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. Various considerations led us to expect that mobility would be divergent – that is, that the individuals who started with the highest initial earnings would enjoy the largest earnings gains in pesos. Contrary to expectations and for a wide range of specifications, mobility is found to be mostly convergent, sometimes neutral, and never divergent. We then demonstrate how generally rising inequality and convergent mobility can be reconciled. Thus, 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.

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

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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 U.S. dollar and excessive borrowing led to an unsustainable fiscal situation and, ultimately, to the collapse of the economy at the end of 2001. Gross Domestic Product fell by 13.5 percent in one year, and the share of the population in poverty reached 58 percent in October 2002 as compared with 38 percent a year earlier. The economy then recovered and has grown consistently since.[1]

This paper addresses earnings mobility in urban Argentina from 1996 to 2003.[2] 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 labor 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 individuals and households *cross sectionally*: those in the poorest 20% 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. As has been noted in our own previous work (Fields *et al*, 2003; Fields *et al*., 2005) as well as in a recent paper by Grimm (2007), the panel results and the cross section results may convey quite different qualitative impressions from one another.

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[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 questions asked, theoretical foundations, data description, and methods used. Section 4 presents our empirical results on mobility patterns, while Section 5 details how the data on inequality and mobility can be reconciled. Section 6 concludes.

2. Literature Review

A. International Literature

In the literature on economic growth and income distribution, the great bulk of the research has been based on data from comparable cross sections. The same is true for Latin America in general (IDB, 1999, 2004; Lustig and Székely, 1999; De Ferranti *et al.*, 2004; Bourguignon, Ferreira, and Lustig, 2004) and Argentina in particular (Gasparini, 2004; Sánchez Puerta, 2005).

Inequality in Argentina has been rising, sometimes slowly and sometimes rapidly, over a long period of time. The evolution of inequality of household per capita incomes since 1980 is displayed in Figure 2.

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. And second, while rising inequality indicates that the dispersion of income has widened, it 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 experience larger earnings changes in pesos on average than the initially non-poor, even as the distribution of income grows more unequal. Mobility analysis using panel data is required to determine which people, when followed over time, are getting richer at faster rates than others.

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 labor market earnings of an individual, and the dependent variable in our analysis is the one-year change in labor market earnings for each individual.[3] The explanatory variables used here include base-year earnings 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, macro-mobility is like macro-growth (how much economic growth an economy has in aggregate), macro-unemployment (how much unemployment an economy has in aggregate), macro-inequality (how much inequality an economy has in aggregate), and macro-poverty (how much poverty an economy has in aggregate.) This paper belongs to the micromobility category.

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' labor 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 (2008).

B. Mobility Studies for Argentina

Given the availability of panel data for Argentina going back to the mid-nineties, it is not surprising that economic mobility is receiving considerable attention from

[3] Other measures of economic well-being in the literature 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.

researchers. The highlights of previous micromobility studies for Argentina are briefly reviewed here.[5]

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 labor market response to the crisis. He studied changes in nominal wages, entry into and exit from the workforce, hours worked, household labor 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 were for males, for managers, and for those who changed jobs. Females in Cuyo did better than before, while females with tertiary education did worse. Along similar lines, Corbacho, Garcia-Escribano, and Inchauste (2003) used panel data from Argentina for the years 1999 to 2002 to analyze the determinants of changes in household income. 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. They concluded that shocks affect different types of people over time. No special attention was given to the different patterns in positive growth and negative growth periods.

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[5] Studies of macromobility in Argentina include Wodon (2001), Gutiérrez (2004), and Inter-American Development Bank (2004).

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, Sánchez Puerta, Duval, and Freije (2005)). Other than that, the question of how earnings dynamics compare in positive growth and negative growth years has not been analyzed in any developing country.

3. Questions, Theoretical Foundations, Data, and Methods

A. Questions

Two principal questions are asked in this paper. First, for each of seven one-year-long panels, which individuals experienced the largest earnings gains in pesos and which the smallest? In particular, was mobility divergent, in that the largest earnings gains in pesos went to those who were initially better-off? And second, are the types of individuals that gained the most in times of economic growth the same as the types that gained the most in times of stagnation or recession?

B. Theoretical Foundations

Four theoretical ideas inspire this research. 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 labor 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 (1976, p. 155) as "self-reinforcing influences which help to sustain the good fortune of the fortunate and the bad fortune of the unfortunate."

A fourth factor operates in the opposite direction. According to the model proposed by Galton (1889), those who start above the grand mean in terms of height tend to converge downward relatively, while those who start below the grand mean tend to converge upward relatively. Galton's ideas were put into an economic context by Zimmerman (1992) and Solon (1992). Following on this line of reasoning, those who have the highest incomes or earnings to start with would be the ones who are observed to gain the least when growth is positive and lose the most when growth is negative.

C. Data

The data for our empirical work come from the Encuesta Permanente de Hogares (EPH), an urban household labor force survey conducted by Argentina's National Statistical Agency, INDEC. During the period analyzed in this paper, 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% of urban areas. Since 87% of Argentines live in urban areas, the sample of the EPH represents around 62 percent of the total population of the country.

For this paper, we construct panels starting with May of one year and ending with May of the next year to avoid capturing changes in earnings due to seasonality. The panels cover periods ranging from very positive growth (+8.1% in 1997-1998) to very negative growth (-13.5% in 2001-2002).

Sampling weights are provided in the survey, but for technical reasons we chose not to use them for the results presented here.[7] Though non-random attrition could in principle be a concern, 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). Furthermore, results with weighted data were found not to alter the central conclusions of the paper.

In the empirical work that follows, the dependent variable is the individual's change in labor market earnings in pesos. The reason for the choice of change in earnings as the variable of interest rather than change in total income 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 labor earnings in explaining changes in total incomes points to the importance of understanding earnings dynamics and employment transitions

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

[7] 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.

more fully. Therefore, the focus of this paper is on analyzing the way in which labor markets distribute rewards.

The unit of analysis for our labor market study is the individual. Our sample consists of individuals in the labor 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 labor market fluctuations due to first-time entries to the labor 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.[8] Nominal earnings are deflated by the April Consumer Price Indices for Greater Buenos Aires to obtain real earnings.[9] 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.[10]

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

[8] The Argentine peso was pegged to equal one U.S. dollar in that year.

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

[10] The methods for predicting initial earnings are described below.

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 this paper, the formal sector consists of 1) workers who have all legislated benefits (pension, paid vacation, etc.), 2) employers in firms with more than five employees, and 3) self-employed workers 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.

D. Methods

Several methods are used to answer our two questions. We start with mobility profiles, which 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 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.

The traditional way of analyzing unconditional mobility is by regressing changes in earnings on initial reported earnings y_0. However, there might be a problem of measurement error with reported earnings. To deal with this possibility, in this study, earnings are also predicted, 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 following six different prediction methods are used. 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 to the previous list of regressors, dichotomous variables for individuals' sector in the base year: informal, formal, or unemployed.

Method 3 abandons the linear structure used so far in doing the predictions, and instead it 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. 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.

4. Empirical Results on Mobility Patterns [11]

This section reports our findings on the question of which individuals experience the largest earnings changes in pesos. Mobility is divergent if, in any given year, those who started in better economic positions gain more or lose less than those who started lower in the income distribution. Specifically, we ask: (1) When, if at all, is mobility divergent? (2) How, if at all, is divergent mobility related to the rate of growth of the economy?

A. Initial Reported Earnings

Starting with initial reported earnings, divergence is decisively rejected, both when initial reported earnings are entered in quintiles (top block of 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 earning gains. Please note that, in growth years, the gains of the poor are largest *in pesos*, which means of course that their *percentage* gains are even larger than the percentage gains of those higher in the earnings distribution.

To test the robustness of the conclusion that the pattern of earnings changes is convergent when initial reported earnings are used as the measure of economic position, we used median earnings changes in place of mean earnings changes. Statistically significant convergence was also found for every year.

[11] 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.

B. Predicted Earnings

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 *convergent* and never divergent. 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. Unlike the results for reported earnings, the results for predicted earnings are sometimes statistically insignificant. Note well the implication of insignificance: workers at different points in the income distribution experience earnings changes in pesos that are *the same as one another in pesos.* Such a pattern of earnings changes is termed "neutral."

C. Analysis for Different Groups

The next robustness test concerns divergence for different groups. We ask, in any given year, are those groups that earn the most the ones that experience the largest earnings gains or the smallest earnings losses in pesos? In every year, the groups of high earners are men, middle-aged workers, the better-educated, formal sector workers, and workers in Greater Buenos Aires.

The simple answer to our question is, no – the high-earning groups did *not* register better earnings changes. We find in Table 2 that when statistically significant:

Men's earnings changes are worse than women's. (Divergent mobility rejected for gender)

Middle-aged and older workers' earnings changes are worse than those of younger workers. (Divergent mobility rejected for age)

Most of the time, those with higher education have the most negative earnings changes. (Divergent mobility rejected for education)

Most of the time, workers who started formal have significantly worse earnings changes than workers who started informal. (Divergent mobility rejected for formal/informal)

Moreover, regional differences are statistically insignificant in six out of the seven panels. (Divergent mobility rejected for region)

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

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

D. Further Robustness Checks

Four additional 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 analyzed the subsample of employed workers, leaving aside the unemployed. And fourth, we analyzed formal sector workers and informal sector workers separately.

For all of these tests, the results were the same. Mobility was found to be mostly convergent, sometimes neutral, but never divergent.

5. How Can the Data on Inequality and Mobility Be Reconciled?

We have seen that Argentina has experienced considerable macroeconomic instability coupled with generally rising relative income inequality. Table 1 displays our calculations of the Gini coefficients of individual earnings for our sample years. We see that although relative inequality was generally rising, in some years, the change in inequality was small or negligible.

In this section, we look in detail 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%, 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 relative earnings inequality in Argentina increased the most, the Gini coefficient rising from 0.53 to 0.58. Yet, as we showed above, earnings changes in pesos between 2001 and 2002 were convergent for each of the methods used.

A. Cross-Sectional Changes versus Panel Changes

Let us now show explicitly how rising relative inequality and convergent mobility are mutually compatible. Column 3 of Table 3 displays the increasing relative inequality in another way. In this table, the data for the panel people are treated as comparable cross sections – that is, individuals are regarded as belonging to whichever quintile their earnings would place them in each of the two years. We see that while earnings fell in the cross section for every quintile, the percentage decline was greatest for the poorest quintile and got monotonically less negative for successively higher quintiles, which is precisely an increase in relative inequality.

Column 4 of Table 3 analyzes the same data exploiting the panel feature – that is, individuals are classified according to their initial earnings quintile regardless of the quintile in which they ended. When we do this, notwithstanding the rising relative inequality that took place in 2001-2002, the pattern of changes is found to be convergent: those who started in the lowest earnings quintile on average gained 164 pesos, those who started in the other quintiles lost, and as we move to higher and higher earnings quintiles the losses got greater and greater.

Comparing Columns 3 and 4 the patterns are completely opposite. Column 3 shows that the lowest earners did the worst, and Column 4 shows that the lowest earners did the best. Let us explore these patterns further.

B. Transition Matrix

Further examination shows that the opposing results in Section A come about because of the large numbers of people moving from one quintile to another. As shown in Table 4, 52.1% of panel people changed earnings quintiles between 2001 and 2002. More specifically, more than half of those who started in the lowest earnings quintile moved up to a higher quintile, while nearly one-third of those who started in the highest earnings quintile moved down to a lower quintile.

For a sample of nearly 8,000 persons, it is impossible to look at earnings changes of stayers and movers in detail. However, what does prove to be highly revealing is an analysis for a sub-sample of twenty-five individuals, to which we now turn.

C. Simulating the Rise in Relative Earnings Inequality

Let us now examine how the earnings changes for twenty-five illustrative individuals generate the rising inequality and convergent mobility patterns demonstrated above. These illustrative individuals are those at the fifth, twenty-fifth, fiftieth, seventy-fifth, and ninety-fifth percentiles of each of the five quintiles in 2001.

Our analysis begins by simulating the 2001 and 2002 earnings distributions for these twenty-five individuals.[12] First, for 2001, we calculate the Gini coefficient for these

[12] As we shall now show, the simulated Ginis turn out to be essentially identical to the actual ones.

twenty-five individuals and find it to be 0.52, virtually the same as the actual value of 0.53 shown in Table 1. The reason that we do not get exactly the same Gini is that the simulation is based on only twenty-five people rather than the full 7,934.

Second, we simulate the 2002 Gini as follows. We assign five people the earnings at the fifth, twenty-fifth, fiftieth, seventh-fifth, and ninety-fifth percentiles in the distribution of their initial quintile. We then assign these people the distributions of earnings changes at the first, twenty-fifth, fiftieth, seventy-fifth, and ninety-ninth percentiles of the earnings change distribution for their specific quintile, but in reverse order of magnitude, consistent with the convergent mobility patterns that we have encountered. For example, the earnings level at the fifth percentile in the distribution of the first quintile is matched with the earnings change at the ninety-ninth percentile in the distribution of the changes for that specific quintile. In the case of the first quintile, the initial earnings levels, the selected earnings changes, and the simulated 2002 earnings are, respectively:

Distribution of Earnings Level within Quintile 1	**2001 Earnings Level**
Fifth percentile of quintile 1	0
Twenty-fifth percentile of quintile 1	0
Fiftieth percentile of quintile 1	0
Seventy-fifth percentile of quintile 1	0
Ninety-fifth percentile of quintile 1	100

Distribution of Earnings Level within Quintile 1	**Earnings Change**
First percentile of quintile 1	-100
Twenty-fifth percentile of quintile 1	0
Fiftieth percentile of quintile 1	0
Seventy-fifth percentile of quintile1	169
Ninety-ninth percentile of quintile 1	2115

2002 Quintile 1	Simulated 2002 Earnings (earnings changes assigned in inverse order to earnings levels)
First simulated individual	0 + 2115 = 2115
Second simulated individual	0 + 169 = 169
Third simulated individual	0 + 0 = 0
Fourth simulated individual	0 + 0 = 0
Fifth simulated individual	100 - 100 = 0

The simulations for the other quintiles proceed analogously. (Note: Any simulated earnings level that was negative was converted to a zero.)

Once we obtain these twenty-five simulated earnings, we calculate the Gini coefficient of the simulated 2002 distribution. This Gini is found to be 0.58, which is the same as the actual Gini for 2002.

Putting these two results together, by using twenty-five individuals drawn from the actual Argentine earnings distribution for 2001 and twenty-five changes drawn from the actual distribution of earnings changes between 2001 and 2002, we have been able to reproduce both the rising earnings inequality that took place and the convergent pattern of earnings changes that also took place.

It bears mention that although this simulation is right on the mark, a simpler simulation would not have worked. If we had taken the mean earnings of each of the five initial quintiles and applied the mean change for members of the respective quintile, the resulting distribution of earnings would have been:

Quintile (Quintile 1 = Lowest)	Simulated 2002 Earnings Distribution Using the Simpler Simulation
Quintile 1	17 + 164 = 181
Quintile 2	229 – 65 = 164
Quintile 3	424 – 127 = 297
Quintile 4	669 – 214 = 455
Quintile 5	1561 – 606 = 955

The Gini coefficient of this simpler simulated distribution is 0.36, which is way too low compared to the actual 2002 value of 0.58. The primary reasons that this simpler simulation understates inequality are: 1) It does not generate earnings that are sufficiently high at the top end, because it fails to recognize the inequality of changes *within* the top earnings quintile, and 2) It does not generate zero earnings at the bottom end for those who became unemployed.

D. Additional Analysis for the Twenty-Five Person Sample

In contrast to the simulation just described in Section C, which combined the actual 2001 earnings levels for these twenty-five individuals with twenty-five simulated earnings changes, one can also examine the earnings levels and actual earnings changes for these twenty-five individuals using the panel feature of the data for 2001 and 2002. This additional examination proves to be quite insightful.

Figure 4 displays the earnings distributions in anonymous cross-sectional form, with the 2001 earnings levels for these twenty-five individuals displayed at the top of the graph and their 2002 earnings levels displayed at the bottom. Consistent with Argentina's economic collapse between 2001 and 2002, the 2002 distribution lies to the left of the 2001 distribution. In the cross-section, the individuals at the top of the earnings distribution suffered large earnings losses in pesos relative to the individuals at the bottom. However, because those at the top were so much richer to begin with, their percentage losses were less, which is what produces the rise in relative inequality from 2001 to 2002.

Figure 5 displays the earnings distributions in panel data form so that we can now identify who is who in the 2001 and 2002 distributions. There are a great many lines crossing each other, implying a large movement of individuals within the distribution. At the top end of the earnings distribution, the three individuals who were the richest of the twenty-five in 2001 remained the richest three in 2002, but they all got poorer. The fourth and fifth richest individuals also got poorer, and in fact, the fifth richest individual became (one of) the poorest by becoming unemployed. At the other end of the distribution, the three initially poorest individuals all remained in the lower part of the distribution, while the fourth and fifth initially poorest diverged, one becoming unemployed and one moving up and becoming one of the third richest in 2002. Together, then, the richest quintile among these twenty-five had large earnings losses while the poorest quintile among these twenty-five had a wide variety of experiences, producing a mean earnings gain for the poor.

E. The Role of Unemployment

Another issue that we examine is the role of unemployment. During the 2001-2002 crisis in Argentina, the unemployment rate increased from 16.4% to 21.5%, 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.

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 between surveys. However, the evidence gives no support for this view. The percentages of those who started out employed and who became unemployed were, from lowest initial earnings quintile to highest, 18%, 17%, 9%, 6%, and 5% respectively. These figures on transitions into unemployment show that while becoming unemployed was something of a factor in contributing to convergent mobility, it was only a small factor: 84% of those who were employed in 2001 were also employed in 2002. Thus, the majority of earnings changes were for individuals who were employed in both years.

Among those who were employed in both 2001 and 2002, large losses might have been concentrated among a small number of losers, with most people retaining their earnings or even experiencing earnings gains. However, we find that of those who started in the lowest quintile 55% had negative earnings changes, and as we move to higher and higher quintiles, the percentages increased monotonically, reaching 89% for those who started in the highest initial earnings quintile. Thus, earnings losses in Argentina were widespread among people who were employed in both years.

Among just those workers who were employed both in 2001 and 2002, did relative earnings inequality rise and was mobility convergent in pesos? Table 7 shows that the patterns of increasing relative inequality and convergent mobility reported in Table 3 for the full sample also arise when the analysis is restricted to those employed in both periods. Therefore, what reconciles these results is not unemployment but rather widespread earnings changes among those employed in both periods.

6. Conclusions

In this paper, we have used panel data following the same people over time to answer two questions. First, is the pattern of earnings mobility in Argentina divergent, meaning that the individuals who started with the highest initial earnings enjoy the largest earnings gains or smallest earnings losses in pesos? Second, how can the findings on inequality and mobility be reconciled?

In answer to the first question, the results are quite strong. The pattern of earnings changes is mostly convergent, occasionally neutral, and never divergent – that is, the initially low-earners do at least well, often very much better, than the higher-earners. This result is confirmed for a wide variety of robustness checks: using medians as well as means, using predicted earnings in place of initial reported earnings, looking at groups that differ in terms of earnings (gender, education, etc.), and using a variety of samples (just those who were employed in both initial year and final year, looking separately at formal sector workers as opposed to informal sector workers, and so on).

Given that we found the opposite of what might have been expected – that generally it was the *lowest* initial earners who experienced the largest earnings gains in pesos – we then asked, how can rising inequality and convergent mobility be reconciled? We performed five tests: comparing cross-sectional changes versus panel changes for the exact same individuals, examining a traditional quintile transition matrix, simulating the rise in relative earnings inequality, doing additional analysis for a twenty-five person sample, and investigating the role of unemployment. What we find reconciles the inequality and mobility results is the widespread and sometimes very large earnings changes that took place for the individuals we followed over time – changes that are concealed when one looks just at cross-sectional data.

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. Much can be learned by analyzing panel data, knowledge that would not have been obtained by analyzing 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.

References

Albornoz, Facundo and Marta Menéndez (2004). "Income Dynamics in Argentina during the 1990s: 'Mobiles' Did Change Over Time," World Bank, processed.

Atkinson, A.B., F. Bourguignon, and C. Morrison,(1992). Empirical Studies of Earnings Mobility. Chur, Switzerland, Harwood Academic Publishers.

Baulch, Bob and John Hoddinott (2000). "Economic Mobility and Poverty Dynamics in Developing Countries," *Journal of Development Studies* 36: 1-24.

Boudon, Raymond. (1973). *Mathematical Structures in the Social Sciences.* (Amsterdam: Elsevier).

Bourguignon, François, Francisco H.G. Ferreira, and Nora Lustig, eds. (2004). *The Microeconomics of Income Distribution Dynamics in East Asia and Latin America.* (Washington: World Bank).

Carter, Michael R. and Christopher B. Barrett (2004). "The Economics of Poverty Traps and Persistent Poverty: An Asset-Based Approach." University of Wisconsin – Madison. Processed.

Chronic Poverty Research Centre (2004). *The Chronic Poverty Report 2004 – 05.* (Glasgow: Bell and Bain Ltd.).

Corbacho, A., Mercedes Garcia-Escribano, M., and Gabriela Inchauste (2003); "Argentina: Macroeconomic Crisis and Household Vulnerability", IMF Working Paper.

Cruces, G. and Quentin Wodon (2002), "Risk-Adjusted Poverty in Argentina: Measurement and Determinants", mimeo. London School of Economics, London, U.K.

de Ferranti, David, Guillermo E. Perry, Francisco H.G. Ferreira, and Michael Walton (2004). *Inequality in Latin America: Breaking with History?* (Washington: World Bank).

Fields, Gary S. (2001). *Distribution and Development: A New Look at the Developing World.* (Cambridge, MA: MIT Press and the Russell Sage Foundation).

Fields, Gary S. (2008). "A Brief Review of the Literature on Earnings Mobility in Developing Countries," Cornell University Working Paper.

Fields, Gary S., Paul Cichello, Samuel Freije, Marta Menéndez and David Newhouse (2003) "Household Income Dynamics: A Four Country Story" *Journal of Development Studies* 40: 30-54.

Fields, Gary S. and María Laura Sánchez Puerta (2005). "How Is Convergent Mobility Consistent with Rising Inequality? A Reconciliation in the Case of Argentina." Background paper for the report "Argentina: Seeking Sustained Growth and Social Equity." World Bank.

Fields, Gary S., María Laura Sánchez Puerta, Robert Duval Hernandez and Samuel Freije (2005) "Earnings Mobility in Argentina, Mexico, and Venezuela: Testing the Divergence of Earnings and the Symmetry of Mobility Hypotheses", processed.

Galton, Francis (1889). *Natural Inheritance.* (London: Macmillan).

Gasparini, L. and Walter Sosa Escudero (1999), Assessing Aggregate Welfare: Growth and Inequality in Argentina, Universidad Nacional de La Plata.

Gasparini, L. (2004), "Monitoring the Socio-Economic Conditions in Argentina, Chile, Paraguay and Uruguay", CEDLAS Universidad Nacional de La Plata.

Gottschalk, Peter (1997). "Inequality, Income Growth, and Mobility: The Basic Facts," *Journal of Economic Perspectives* 11: 21-40.

Grimm, Michael (2007). "Removing the Anonymity Axiom in Assessing Pro-Poor Growth," *Journal of Economic Inequality* 5: 179-197.

Gutierrez, F. (2004), Dinamica Salarial y Ocupacional: Analisis de Panel para Argentina: 1998-2002, Working Paper 11, CEDLAS Universidad Nacional de La Plata.

Huber, J.C. (1998). "Cumulative Advantage and Success-Breeds-Success: The Value of Time Pattern Analysis." *Journal of the American Society of Information Science* 49.

INDEC, Instituto Nacional de Estadisticas y Censos (2004) National Accounts: Evolution of GDP; www.indec.mecon.ar

Inter-American Development Bank (1999). *Facing Up to Inequality in Latin America.* (Washington: Inter-American Development Bank).

Inter-American Development Bank (2004). *Good Jobs Wanted.* (Washington: Inter-American Development Bank).

Johnson, George E. (1997). "Changes in Earnings Inequality: The Role of Demand Shifts," *Journal of Economic Perspectives* 11: 41-54.

Lustig, Nora and Miguel Székely (1999). "Tendencias 'Ocultas' en la Desigualdad y la Pobreza en México," en M. Cárdenas y N. Lustig, eds., *Pobreza y Desigualdad en América Latina* (TM Editores – FEDESSARROLLO – LACEA – COLCIENCIAS).

McKenzie, D. (2004), Aggregate Shocks and Labour Market Responses: Evidence from Argentina's Financial Crisis, *Economic Development and Cultural Change*, 52(4): 719-758.

Meade, James E. (1976). *The Just Economy*. (London: Allen and Unwin).

Merton, Robert E. (1968). "The Matthew Effect in Science," *Science*, 159.

Sachs, Jeffrey (2005). *The End of Poverty: Economic Possibilities for Our Time.* (New York: Penguin).

Sánchez Puerta, María Laura. (2005). "Stylized Facts on Poverty, Inequality and Economic Growth," Background paper for the report "Argentina: Seeking Sustained Growth and Social Equity." World Bank.

Solon, Gary (1992). "Intergenerational Income Mobility in the United States," *American Economic Review* 82(3): 393-408.

Topel, Robert H. (1997). "Factor Proportions and Relative Wages," *Journal of Economic Perspectives* 11: 55-74.

Wodon, Quentin (2001). "Income Mobility and Risk During the Business Cycle: Comparing Adjustments in Labor Markets in Two Latin-American Countries", *Economics of Transition* 9 (2): 449-461.

Zimmerman, David J. (1992). "Regression Toward Mediocrity in Economic Stature," *American Economic Review* 82(3): 409-429.

Table 1.
Gini Coefficient of Labor 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

Source: Authors' calculations.

Note: These are the Gini coefficients of labor 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.

Table 2

Unweighted Reported Earnings Changes by Initial Position

Dependent Variable: Change in Reported Earnings

	1996-1997 Growth Rate +8.1			1997-1998 Growth Rate +6.9			1998-1999 Growth Rate -4.9			1999-2000 Growth Rate -0.4			2000-2001 Growth Rate -0.2			2001-2002 Growth Rate -13.5			2002-2003 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.
Earnings Changes by Quintile: Rising Relative Inequality and Convergent Mobility, 2001-2002.

Initial Earnings Quintile (Quintile 1 = Lowest) (1)	Quintile Mean, 2001 (2)	Percentage Change in the Cross Section (3)	Mean Earnings Change in Pesos of Those Who Started in this Quintile (4)
Quintile 1	17	-100%	164
Quintile 2	229	-48%	-65
Quintile 3	424	-35%	-127
Quintile 4	669	-30%	-214
Quintile 5	1561	-25%	-606

Table 4.
Quintile Transition Matrix, 2001-2002

Quintile 2001	Quintile 2002					
	Quintile 1	**Quintile 2**	**Quintile 3**	**Quintile 4**	**Quintile 5**	**Total**
Quintile 1						
Number	786	418	194	99	117	1614
Row percentage	48.7	25.9	12.02	6.13	7.25	100
Column percentage	42.14	31.55	11.04	6.54	7.94	20.34
Table percentage	9.91	5.27	2.45	1.25	1.47	20.34
Quintile 2						
Number	409	684	593	107	13	1806
Row percentage	22.65	37.87	32.83	5.92	0.72	100
Column percentage	21.93	51.62	33.73	7.07	0.88	22.76
Table percentage	5.16	8.62	7.47	1.35	0.16	22.76
Quintile 3						
Number	288	161	735	505	89	1778
Row percentage	16.2	9.06	41.34	28.4	5.01	100
Column percentage	15.44	12.15	41.81	33.38	6.04	22.41
Table percentage	3.63	2.03	9.26	6.37	1.12	22.41
Quintile 4						
Number	188	38	169	621	284	1300
Row percentage	14.46	2.92	13	47.77	21.85	100
Column percentage	10.08	2.87	9.61	41.04	19.28	16.39
Table percentage	2.37	0.48	2.13	7.83	3.58	16.39
Quintile 5						
Number	194	24	67	181	970	1436
Row percentage	13.51	1.67	4.67	12.6	67.55	100
Column percentage	10.4	1.81	3.81	11.96	65.85	18.1
Table percentage	2.45	0.3	0.84	2.28	12.23	18.1
Total	1865	1325	1758	1513	1473	7934
Row percentage	23.51	16.7	22.16	19.07	18.57	100
Column percentage	100	100	100	100	100	100
Table percentage	23.51	16.7	22.16	19.07	18.57	100

Table 5.
Earnings Changes by Quintile Only for Those People Employed in Both Periods: Rising Relative Inequality and Convergent Mobility, 2001-2002.

2001 Earnings Quintile (Quintile 1 = Lowest) (1)	Quintile Mean, 2001 (2)	Percentage Change in the Cross Section (3)	Mean Earnings Change in Pesos of Those Who Started in this Quintile (4)
Quintile 1	167.3	-29%	13.7
Quintile 2	343.4	-28%	-53.4
Quintile 3	521.9	-28%	-90.7
Quintile 4	764.9	-26%	-175.9
Quintile 5	1647.9	-21%	-478.6

Figure 1.

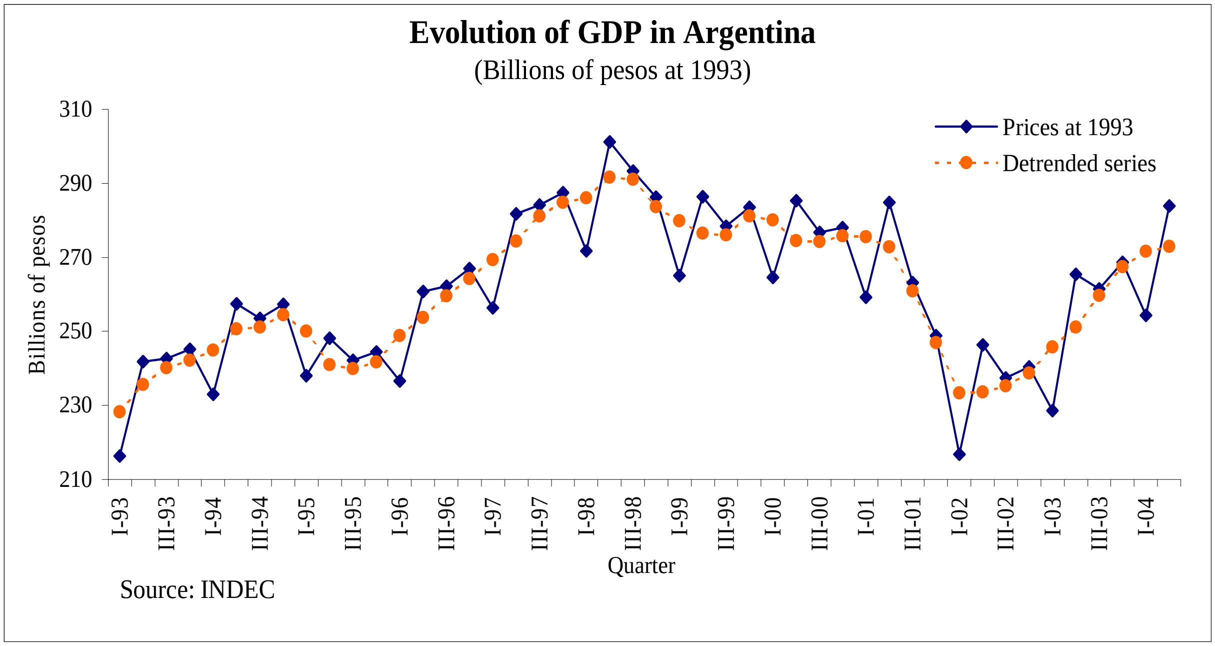
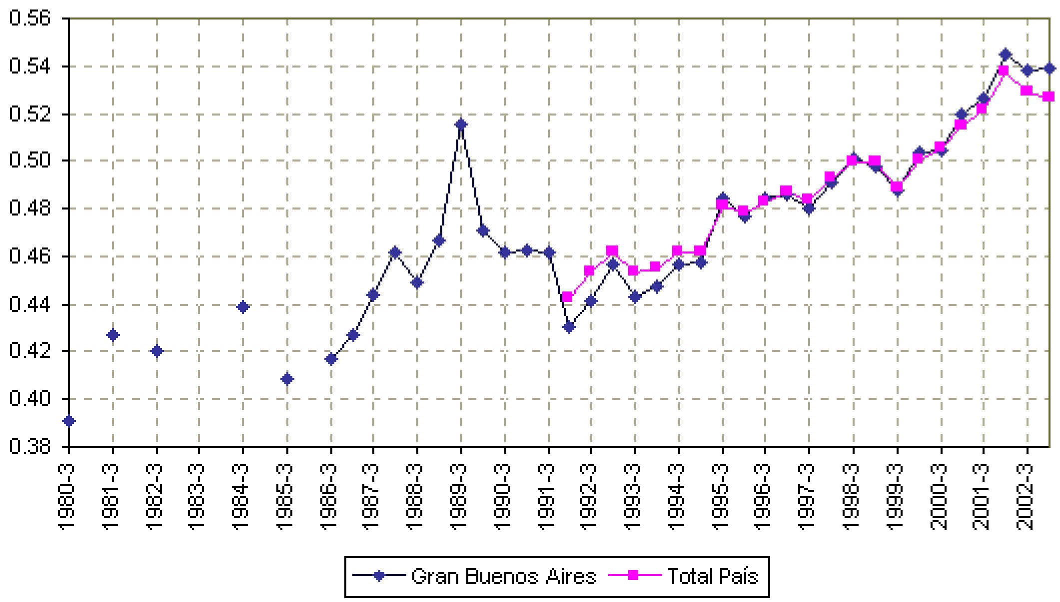

Evolution of GDP in Argentina
(Billions of pesos at 1993)
310
290
270
250
230
210
Billions of pesos
Prices at 1993
Detrended series
I-93
III-93
I-94
III-94
I-95
III-95
I-96
III-96
I-97
III-97
I-98
III-98
I-99
III-99
I-00
III-00
I-01
III-01
I-02
III-02
I-03
III-03
I-04
Quarter
Source: INDEC

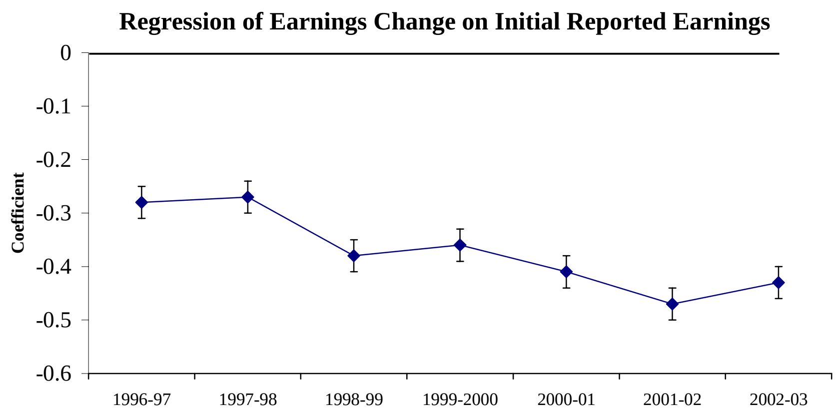
Figure 2.

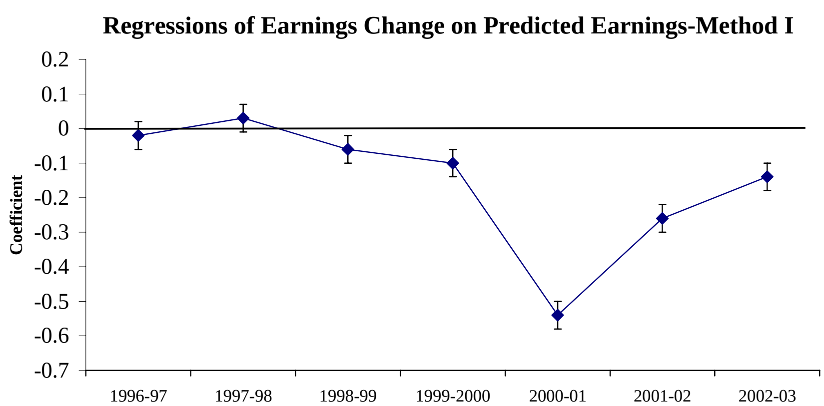
Gini Coefficient of Household Per Capita Income

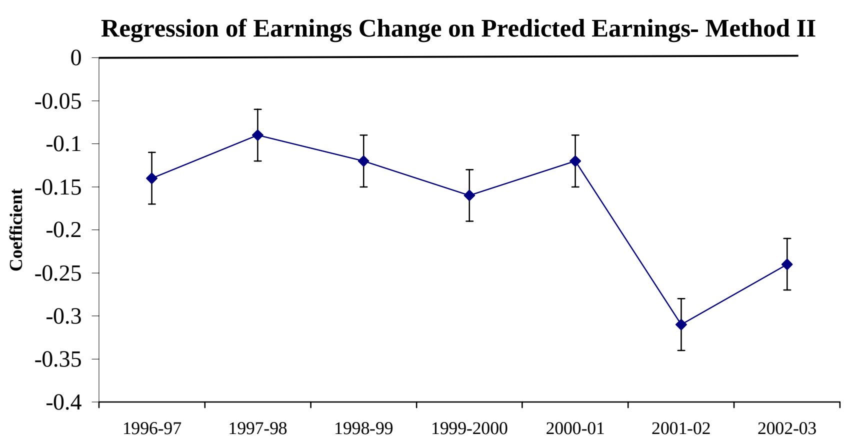


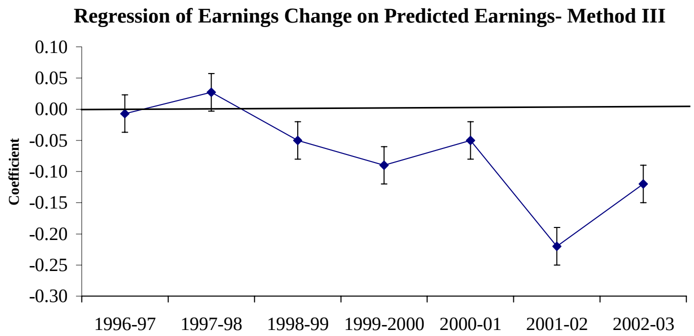
Source CEDLAS (2004)

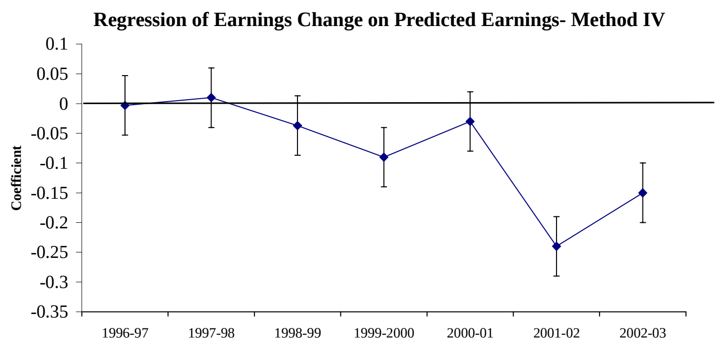
Figure 3.
Regression Coefficient for Each Panel:
Earnings Change as a Function of Initial Earnings

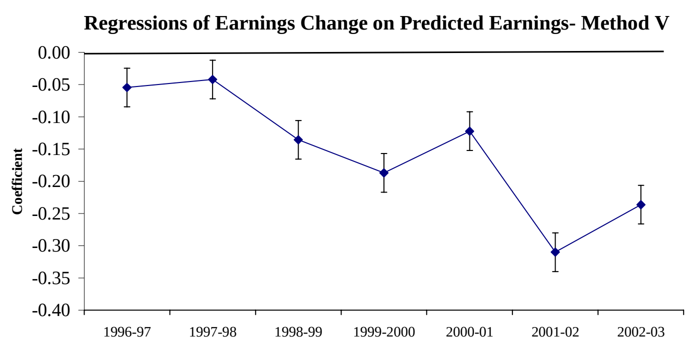







Regression of Earnings Change on Predicted Earnings- Method III
Coefficient
0.10
0.05
0.00
-0.05
-0.10
-0.15
-0.20
-0.25
-0.30
1996-97
1997-98
1998-99
1999-2000
2000-01
2001-02
2002-03


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

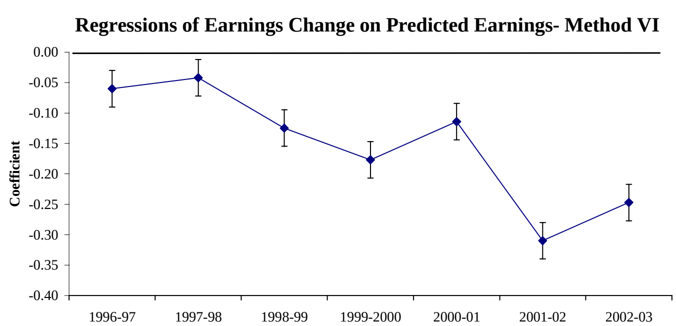

Regressions of Earnings Change on Predicted Earnings- Method VI
Coefficient
0.00
-0.05
-0.10
-0.15
-0.20
-0.25
-0.30
-0.35
-0.40
1996-97
1997-98
1998-99
1999-2000
2000-01
2001-02
2002-03

Figure 4.
Earnings Distributions for Twenty-Five Illustrative Individuals Treated Anonymously, 2001 and 2002

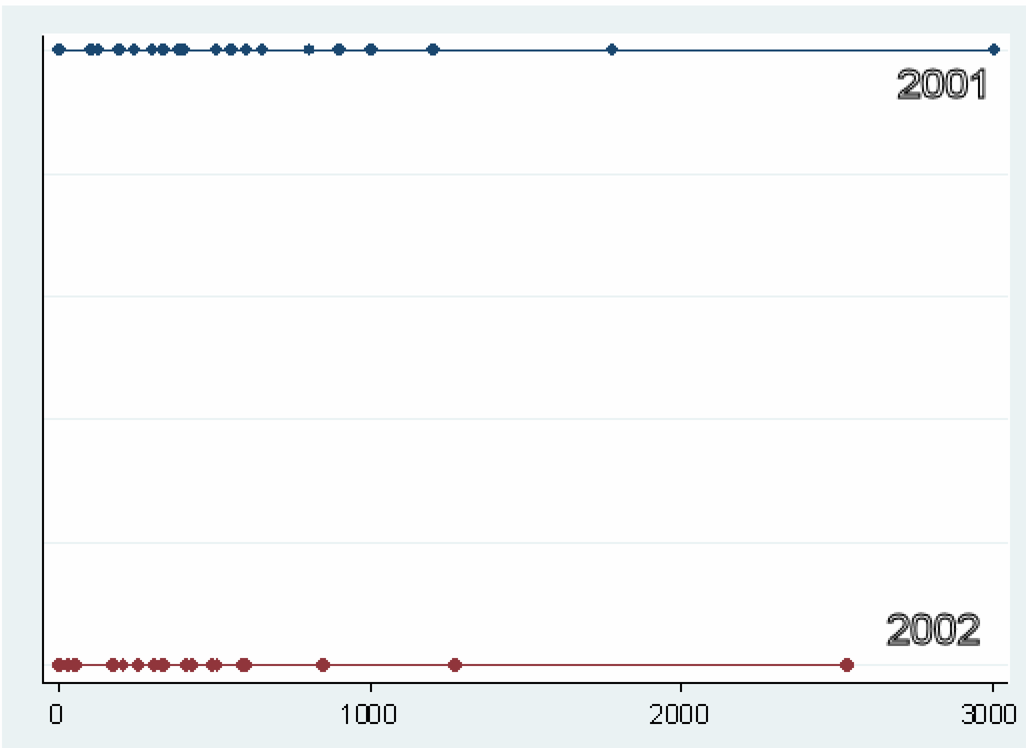


Figure 5.
Earnings Distributions for Twenty-Five Illustrative Individuals Treated as a Panel, 2001 and 2002