flows vary over the business cycle, or how incomes changed for those who made various transitions compared to those who did not.

Two studies examined income mobility during the 2002 financial crisis in Argentina. McKenzie (2004) constructed panels to assess the adjustments of household and individual incomes and the labour market response to the crisis. He studied changes in nominal wages, entry into and exit from the workforce, hours worked, household labour supply and work program participation separately. The income mobility analysis consisted of an OLS regression of change in log income on individual characteristics and regions, with a dummy variable for the period of crisis with interactions. His conclusions were that the larger income falls applied to males, managers, and those who changed jobs. Females in Cuyo did better than before, while females with tertiary education did worse. Along similar lines, Corbacho et al. (2003) also used panel data from Argentina for the years 1999–2002 and analysed the determinants of changes in household income to draw inferences regarding socioeconomic characteristics and vulnerability. They found that households whose heads were male, less educated, and employed in the construction sector were more vulnerable to the crisis, experiencing larger than average declines in income and higher dispersion. Base year income was not included as an explanatory variable in either McKenzie's or Corbacho et al.'s regressions as would be usual in the mobility literature, and therefore these results are not directly comparable to ours.

The work that comes closest to ours is Albornoz and Menéndez (2004). These authors used the changes in logarithm of household income per capita to determine the principal socioeconomic factors driving income dynamics in Argentina. For this purpose, they performed multiple regression analysis to test, ceteris paribus, whether there are structural patterns in the variables explaining income changes over time in their five one-year panels. They did not find any structural patterns for the determinants of income change and concluded that shocks affect different types of people over time. No special attention was given to the different patterns in positive and negative growth periods.

Thus, to the best of our knowledge, the present study constitutes the first analysis of patterns of earnings dynamics comparing periods of positive and negative economic growth in Argentina. This work is part of a larger project also covering Venezuela and Mexico (Fields et al. 2005). Other than that the question of how earnings dynamics compare in positive and negative growth years has not been analysed in any developing country (to the best of our knowledge).

3 Theoretical foundations: divergence of earnings and symmetry of mobility

In this research, we test two major hypotheses. The 'divergent mobility hypothesis' holds that the initially advantaged are the ones that gain the most in pesos and lose the least in any given year. The 'symmetry of mobility hypothesis' holds that those who gain the most in pesos when the economy grows are the ones that lose the most in pesos when the economy contracts.

Why might these hypotheses be expected to hold? We have seen that Argentina has experienced considerable macroeconomic instability coupled with generally rising relative income inequality. Table 1 displays our calculations of the corresponding Gini coefficients. We see that although relative inequality was generally rising, in some years, the change in inequality was small or negligible.[5]

Such relative inequality changes imply that each anonymous income group (e.g., bottom quintile, second quintile, etc.) had approximately the same *percentage* change in income as every other. Of course, a given percentage change produces a larger change *in pesos*

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5 Inequality changed so little in each year from 1996–1997 to 2000–2001 that when two successive years' Lorenz curves are plotted, only one Lorenz curve is visible, because the base year curve and the final year curve lie entirely on top of one another. On the other hand, the data also show a substantial Lorenz worsening from 2001–2002 and a substantial Lorenz improvement from 2002–2003.

the higher one's income is. Therefore, the *anonymous* pattern of income changes was twofold: i) in times of economic growth, high income people gained more in pesos than low income people did; ii) in times of economic decline, high income people lost more in pesos than low income people did. Pattern i) is the divergent mobility hypothesis applied to *anonymous* individuals in times of positive economic growth. Patterns i) and ii) together are the symmetry of mobility hypothesis applied to *anonymous* individuals.

From here, it is only a small step to hypothesize that *those particular individuals* who started with the highest initial incomes are those who gained the most pesos in periods of economic growth and lost the most pesos in periods of economic decline. And, it might be hypothesized that those particular groups that gained the most when the economy was growing (men, for example) would be the ones that lost the most when the economy was contracting.

This idea is what we are calling the 'symmetry of mobility' hypothesis. It states that the groups which gain the most in pesos in periods of positive growth are the same ones that get hurt the most in periods of negative growth.

Other considerations lead to a different conjecture, what we are calling the 'divergent mobility hypothesis'. One is the theory of cumulative advantage, which posits that individuals with higher incomes and earnings in the base year experience the largest earnings gains (Merton, 1968; Boudon, 1973; Huber, 1998). Wealthier individuals' ownership of physical and human capital, access to social and political connections, and greater ability to borrow and save could all contribute to cumulative advantage.

Complementing cumulative advantage in contributing to the divergent mobility hypothesis is the notion of poverty traps (Carter and Barrett, 2004; Chronic Poverty Research Centre, 2004; Sachs, 2005). According to this theory, those individuals who lack a minimum level of human, physical, and social assets are consigned to a life in poverty from which they cannot escape.

A third factor that may contribute to larger gains for the initially well-to-do compared with others is labour market twist. This idea holds that in an increasingly globalized and technology dependent world, the demand for skills is outpacing the available supply, bidding up the earnings of skilled workers while lowering those of the unskilled (Johnson, 1997; Gottschalk, 1997; Topel, 1997). Skill biased technical change would act to propel individuals with the highest human and physical capital endowments ahead the most.

Together, the first three factors reinforce one another. These three factors exemplify positive feedback, defined by Nobel laureate James Meade as

> self-reinforcing influences which help to sustain the good fortune of the fortunate and the bad fortune of the unfortunate. (1976: 155)

A fourth factor operates in the opposite direction. According to the model proposed by Galton (1889), those who start above the grand mean tend to converge downward relatively, while those who start below the grand mean to converge upward relatively. Thus, those who have the highest incomes or earnings to start with are the ones who gain the least when growth is positive and lose the most when growth is negative.

We turn now to the data we use to test these hypotheses.

4 Data

The data for our empirical work come from the Encuesta Permanente de Hogares (EPH), an urban household labour force survey conducted by Argentina's National Statistical Agency (INDEC, 2004). The survey is a rotating panel, with one quarter of the households rotated out each period, so that a given household can be followed for up to four periods. The survey is conducted in May and October each year in provincial capitals and areas with more than 100,000 inhabitants for a total of twenty-eight cities.[6] The EPH is representative of 71 per cent of urban areas. Since 87 per cent of Argentines live in urban areas, the sample of the EPH represents around 62 per cent of the total population of the country. The EPH is carried out via a two stage random sample. Within each urban area, a random sample of geographic units is chosen in the first stage, and then a random sample of houses within the selected units is drawn in the second stage.

The survey contains detailed questions on employment and incomes, together with information on household demographics, basic housing questions, and questions on education.

For this paper, we take the microdata for two consecutive years (May to May) to avoid capturing changes in earnings due to seasonality. The panels cover periods of positive growth (1996–1997, 1997–1998 and 2002–2003) and of negative growth (1998–1999, 1999–2000, 2000–2001, and 2001–2002).[7] We match dwellings by an identification code that uniquely characterizes each housing unit surveyed. Due to the rotating nature of the EPH survey, around 50 per cent of the original sample would be expected not to be present in the second year. In fact, the actual proportion is higher, since households that move and are not found at the time of the reinterview are not traced but replaced.

In order to avoid mismatching, additional matches of gender and date of birth of the individual are required. If these two variables were missing or were misreported for some individuals, the observations could not be matched and were dropped from the analysis. Non-random attrition could be a concern given that the final samples represent around 35 per cent of the initial surveys, where 50 per cent would correspond to zero attrition. Besides, not all the individuals selected to respond to the EPH answer the questions about earnings. This phenomenon can bias the mobility estimations if (i) non-response depends on income, and (ii) the percentage of non-response varies over time.[8] Fortunately though, past researchers have not found attrition bias to be a serious issue in the EPH (Gasparini and Sosa Escudero, 1999; Cruces and Wodon, 2002; Albornoz and Menéndez, 2004).

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6 An additional three areas were added to the survey in the October 2002 round. To maintain comparability with earlier rounds of the survey, we did not use observations from these new areas.

7 The real per capita GDP growth rates were as follows: 1996–97, +8.1 per cent; 1997–98, +6.9 per cent; 1998–99, -4.9 per cent; 1999–2000, -0.4 per cent; 2000–01, -0.2 per cent; 2001–02, -13.5 per cent; 2002–03, 7.7 per cent.

8 The number of people with incomplete household income reports was about 8 per cent for the survey years that we used.

Sampling weights are provided in the survey, but for technical reasons we chose not to use them.[9] Results with weighted data do not alter the central conclusions of the paper and are available from the authors upon request.

In the empirical work that follows, the dependent variable is the individual's change in labour market earnings in pesos. The reason for the choice of change in earnings as the variable of interest is that in a number of economies including South Africa, Indonesia, Spain and Venezuela, earnings changes have been shown to constitute the single most important source of variation of change in total income, more so than all the other income sources combined (Fields et al., 2003). The paramount role of changes in labour earnings in explaining changes in total incomes points to the importance of understanding earnings dynamics and employment transitions more fully. Therefore, the focus of this paper is on analysing the way in which labour markets distribute rewards.

The unit of analysis for our labour market study is the individual. Our sample consists of individuals in the labour force in both base and final years of the panel who were between the ages of twenty-five and sixty. The age range is restricted in order to avoid interpreting as earnings mobility labour market fluctuations due to first time entries to the labour force and retirements.

The analyses are conducted using earnings change in pesos, which measures absolute earnings gains. All earnings are expressed in 1999 pesos per month.[10] Nominal earnings are deflated by the April Consumer Price Indices for Greater Buenos Aires to obtain real earnings.[11] Earnings include wage or salary, self-employment income, and earnings as owner or employer.

One explanatory variable used in this study is initial earnings, sometimes in pesos and sometimes in quintiles (where quintile 1 is the lowest and quintile 5 is the highest). To allow for the possibility that measurement error influences our results, we use both reported and predicted initial earnings as variables explaining earnings change.[12]

Other explanatory variables are also used. These include gender, age, education, sector, and region. *Male* is a binary variable taking on the value one for men and zero for women. The individual's *age* in the first year of the panel is grouped into three categories in the mobility profiles and is entered linearly and quadratically in the regressions. *Education* is highest level of education attained. It is grouped into three categories in the mobility profiles: primary education or less; secondary education (national, commercial, normal or technical schools); and tertiary education (superior or university studies). In the regressions, years of education are included linearly and quadratically. *Sector of employment* is grouped into three categories (formal, informal, and unemployed) in both base year and final year. In Argentina, the formal sector consists of i) workers who have all legislated benefits like pension, paid vacation, etc., ii) employers in firms with more than five employees, and iii) self-employed workers

9 This is because although the weights apply to the base period, there is no assurance that they apply equally to changes from base period to final period among panel people.

10 The Argentine peso was pegged to equal one US$ dollar in that year.

11 Regional price indices are available for other cities, although they are based on a smaller number of prices and are not strictly comparable.

12 The methods for predicting initial earnings are described below.

with more than a secondary education. *Sector transition* is a nine category variable: remaining formal, moving from formal to informal work, etc. In the regressions, the omitted category is remaining unemployed. *Region* is a grouping of six geographic areas: Greater Buenos Aires, Pampeana, Patagonica, Noreste, Noroeste, and Cuyo.

5 Hypotheses and methods

Based on the empirical patterns and theoretical considerations discussed above, we test five hypotheses concerning the patterns of earnings gains and losses in Argentina:

- (H1) Divergence of earnings in pesos, unconditional version:
  In any given year, the highest earning individuals are those who experience the largest earnings gains or the smallest earnings losses in pesos.
- (H2) Divergence with other indicators, unconditional version:
  In any given year, those groups that earn the most to begin with are those that experience the largest earnings gains or the smallest earnings losses in pesos.
- (H3) Symmetry of gains and losses, unconditional version:
  Comparing positive and negative growth years, those groups for whom earnings changes in pesos are the most positive when the economy is growing are those for whom earnings changes in pesos are the most negative when the economy is contracting.
- (H4) Symmetry of gains and losses, conditional version:
  Other things equal, comparing positive and negative growth years, those groups for whom earnings changes in pesos are the most positive when the economy is growing are those for whom earnings changes in pesos are the most negative when the economy is contracting.
- (H5) Determinants of earnings changes:
  The conditional determinants of earnings changes are the same as the unconditional ones, both in positive and in negative growth years.

Several methods are used to test these hypotheses. Starting with the unconditional analysis, we generate mobility profiles for positive and negative growth years. These profiles give the mean and median earnings change by category, such as quintile of initial reported and predicted earnings, age range, and so on. Statistical significance of the different factors is also presented, using t tests to determine if an individual variable (e.g., Quintile 1) differs significantly from zero and F tests to determine if a group of variables (e.g., the five quintile variables taken together) have means that are significantly different from one another. As a measure of economic significance, this analysis is supplemented with the R-squareds of simple regressions of change in earnings on each of the factors. In this paper, a variable is considered economically significant if it explains more than one per cent of the variation in earnings changes.

Turning to the conditional analysis, we estimate OLS and median multiple regressions. In the regressions, t tests are used to test the statistical significance of a single regressor, and F tests are used to test the statistical significance of groups of regressors, e.g., the various regional groupings. The economic significance of the variables in the conditional analysis is assessed by the share of each factor in accounting for the observed inequality of earnings changes using the method proposed by Fields (2003) which decomposes the observed inequality in earnings and assigns so called 'factor inequality weights' to each factor. A variable is considered to be economically significant in the conditional analysis if its share in accounting for observed inequality in the multiple regression is at least one per cent.

All of these analyses are performed on the full sample of workers, on just the workers with positive earnings in base and final years, and separately for the formally and informally employed.

The traditional way of analysing unconditional mobility is by regressing changes in earnings on initial reported earnings. However, there might be a problem of measurement error with reported earnings. Therefore, we also perform a robustness test by including the individual's predicted earnings as another measure of economic advantage.

Throughout this analysis, we assume that there is a classical measurement error in the measures of earnings. In other words, the error term is mean zero, normally distributed, and independent of any other household or personal characteristics

$$\Delta y_{i,t+1} = \alpha + \beta y_{i,t} + u_{i,t+1} \tag{1}$$

where

$$y_{i,t} = y^{*P}_{i,t} + y^{*T}_{i,t} + \mu_{i,t}$$

$y^{*P}_{i,t} + y^{*T}_{i,t}$ being true permanent and transitory earnings respectively, and $\mu_{i,t}$ measurement error (orthogonal to true earnings).

The OLS estimator for this equation is

$$\hat{\beta}_{OLS} = \frac{\text{cov}(y_{i,t+1} - y_{i,t}, y_{i,t})}{V(y_{i,t})} \text{ =========> } \hat{\beta}_{OLS} = \beta_0 \frac{V(y^*_{i,t})}{V(y^*_{i,t}) + V(\mu_{i,t})} - \frac{V(\mu_{i,t})}{V(y_{i,t}{}^*) + V(\mu_{i,t})}$$

By running OLS, any reporting error or other type of measurement error in initial income leads to a spurious negative correlation between reported initial earnings and change, captured by the second term of the OLS estimate. In addition, the stochastic independent variable causes attenuation bias, reflected in the first term of that equation. If true incomes diverge from the mean, so that β_0 is positive, the reported regression coefficient unambiguously underestimates the extent of that divergence. On the other hand, if true incomes converge to the mean, so that β_0 is negative, these effects work in opposite directions and the bias is of indeterminate sign.

To try to overcome the problems associated with reporting error, a two stage least squares regression using identifying instruments can be performed. Under the assumption that these instruments are orthogonal to reporting error, the estimated IV coefficient

$$\tilde{\beta}_{IV} = \frac{\mathrm{cov}(y^{*T}_{i,t+1} - y^{*T}_{i,t} + \mu_{i,t+1} - \mu_{i,t}, y^{*P}_{i,t})}{V(y^{*P}_{i,t})} = \frac{\mathrm{cov}(y^{*T}_{i,t+1} - y^{*T}_{i,t}, y^{*P}_{i,t})}{V(y^{*P}_{i,t})}$$

is consistent.

In this study, earnings are predicted by instrumenting the permanent component of earnings, which generates a regressor that can be interpreted as a measure of longer term earnings as opposed to current earnings. The variables used to make these predictions include the individual's age, education, gender, sector of occupation, and dwelling characteristics (dwelling ownership, number of rooms, and a measure of comfort including data on sewage, running water, and electricity).

The prediction of initial earnings y_0 is done following several different methods:

- Method 1 consists of predicting y_0 with a linear regression based on time invariant characteristics and long term income proxies. These variables are age and its square, education and its square, gender, and dwelling characteristics.

- Method 2 consists of extending the previous prediction by adding dichotomous variables for individuals' sector in the base year: informal, formal, or unemployed.

- Method 3 abandons the linear structure used so far, and instead generates a predicted y_0 by accounting explicitly for the probability of being unemployed. In particular, predicted y_0 will equal P($y_0 > 0 \mid X$) * E($y_0 \mid X$, $y_0 > 0$), where the components are estimated by a Heckman selectivity correction method. The variables included in X are the same as in Method 1. Similarly, Method 4 extends Method 3 by including the informal sector dummy as an additional regressor in the E($y_0 \mid X$, $y_0 > 0$) term.

- Finally, Methods 5 and 6 repeat the linear exercise performed in Methods 1 and 2, but obtaining the parameters used for the predictions from linear regressions fit only for employed individuals.

In the analysis that follows, regardless of whether initial reported earnings or predicted earnings is used as an explanatory variable, the dependent variable is always the change in reported earnings. This is because under the above stated assumptions, the measurement error would be averaged out in the estimation of means, and in the regressions it would not affect the consistency of the parameter estimates as long as the misreported regressors are instrumented.

To test the hypothesis of conditional symmetry, as stated above, we perform multiple regressions using OLS. The change in earnings from one year to the next is regressed on initial reported earnings, gender, age, education, sector transition, and geographic region. Earnings variables are used in continuous forms. The regression equation is

$$\Delta y_{i,t} = \Delta X_{i,t}\phi + Z_i\gamma + \delta y_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

where ΔX denotes sector transitions, Z denotes time invariant characteristics like gender, age, education, and region, and $y_{i,t\text{-}1}$ is initial reported income. Equation (2), which is linear in the variables, is estimated through OLS regression. We also perform median regressions with bootstrapped standard errors to check whether outliers in the data excessively influence OLS estimates.

6 Empirical findings[13]

H1: Unconditional divergence of earnings

This hypothesis holds that in any given year, the highest earning individuals are those who experience the largest earnings gains in pesos and the smallest earnings losses. Starting with initial reported earnings, unconditional divergence is decisively rejected, both when initial reported earnings are entered in quintiles (Table 2) and when initial reported earnings are entered linearly (top graph in Figure 3). Rather, what we find in each year is statistically significant *convergence* – that is, it is the initially *poorest* who exhibit the largest gains. Please note that the gains of the poor are largest *in pesos*, which means of course that their *percentage* gains are even larger.

To test the robustness of the conclusion that the pattern of earnings changes is convergent, we performed several tests. First, we used median earnings changes in place of mean earnings changes. Second, in place of initial reported earnings, we used predicted earnings for each of the six different prediction methods described in the previous section. Predicted earnings were entered both linearly and by quintile.

The results for the robustness tests are similar to those for the base tests in that, when the differences are statistically significant, the pattern is one of unconditional *convergence*. The linear regression results for predicted earnings using the six methods are displayed in Figure 3; the results for the quintile analysis for predicted earnings for Method 1 are displayed in the second block of Table 2. However, unlike the results for reported earnings, the results for predicted earnings are often statistically insignificant. Note well the implication of insignificance: workers at different points in the income distribution experience earnings changes in pesos that are not significantly different from one another, which implies that in periods of growth lower income people have much larger percentage changes than higher income people do.

H2: Unconditional divergence with other indicators

This hypothesis holds that in any given year, those groups that earn the most are those that experience the largest earnings gains or the smallest earnings losses in pesos. To know which groups of workers are the high earners, we performed a supplemental analysis, which indicated that in both positive and negative growth years men earn significantly more than women; middle-aged workers earn significantly more than younger and older workers; earnings rise significantly with education; formal sector workers earn significantly more than informal sector workers; and workers in Greater Buenos Aires are at or near the top of the earnings distribution compared to workers in other regions.

[13] This section displays the results of the main tests and selected robustness tests. The results of the remaining robustness tests are available from the authors upon request.

H2 would be confirmed if the initially high earning groups are the ones with the most positive or least negative earnings changes in pesos. In general, though, this is *not* what we find when we look at the data in Table 2. Rather, when statistically significant:

- Men's earnings changes are worse than women's. (H2 rejected)
- Middle-aged and older workers' earnings changes are worse than those of younger workers. (H2 rejected)
- Most of the time, those with higher education have the most negative earnings changes. (H2 rejected)
- Most of the time, workers who started formal have significantly worse earnings changes than workers who started informal. (H2 rejected)
- Moreover, regional differences are statistically insignificant in six out of the seven panels. (H2 rejected)

In summary, when higher and lower income groups are compared with respect to earnings changes, we find *unconditional convergence or a statistically insignificant relationship*; unconditional divergence is *never* found for these other indicators.

As we did for H1, we performed a robustness test of these results by analysing median earnings changes and found the same patterns using medians as we did using means. We therefore reject unconditional divergence for all variables.

<u>H3: Symmetry of gains and losses, unconditional version</u>

This hypothesis holds that when positive and negative growth years are compared, those groups for whom earnings changes in pesos are the most positive when the economy is growing are those that experience the largest earnings losses in pesos when the economy is contracting. Such a result, if found, will be termed 'symmetric'. If symmetry is rejected and the same groups gain significantly more regardless of whether the economy is growing or contracting, the pattern of gains and losses will be called 'structural'. However, if the symmetry hypothesis is rejected because the gains for the different groups are not significantly different from one another in positive growth years compared to negative growth ones, this pattern will be referred to as 'insignificant'.

Comparing the positive and negative growth years in Table 2, unconditional symmetry would be found if the signs reverse when moving from the positive to the negative growth years. However, a statistically significant sign reversal *never* happens. Therefore, the main tests reveal *no* case of a symmetric relationship. Rather, all of the indicators, when statistically significant, exhibit structural relationships.

Four robustness checks were performed. First, we repeated the analysis based on comparisons of *median* earnings changes rather than means. Second, we also did the analysis for *predicted quintile* instead of initial reported quintile. Third, we analysed the subsample of employed workers, leaving aside the unemployed. And fourth, we analysed formal sector workers and informal sector workers separately. For all four of these tests *no evidence of unconditional symmetry* was found. Rather, for initial reported earnings and sector transitions, the patterns are structural while the other variables show no significant patterns.

H4: Symmetry of gains and losses, conditional version

This hypothesis posits that, other things equal, when positive and negative growth years are compared, those groups for whom earnings changes in pesos are the most positive when the economy is growing are those for whom earnings changes in pesos are the most negative when the economy is contracting. For each year, conditional tests of symmetry of gains and losses were performed using initial reported earnings in continuous form, gender, age and its square, years of education and its square, sector transition (with those who remain unemployed as the omitted category), and region.

The results of the OLS multiple regressions are reported in Table 3. The general result is that the patterns are overwhelmingly structural – that is, other things equal, those who gain the most when the economy is growing are for the most part also those who lose the *least* when the economy is contracting.

Specifically, the relationship between *initial reported earnings* and earnings change is always significantly negative. This means that there is a convergent pattern to the conditional mean of reported earnings, i.e., those with the highest initial reported earnings experience the worst changes in positive and in negative growth years, ceteris paribus.

Other things equal, *men* always have significantly higher earnings changes than women in both periods. Being a male in urban Argentina leads to both higher earnings levels on average, and also to higher upward mobility, ceteris paribus.

When evaluated at the mean age (forty), *age* has a positive and significant effect on earnings changes in both positive and negative growth years, other things equal. The older the individual, the more positive earnings changes they experience.

When evaluated at the mean years of *education* (approximately nine years), those with more education have larger earnings gains, other things equal. A convex pattern is found, and the turning point for the education variables is around five years of schooling.

Turning to the analysis of *sector transitions*, earnings changes among the ones who stay (formal–formal and informal–informal) are always found to be significantly positive, ceteris paribus. Also, among the movers from the informal to formal and the formal to informal sector always have significantly positive effects in the multiple regressions. Individuals moving from the informal sector into the formal sector have large positive earnings gains, larger than the gains of the workers who stayed in the informal sector. Individuals who started in the formal sector and moved to the informal sector experience lower earnings changes than those who stayed in the formal sector. As for transitions into and out of employment, losing a formal sector job entails larger earnings losses than losing an informal sector job.

Finally, the coefficients for *region* are frequently insignificant, but when they are significant, it is always workers in Greater Buenos Aires who do better in terms of earnings changes, ceteris paribus.

In summary, our main tests reveal structural patterns for all of the variables; conditional symmetry is rejected without exception.

We turn now to our robustness tests. The first robustness test we performed was to use median regressions. These regressions deliver the same answer to the conditional symmetry hypothesis as the OLS regressions did – namely, there is no symmetry of mobility. As a second robustness test, we restricted the sample to individuals with positive earnings in both periods. As in the case of the main test, the conditional symmetry of mobility hypothesis is rejected when we analyse this subsample. The last robustness test was to divide the sample into initially formal and initially informal workers and compare the results with the ones for the whole sample. Again, we reject the symmetry hypothesis for all of the variables in each of the subsamples. Instead, we find a structural pattern within both the formal and the informal sectors: the initially poor, men, the more experienced, the more educated, and those in Greater Buenos Aires have the largest earnings changes in positive as well as in negative growth years.

In summary, contrary to the hypothesis of conditional symmetry of gains and losses, the results for the main tests and the robustness tests demonstrate predominantly a structural pattern or else an insignificant relationship. Conditional symmetry is decisively rejected.

H5: Comparing the unconditional and conditional determinants of earnings changes

This section analyses whether the unconditional determinants of earnings changes are the same as the conditional ones. The coefficients of unconditional regressions show the *total* effect of a variable on changes in earnings, while the coefficients of conditional regressions show the *partial* effect of a variable controlling for the effects of other variables. For this test, the positive growth years are pooled with one another and the negative growth years are pooled with one another. We first compare the statistical significance and signs of the variables and then analyse their economic significance.

Regarding statistical significance and sign, the results are summarized in Table 4. We see that only one of the determinants of earnings changes is the same unconditionally and conditionally, and the others are not. The one that is always the same is initial reported earnings, which has a statistically significant negative sign. The other variables differ in sign or significance between the unconditional and conditional analysis. It is nearly always the case that in going from an unconditional regression to a conditional one, initial reported earnings is essential for the change in sign in the variables to take place and for the coefficients to become significant (if they were not already so.)

Turning from statistical to economic significance, the results are presented in Table 5. Unconditional economic significance is gauged by the R-squareds of simple regressions; conditional economic significance is gauged by the factor inequality weights coming from the Fields decomposition. Using 1 per cent explanatory power as the dividing line between economically significant and economically insignificant, we see that the economically significant variables in the conditional analysis are the same as in the unconditional analysis. Despite the statistical significance of all explanatory variables in the multiple regressions, only two variables turn out to be economically significant. They are initial reported earnings and sector transitions.

Given the importance of sector transitions, both statistically and economically, we looked for the determinants of sector change for initially unemployed, initially informal, and initially formal individuals. Some statistically significant variables appeared, but they did such a poor job explaining the variance of sector transitions (R-squareds of around 1 per cent) that we have not pursued this line of inquiry further.

7 How can the data on growth, inequality, poverty, and mobility be reconciled?

In this section, we look at Argentina for the period 2001–2002. That year was chosen because it was a time of dramatic economic change. The Argentine economy had a dreadful experience: GDP contracted by 13.9 per cent, capital markets crashed, inflation soared, and the peso lost two thirds of its value *vis-à-vis* the dollar, to which it previously had been pegged. The 2001–2002 period was also the year in which income inequality in Argentina increased the most, the Gini coefficient rising from 0.53 to 0.58.

Notwithstanding the rising inequality that took place in that year, when workers were classified according to their quintile of initial reported earnings, the pattern of changes is found to be convergent as can be seen in Table 6.

Let us now show explicitly how rising inequality and convergent mobility are mutually compatible. A lengthier analysis may be found in a companion paper (Fields and Sánchez Puerta, 2007).

The difference between the various quintiles' earnings changes, though large (770 pesos difference between the top and bottom quintile, for example), are smaller than the distribution of earnings changes, 96 per cent of which fell within the range -1000 pesos to +1000 pesos. To quantify the relative importance of these two effects, we performed supplementary calculations which reveal that in that year, only 3 per cent of the variance of the earnings changes was accounted for by convergence to the grand mean, whereas 97 per cent was accounted for by the inequality of earnings changes.[14]

Figure 4 displays the distribution of earnings changes for the full sample along with the mean changes for each of the five quintiles. This figure shows in another way that it is the large variance in individual earnings changes from one year to the next – some low income individuals moving way up in the earnings distribution and some high income individuals moving way down in the distribution – that reconciles rising inequality and convergent mobility.

Another issue that can be examined is the role of unemployment. During the 2001–2002 crisis in Argentina, the unemployment rate increased from 16.4 per cent to 21.5 per cent, which caused the number of individuals earning zero pesos to rise. Of course, a worker who became unemployed started with positive earnings and ended with zero earnings, thus experiencing a, possibly quite large, earnings loss. The percentages of those who started out employed and who became unemployed were, from lowest initial earnings quintile to highest, 18 per cent, 17 per cent, 9 per cent, 6 per cent, and 5 per cent respectively. These figures on transitions into unemployment show that while

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14 Fields et al. (2007) derive the following decomposition: $100\% = \frac{v(\Delta y)}{\Delta v(y)} + \frac{2\beta}{\%\Delta v(y)}$, where $v(\Delta y)$ is the variance of income changes, $\Delta v(y)$ is the change in the variance, β is the regression coefficient when income change is regressed on initial income, and $\%\Delta v(y)$ is the percentage change in the variance. The term $\frac{v(\Delta y)}{\Delta v(y)}$ in this decomposition tells us what share of the change in inequality is due to the inequality of income changes; the term $\frac{2\beta}{\%\Delta v(y)} \equiv s_m$ tells us what share of the change in inequality is due to divergence from or convergence to the grand mean. It is s_m that is found to equal 3 per cent in 2001–2002.

becoming unemployed was something of a factor in contributing to convergent mobility, it was only a small factor: 84 per cent of those who were employed in 2001 were also employed in 2002. Thus, the majority of earnings changes were for individuals who were employed both in 2001 and in 2002.

The group of individuals who were employed at the time of both the 2001 and 2002 surveys consists of two types of workers: those who remained in the same job from 2001 to 2002 and those who changed jobs from one year to the next but who were employed at the time of both surveys. Unfortunately, it is not possible in the Argentine data set to distinguish between the two. It can be hypothesized that strong trade unions and a powerful civil service might have maintained the earnings levels of their members and that consequently the earnings changes for those who remained employed would have been small, with the bulk of the earnings losses taking place among those who became unemployed in between surveys. However, the evidence shown in Table 7 gives no support for this view. We see that among those who were employed in both 2001and 2002, the same convergent mobility pattern that was discovered for the full sample of workers is found again.

The last column in Table 7 also shows that most of the average change comes about because of widespread earnings losses and not because of earnings losses that were concentrated among a small number of job losers.

Space does not permit a fuller analysis of the compatibility between rising inequality and convergent mobility. The interested reader is referred to Fields and Sánchez Puerta (2007) for additional analysis.

8 Conclusions

In this paper, we have asked who gained the most when the Argentine economy grew, who lost the most when the economy contracted, and whether those who started richer were getting richer in positive growth periods and losing more in negative growth periods than those who started poorer. This study used panel data following the same people over time to test two hypotheses. The 'divergence of earnings' hypothesis held that in any given year, the highest earning individuals are those who experience the largest earnings gains or the smallest earnings losses in pesos. The 'symmetry of gains and losses' hypothesis held that those groups that gained the most in pesos when the economy grew are those that lost the most in pesos when the economy contracted.

We performed unconditional and conditional tests for the years 1996–1997 to 2002–2003 in urban Argentina, considering women and men aged 25–60 who participated in the labour market in both periods of the panel. The unconditional divergence hypothesis is always rejected. Rather, for reported earnings, statistically significant *convergence* is found in every year, and for other indicators, the relationship is either one of unconditional convergence or statistical insignificance. We find that when the differences between groups are significant, those groups that earn the most in the base year are those that experience the smallest earnings gains or largest earnings losses. The statistically significant convergent pattern holds regardless of whether economy wide inequality, gauged by Lorenz curves and Gini coefficients, was rising, remaining the same, or falling. These results hold up to a number of robustness tests, including the use of medians in place of means and the use of predicted earnings in place of initial reported earnings.

As for the symmetry of mobility hypotheses, the results offer *no support* for either the unconditional or the conditional version. The *unconditional* analyses of mean and median earnings changes show a strong structural pattern when both mean and median earnings changes are used – that is, those who gain the most when the economy is growing are also those who gain the most (or lose the least) when it is contracting. In no case do those who gain the most when the economy is growing lose the most when the economy is contracting. In short, the unconditional symmetry hypothesis does not hold for Argentina. *Conditional* symmetry receives no support either. In the conditional case, the general result is that the patterns are also structural, i.e., other things equal, those individuals who started poor are getting ahead faster and converging to their conditional mean. Gender, age, education, sector transitions, and region are also structural. These unconditional and conditional results for the full sample are robust to a number of alternative specifications: using median regression in place of mean regression, using just the individuals employed in both periods, and analysing informal and formal workers separately.

In both the unconditional and conditional analysis, the variables that are both statistically and economically significant determinants of earnings change are initial earnings and sector transition; the variables that are mostly statistically significant but economically insignificant are gender, age, and education; and the variable that is mostly statistically insignificant and always economically insignificant is geographic region.

In conclusion, the panel data analysis performed in this paper presents a picture of economic growth that is much more pro-poor than what one gets from cross sectional inequality comparisons. The pattern of income changes in pesos has been found to be consistently convergent or insignificantly different from uniform, never divergent. Thus, those panel people who started out with low earnings experienced changes *at least as high in pesos* as the ones experienced by those who started out higher in the earnings distribution. Furthermore, in times of economic growth, the changes in pesos for low earners are *even larger in proportionate terms* than for others. On the other hand, cross section analysis shows that inequality is trending upward in Argentina, e.g., those anonymous individuals at the upper end of the earnings distribution gained at least as much in percentage terms, and therefore much more in pesos, than those at the lower end of the earnings distribution.

These two sets of results (increasing inequality and convergent mobility) seem contradictory but they are not. It is the large variance in individual changes from one year to the next – some low income individuals moving way up in an earnings distribution that is often becoming more unequal and some high income individuals moving way down in the distribution – that reconciles the mobility and inequality results.

Overall, we have found that much can be learned by analysing panel data, knowledge that would not have been obtained by analysing comparable cross sections. In the future, researchers would do well to perform both panel data analysis and cross section analysis. Both types of analysis are meaningful, they are, however, different from one another.

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Table 1: Gini coefficient of labour earnings inequality by year

Year	Gini Coefficient
1996	0.4908
1997	0.4808
1998	0.5014
1999	0.5008
2000	0.5176
2001	0.5246
2002	0.5806
2003	0.5296

Note: These are the Gini coefficients of labour market earnings for panel individuals aged 25–60 when they are observed in the second year, with the exception of year 1996 when they are observed in the first year.

Source: Authors' calculations.

Table 2

Unweighted Reported Earnings Changes by Initial Position
Dependent Variable: Change in Reported Earnings

	1996-1997			1997-1998			1998-1999			1999-2000			2000-2001			2001-2002			2002-2003		
	Growth Rate +8.1			Growth Rate +6.9			Growth Rate -4.9			Growth Rate -0.4			Growth Rate -0.2			Growth Rate -13.5			Growth Rate +7.7		
	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.
Total Population	2.0	496.7	8130	21.1	570.7	8889	-18.6	577.7	7777	-23.1	531.5	7818	-23.5	542.3	7396	-154.8	501.2	7935	-19.7	386.4	5402
By Initial Reported Quintile	H_{02}: ***			H_{02}: ***			H_{02}: ***			H_{02}: ***			H_{02}: ***			H_{02}: ***			H_{02}: ***		
Lowest Quintile	207.2	494.7	1840	264.9	501.7	1796	243.4	479.2	1560	249.3	536.3	1656	238.1	552.8	1502	163.6	410.4	1614	216.8	401.0	1241
Quintile 2	22.2	207.6	1487	33.3	207.0	1963	20.8	200.2	1643	2.2	184.8	1480	2.7	183.4	1619	-65.5	139.3	1807	28.2	204.5	956
Quintile 3	7.7	262.5	1663	13.8	301.1	1807	-18.1	238.1	1646	-18.4	232.4	1804	-23.8	196.4	1318	-126.9	204.1	1778	-31.4	165.6	1220
Quintile 4	-25.4	376.0	1521	-39.1	368.0	1581	-36.1	345.7	1435	-61.2	322.0	1348	-49.4	315.0	1688	-213.7	287.7	1300	-72.2	212.1	1022
Highest Quintile	-230.1	784.4	1619	-181.8	1016.0	1742	-319.7	1055.3	1493	-314.2	882.0	1530	-331.7	980.0	1269	-606.3	846.3	1436	-301.3	591.7	963
By Predicted Quintile	H_{02}:			H_{02}:			H_{02}:			H_{02}: ***			H_{02}: *			H_{02}: ***			H_{02}: ***		
Quintile 1	-1.2	212.9	1627	21.3	254.0	1779	-5.1	218.5	1570	-4.0	202.3	1567	-6.6	206.2	1481	-83.5	234.5	1589	4.0	165.8	1108
Quintile 2	3.3	325.8	1646	18.6	325.2	1783	-22.1	356.7	1541	-3.9	308.9	1561	-10.4	434.8	1479	-110.5	310.2	1597	3.2	236.3	1055
Quintile 3	6.4	384.4	1611	12.8	350.2	1781	-12.4	355.3	1577	-19.5	346.0	1569	-15.3	348.6	1482	-135.6	386.5	1575	-18.0	249.9	1084
Quintile 4	8.1	500.2	1639	6.5	556.6	1769	-15.0	563.7	1536	-6.0	472.6	1558	-57.6	550.3	1475	-174.4	463.1	1587	-25.5	355.4	1075
Quintile 5	-6.9	831.1	1607	46.1	1013.5	1777	-38.8	1027.0	1553	-82.0	964.5	1563	-27.6	902.3	1479	-270.3	848.9	1587	-62.0	688.0	1080
By Gender	H_{02}: *			H_{02}:			H_{02}: ***			H_{02}: ***			H_{02}: *			H_{02}: ***			H_{02}:		
Men	-0.8	574.0	5012	18.6	662.1	5609	-29.8	661.7	4891	-34.2	585.6	4929	-32.5	583.4	4563	-176.3	568.0	4898	-20.0	447.4	3350
Women	6.3	337.3	3118	25.4	364.8	3280	0.2	396.3	2886	-4.1	423.1	2889	-9.0	468.2	2833	-120.2	366.0	3037	-19.1	257.5	2052
By Age	H_{02}: *			H_{02}:			H_{02}: **			H_{02}: **			H_{02}: **			H_{02}: ***			H_{02}: ***		
25-36 yrs	2.3	397.5	3415	25.8	427.4	3540	0.2	424.7	3019	-7.9	434.3	3039	-8.8	437.5	2869	-140.5	426.7	3035	-5.8	316.3	2042
37-48 yrs	-4.5	482.9	3200	28.2	643.8	3559	-24.1	688.6	3071	-35.7	575.4	3094	-32.5	502.3	2846	-159.8	505.5	3066	-30.7	389.7	2150
49-60 yrs	15.0	689.4	1515	-2.3	657.1	1790	-42.4	593.2	1687	-27.4	601.9	1685	-33.2	734.7	1681	-170.1	598.2	1834	-23.3	477.0	1210
By Education Level	H_{02}:			H_{02}: *			H_{02}:			H_{02}: ***			H_{02}:			H_{02}: ***			H_{02}: ***		
Primary or less	2.1	354.7	2829	7.1	327.7	3002	-25.3	306.1	2430	-17.3	284.2	2730	-15.9	349.3	2316	-102.7	274.9	2289	9.0	221.4	1523
Secondary	53.4	547.8	3026	-9.8	599.8	3032	-17.9	466.5	2498	-4.8	405.4	3016	-18.6	500.8	2484	-147.9	431.9	2713	-5.8	270.1	1898
Higher	70.1	939.9	1804	92.2	1052.9	1986	21.1	917.0	1744	-57.2	848.0	2072	0.4	789.7	1686	-229.6	717.8	1952	-49.1	850.1	1280
By Sector Transition	H_{02}: ***			H_{02}: ***			H_{02}: ***			H_{02}: ***			H_{02}: ***			H_{02}: ***			H_{02}: ***		
Unemployed to Informal	317.0	324.2	451	316.5	304.1	437	302.5	331.7	293	259.2	221.8	326	228.7	217.2	346	161.4	165.0	300	162.3	131.4	469
Unemployed to Formal	486.4	498.6	115	611.3	681.1	101	490.6	408.8	77	522.7	665.0	85	400.9	326.8	69	331.3	314.0	68	307.6	250.7	75
Informal to Formal	21.4	441.7	699	56.8	592.0	720	5.9	696.8	801	-34.8	605.4	676	-3.1	660.9	616	-136.5	518.8	539	-36.9	321.9	453
Informal to Informal	19.1	413.7	1904	21.3	520.8	3076	-20.5	442.7	2696	-4.5	449.6	2536	-26.8	430.3	2510	-119.6	417.9	2549	-4.4	260.0	1855
Informal to Unemployed	-336.2	388.0	231	-318.2	329.1	288	-358.0	530.8	312	-332.2	347.3	386	-260.7	236.8	370	-297.3	383.5	559	-200.3	211.5	164
Formal to Formal	-28.5	518.7	3448	14.3	648.1	3032	-8.5	661.1	2558	-9.4	601.9	2770	-16.3	615.4	2579	-182.7	564.0	2603	-57.3	531.9	1698
Formal to Informal	23.4	635.1	785	-5.5	529.2	857	-60.1	651.1	734	-70.4	534.6	621	0.4	750.4	520	-226.1	642.4	689	-50.5	444.0	373
Formal to Unemployed	-584.4	569.1	131	-565.0	507.9	117	-497.1	341.5	87	-574.7	530.9	133	-575.1	518.3	127	-620.1	614.9	199	-476.5	475.7	66
By Region	H_{02}: ***			H_{02}:			H_{02}:			H_{02}:			H_{02}:			H_{02}:			H_{02}:		
GBA	60.6	692.7	973	21.0	756.7	971	1.1	546.0	1204	-27.4	515.1	1403	-3.5	508.9	1318	-149.7	465.2	1350	-22.4	578.2	746
Pampeana	1.0	452.3	2436	27.6	612.2	3246	-19.0	617.6	2522	-3.2	560.8	2381	-24.5	590.3	2269	-168.1	499.2	2448	-21.5	320.5	1686
Patagonica	-15.8	545.6	1067	17.7	447.4	957	9.6	504.5	970	-45.4	566.0	897	-28.9	448.6	853	-170.1	595.7	995	-28.7	317.6	705
Noreste	-9.6	498.6	1289	13.1	523.7	933	-44.9	538.8	864	-23.5	493.4	969	-31.1	586.6	830	-134.3	449.3	874	-28.7	401.4	661
Noroeste	6.4	397.3	1312	4.6	424.0	1593	-19.7	560.4	1338	-34.5	476.9	1324	-23.0	462.6	1323	-152.5	521.3	1506	-12.5	397.4	1040
Cuyo	-23.5	427.0	1053	34.6	572.5	1189	-48.3	636.4	879	-29.8	558.4	844	-40.6	614.4	803	-129.2	446.2	762	-1.7	274.5	564

***, **, * H_{02} rejected at 99, 95, 90% of significance

H_{02} : equality of means by groups

Table 3
OLS Regressions, Year by Year
Dependent Variable: Change in Reported Earnings

	Positive Growth Years			Negative Growth Years			
	1996-97	**1997-98**	**2002-03**	**1998-99**	**1999-2000**	**2000-01**	**2001-02**
Initial Reported Earnings	-0.35	-0.35	-0.53	-0.49	-0.45	-0.52	-0.55
	[0.04]***	[0.05]***	[0.04]***	[0.06]***	[0.04]***	[0.05]***	[0.03]***
Male	83.21	86.87	66.01	104.97	68.88	87.52	55.6
	[11.24]***	[12.90]***	[10.06]***	[13.67]***	[12.41]***	[14.14]***	[8.95]***
Age	H_{02}: ***	H_{02}: ***	H_{02}: ***	H_{02}: ***	H_{02}: ***	H_{02}: ***	H_{02}: ***
Linear	17.87	18.28	7.91	21.74	12.44	11.32	8.85
	[5.02]***	[5.41]***	[3.97]**	[4.85]***	[4.55]***	[6.57]*	[4.20]**
Squared	-0.18	-0.2	-0.06	-0.23	-0.12	-0.1	-0.08
	[0.06]***	[0.07]***	[0.05]	[0.06]***	[0.05]**	[0.08]	[0.05]
Years of Education	H_{02}: ***	H_{02}: ***	H_{02}: ***	H_{02}: ***	H_{02}: ***	H_{02}: ***	H_{02}: ***
Linear	2.9	-19.28	-10.65	-22.83	-1	-25.94	-14.17
	[5.05]	[6.19]***	[5.26]**	[5.78]***	[5.43]	[5.75]***	[4.16]***
Squared	0.79	1.99	1.24	2.27	0.87	2.39	1.37
	[0.30]***	[0.36]***	[0.33]***	[0.34]***	[0.31]***	[0.34]***	[0.24]***
Sector Transition	H_{02}: ***	H_{02}: ***	H_{02}: ***	H_{02}: ***	H_{02}: ***	H_{02}: ***	H_{02}: ***
Unemployed- Unemployed	omitted	omitted	omitted	omitted	omitted	omitted	omitted
Unemployed- Informal	323.24	323.83	184.62	319.1	271.04	249.74	169.66
	[15.39]***	[15.53]***	[8.15]***	[19.45]***	[12.94]***	[13.30]***	[9.79]***
Unemployed- Formal	439.73	526.52	265.28	416.43	484.33	337.7	279.32
	[45.20]***	[64.28]***	[31.70]***	[46.03]***	[70.71]***	[38.46]***	[39.06]***
Informal- Unemployed	-227.15	-193.93	-75.84	-170.38	-166.94	-109.37	-127.53
	[21.80]***	[23.23]***	[15.15]***	[26.84]***	[19.82]***	[16.78]***	[12.93]***
Informal- Informal	204.92	201.11	168.79	214.72	207.76	220.24	132.89
	[19.65]***	[27.58]***	[15.49]***	[28.00]***	[21.01]***	[23.28]***	[16.88]***
Informal- Formal	203.1	218.14	189.53	293.12	235.59	283.96	183.84
	[22.89]***	[34.65]***	[22.27]***	[37.84]***	[29.62]***	[32.78]***	[24.93]***
Formal- Unemployed	-399.27	-431.94	-258.35	-294.98	-357.31	-321.99	-316.21
	[38.65]***	[44.01]***	[36.50]***	[33.95]***	[35.38]***	[36.01]***	[26.99]***
Formal- Informal	222.29	176.02	174.61	232.5	195.43	284.42	138.57
	[29.75]***	[36.81]***	[26.70]***	[39.10]***	[31.05]***	[42.47]***	[27.79]***
Formal- Formal	195.37	212.82	202.89	315.8	299.96	309.79	198.78
	[22.17]***	[31.22]***	[20.81]***	[35.11]***	[27.68]***	[29.65]***	[20.27]***
Region	H_{02}: ***	H_{02}: **	H_{02}:	H_{02}: ***	H_{02}:	H_{02}: ***	H_{02}:
Greater Buenos Aires	omitted	omitted	omitted	omitted	omitted	omitted	omitted
Pampeana	-102.81	-31.68	-22.72	-74.79	-1.4	-56.64	-25.45
	[22.14]***	[24.50]	[17.47]	[20.53]***	[15.63]	[15.68]***	[12.19]**
Patagonica	-87.34	-37.05	-15.3	-69.04	-14.79	-31.73	-10.97
	[24.69]***	[24.42]	[18.38]	[20.92]***	[19.21]	[17.69]*	[16.17]
Noreste	-93.79	-56.75	-18.67	-77.79	-19.75	-50.18	3.17
	[23.25]***	[26.12]**	[19.93]	[20.55]***	[16.86]	[19.66]**	[16.69]
Noroeste	-90.61	-48.84	-18.27	-59.21	-24.62	-54.03	-18.85
	[22.53]***	[22.95]**	[19.33]	[19.41]***	[16.60]	[16.01]***	[13.63]
Cuyo	-103.36	-10.24	-3.78	-91.93	-5.36	-58.94	-3.83
	[22.87]***	[25.55]	[19.59]	[22.41]***	[19.93]	[23.06]**	[15.66]
Constant	-461.63	-427.82	-261.63	-491.91	-392.13	-287.53	-235.65
	[100.56]***	[113.98]***	[82.48]***	[102.92]***	[99.05]***	[132.11]**	[86.68]***
Number of Observations	8130	8889	5402	7777	7818	7396	7935
R^2	0.24	0.17	0.35	0.32	0.3	0.37	0.47

***, **, * H_{0j} rejected at 99, 95, 90% of significance H_{02} : equality of coefficients by groups

Table 4
Signs and Tests of Statistical Significance
Dependent Variable: Change in Reported Earnings

Explanatory Variable	Positive Growth				Negative Growth			
	Unconditional		Conditional		Unconditional		Conditional	
Initial Reported Earnings	-	***	-	***	-	***	-	***
Male	-		+	***	-	***	+	***
Years of Education	-		-	***	+	***	-	***
Years of Education Sq	+		+	***	-	***	+	***
Age	-		+	***	-	***	+	***
Age Sq	+		-	***	+	***	-	***
Sector Transition	started informal > started formal		ended formal > ended informal	***	started informal > started formal	***	ended formal > ended informal	***
Region	GBA > others		GBA > others	***	GBA > others		GBA > others	***

***, **, * H_{0j} rejected at 99, 95, 90% of significance

Table 5
Tests of Economic Significance
Dependent Variable: Change in Reported Earnings

Explanatory Variable	Positive Growth		Negative Growth	
	R^2 in Unconditional Analysis	Factor Ineq Weight in Conditional Analysis	R^2 in Unconditional Analysis	Factor Ineq Weight in Conditional Analysis
Initial Reported Earnings	0.13	0.16	0.27	0.33
Male	0	0	0	0
Years of Education and its Square	0	0	0	0
Age & Age Sq	0	0	0	0
Sector Transition	0.06	0.04	0.05	0.04
Region	0	0	0	0
Total		0.20		0.37

Table 6: Earnings changes in pesos for the full sample, 2001–2002

Initial earnings quintile (Quintile 1 = lowest)	Mean earnings change of those who started in that quintile
Quintile 1	164
Quintile 2	-65
Quintile 3	-127
Quintile 4	-214
Quintile 5	-606

Table 7: Earnings changes in pesos for those individuals who were employed in both years, 2001–2002

Initial earnings quintile (Quintile 1 = Lowest)	Mean (median) earnings change of those who started in that quintile	Percentage of negative earnings changes for those who started in that quintile
Quintile 1	300 (69)	55 per cent
Quintile 2	-35(-39)	76 per cent
Quintile 3	-97 (-78)	82 per cent
Quintile 4	-187 (-167)	86 per cent
Quintile 5	-564 (-409)	89 per cent

Figure 1

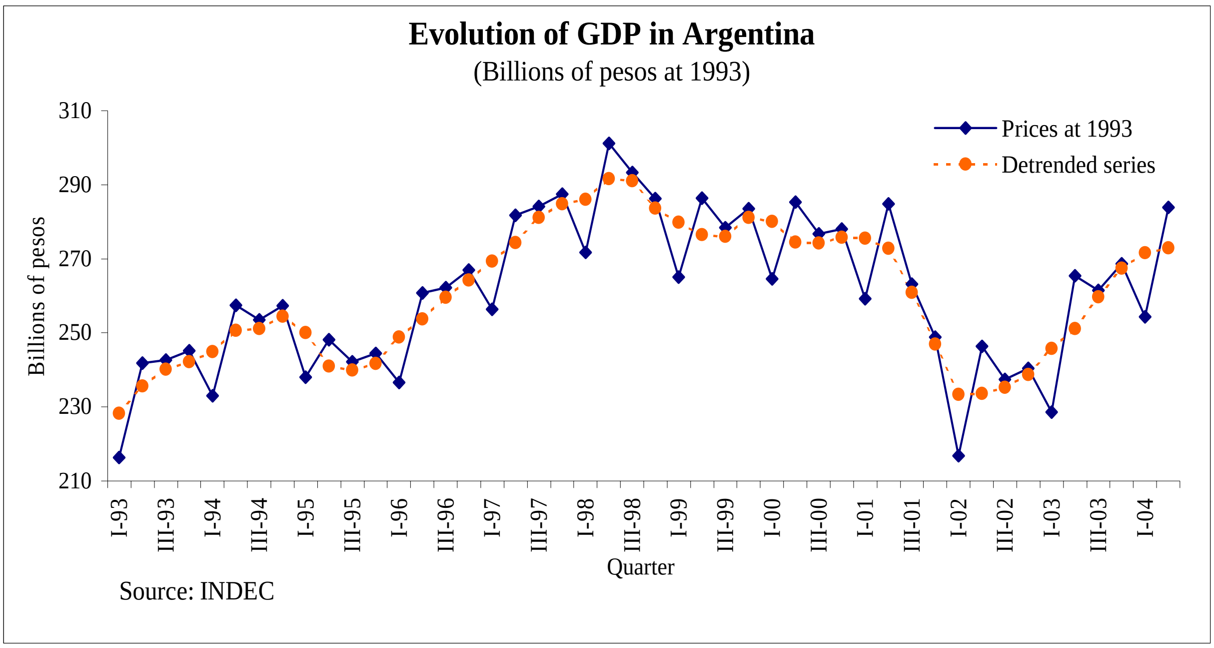
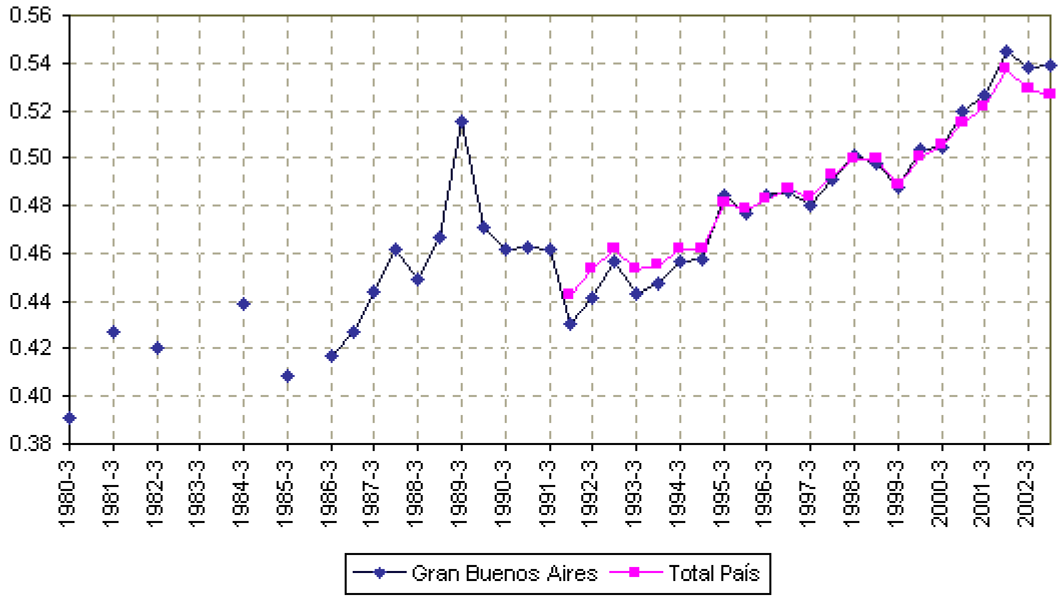
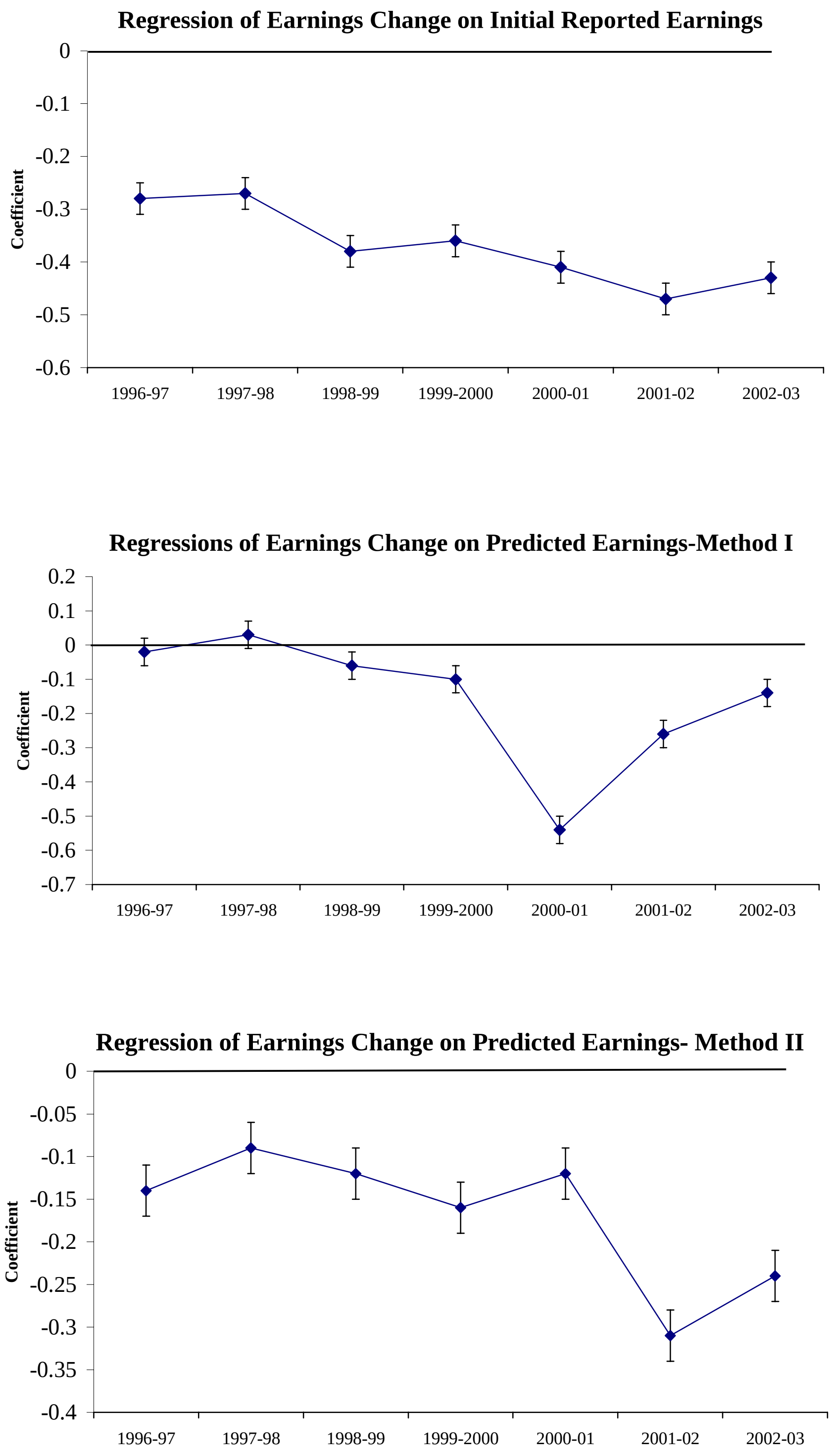


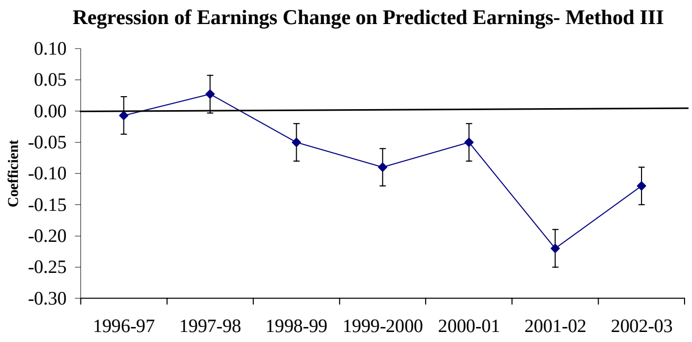
Figure 2: Gini coefficient of household per capita income

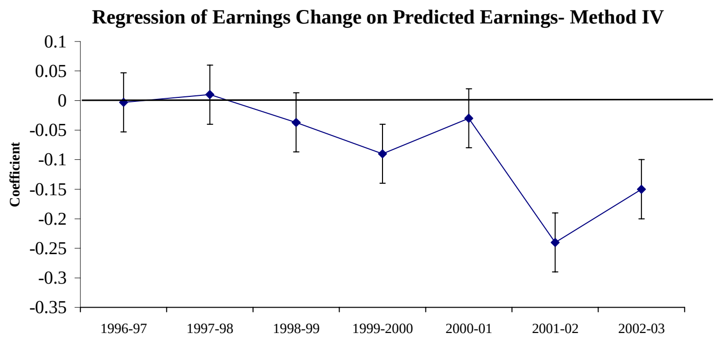


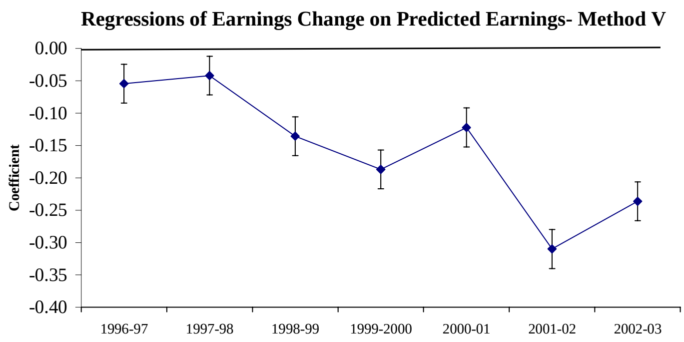
Source CEDLAS (2004)

Figure 3: Regression coefficient for each panel:
earnings change as a function of initial earnings




Regression of Earnings Change on Predicted Earnings- Method III
Coefficient
0.10
0.05
0.00
-0.05
-0.10
-0.15
-0.20
-0.25
-0.30
1996-97
1997-98
1998-99
1999-2000
2000-01
2001-02
2002-03


Regression of Earnings Change on Predicted Earnings- Method IV
Coefficient
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
-0.35
1996-97
1997-98
1998-99
1999-2000
2000-01
2001-02
2002-03


Regressions of Earnings Change on Predicted Earnings- Method V
Coefficient
0.00
-0.05
-0.10
-0.15
-0.20
-0.25
-0.30
-0.35
-0.40
1996-97
1997-98
1998-99
1999-2000
2000-01
2001-02
2002-03

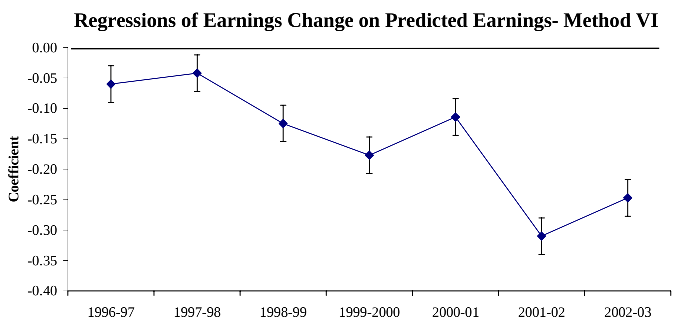

Regressions of Earnings Change on Predicted Earnings- Method VI
Coefficient
0.00
-0.05
-0.10
-0.15
-0.20
-0.25
-0.30
-0.35
-0.40
1996-97
1997-98
1998-99
1999-2000
2000-01
2001-02
2002-03

Figure 4: Distribution of earnings changes between -1000 and +1000 Pesos,

overall, with quintile-specific means displayed, 2001–2002