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How Is Convergent Mobility Consistent with Rising Inequality? A Reconciliation in the Case of Argentina

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Abstract

[Excerpt] This is a paper on earnings mobility in Argentina during the macroeconomic growth and contractions that have characterized that nation's economy from 1996 to the present. Since 1996, real GDP growth has fluctuated widely. For most of the 1990s, Argentina was seen as a model of successful policymaking. 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. Greater economic stability attracted foreign investment inflows, contributing to an acceleration in economic growth; indeed, even as lenders withdrew their financing in 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 (See Figure 1). Gross Domestic Product fell by 13.5 percent from the second quarter of 2001 to the second quarter of 2002, and the share of the population in poverty reached 58 percent in October 2002, versus 38 percent in October 2001, according to the official moderate poverty line.

This paper addresses the distributional consequences of these macroeconomic events. (Note: Here and throughout the paper, "distribution of income" means the entire density or cumulative distribution function; it does *not* mean "inequality.") Who benefited the most from Argentine economic growth? Who lost the most in economic decline? Are those who started rich getting richer in growth periods and losing more in recessionary periods, or is it the other way around? Are the answers to these questions the same for all measures of initial advantage?

Keywords

Argentina, economic growth, earnings, mobility, inflation, economic development

Comments

How Is Convergent Mobility Consistent with Rising Inequality?

A Reconciliation in the Case of Argentina

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1. Introduction

This is a paper on earnings mobility in Argentina during the macroeconomic growth and contractions that have characterized that nation's economy from 1996 to the present. Since 1996, real GDP growth has fluctuated widely:

Real GDP Growth Rate, Second Quarter to Second Quarter

Year	Real GDP Growth Rate
1996-97	+8.1%
1997-98	+6.9%
1998-99	-4.9%
1999-2000	-0.4%
2000-2001	-0.2%
2001-2002	-13.5%
2002-2003	7.7%

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October 2002, versus 38 percent in October 2001, according to the official moderate poverty line.[1]

This paper addresses the distributional consequences of these macroeconomic events. (Note: Here and throughout the paper, "distribution of income" means the entire density or cumulative distribution function; it does *not* mean "inequality.") Who benefited the most from Argentine economic growth? Who lost the most in economic decline? Are those who started rich getting richer in growth periods and losing more in recessionary periods, or is it the other way around? Are the answers to these questions the same for all measures of initial advantage?

We adopt the perspective of pro-poor growth in this paper.[2] The weakest definition is that growth is pro-poor if poverty falls when growth takes place (Kraay, 2003). A somewhat stronger definition is that pro-poor growth takes place if the poor enjoy the same proportionate increases in income or consumption as do others (Ravallion, 2004). Stronger yet is the notion that growth is pro-poor if poverty falls by more than it would have if all incomes had grown at the same rate (Baulch and McCulloch, 2000; Kakwani and Pernia, 2000; Duclos and Wodon, 2004). Strongest of all is to see to it that the poorest 20% of the population gets 20% of the benefits (Harberger, 1998; Summers, 1998.)

What is novel about this analysis compared with virtually all previous work on Argentina is that it is based on a series of panels of individual workers. 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. The data set covers workers in twenty-eight cities in Argentina. Analyzing changes for the same

[1] GDP numbers from INDEC; poverty numbers from Gasparini (2004). The official moderate poverty line 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 to achieve a minimum level of material welfare. It is set at a higher level than US$2 a day at PPP and is constant in real terms.

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

people contrasts fundamentally with the great bulk of the previous literature in Argentina, which is based not on panels but on comparable cross-sections. Mobility provides a better measure of changing opportunities than do traditional measures of inequality. Measures of inequality are like snapshots; they reflect differences in income at a specific point in time. Researchers who have studied distributional change in Argentina have looked at *anonymous* individuals and households: those in the poorest 20% of the income distribution versus others, men versus women, and so on. They have not, however, looked at *the same individuals and households*, following them and gauging changes in their economic circumstances over time. These studies can say nothing about the earnings changes of the initially poor or rich individuals, such as whether those at the top or bottom of the income ladder are moving up or down or expect to do so. To investigate if pro-poor income changes occurred in countries with rising cross-sectional income inequality, one can measure changes in individual earnings directly.

To learn about earnings changes for identified individuals during years of growth and recession, we study the variations in patterns of individual earnings changes over seven one-year panels in twenty-eight cities in Argentina. For a sample of women and men aged 25-60, we analyze earnings changes both in an unconditional way in a univariate framework and in a conditional way using multiple regression. The emphasis is given to how earnings changes relate to individuals' initial economic position. We test whether the initially most advantaged individuals are the ones gaining the most in booms and losing the most in busts in Argentina.

One major conclusion that we reach from our panel data analysis is that the pattern of changes is much more progressive than would appear from the more standard cross-sectional analysis. Most importantly, we find that both in positive growth periods and in negative growth periods, those who start in the least advantaged positions to begin with enjoy the most positive changes *in pesos*, not just in percentages. This finding runs precisely counter to the view held by many that the poor are the big losers in recessions;

as one recent survey article put it, “there is quite a lot of evidence that poorer households may be less able than richer ones to protect themselves against adverse effects or to take advantage of positive opportunities created by policy reform.” (Winters, McCulloch, and McKay, 2004, p. 107).

A second major conclusion that we reach concerns the patterns of earnings changes in good times and bad. Our seven panels include three positive-growth years and four negative-growth years. A naïve view, which we term the "symmetry hypothesis," holds that those who gain the most when the economy is growing are those who lose the most when the economy is contracting.[3, 4] However, we find that this hypothesis is decisively rejected for urban Argentina. Rather, our results show that when there are significant differences between groups, those who gain the most when the economy is growing are also those who gain the most or lose the least when the economy is contracting. In other words, the pattern of changes is structural and not symmetric.

Our third major conclusion is about the determinants of earnings changes in Argentina. The explanatory variables available for this analysis are initial earnings, gender, age, education, sector of employment, and geographic region. As explained further in Section 5, a variable is judged to be statistically significant using standard t tests or F tests; it is judged to be economically significant if it explains one percent or more of the variance in earnings changes. Surprisingly, not all of the explanatory variables are statistically significant determinants of earnings change all the time, even in a sample of more than fifty thousand workers. Moreover, among the variables that are statistically significant, some are economically insignificant. To summarize the results presented below: the variables that are both statistically and economically significant

[3] Reasons for expecting the symmetry hypothesis to hold are presented in Section 3.

[4] This symmetry hypothesis is different from the one that holds that cyclical downturns have an asymmetric effect on poverty: recessions tend to increase poverty rates significantly, but expansions tend to have a more limited effect (Agénor, 2002).

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.

The rest of the paper is laid out as follows. Section 2 discusses the notion of economic mobility and how it differs from inequality and poverty. Section 3 presents the theoretical foundations for ideas 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 hypotheses are presented in Section 6, along with evidence on our attempts to predict the major determinants of earnings changes. Section 7 deepens the analysis of mobility and inequality, and Section 8 concludes.

2. Mobility, Inequality, and Poverty

A. An Introduction to Research on Economic Mobility

This paper presents the results of a mobility study for urban Argentina. 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 change in labor market earnings.[5] The explanatory variables used here include base-year income, education, gender, sector of employment, and other time-varying and time-invariant characteristics. By contrast, *macromobility studies* gauge how much mobility there is in an economy as a whole, often comparing differences in aggregate mobility over time or for different groups. As an

[5] 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).

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), and macro-poverty (how much poverty an economy has in aggregate.)[6]

The study of earnings and income micro-mobility 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, mobility studies have been until recently confined to developed countries.

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 (2001). In many developing country studies, questions about convergence of income over time have been asked and answered by regressing change in economic position on base year economic position with no other variables present. It has been shown that household incomes sometimes converge towards the grand mean, sometimes diverge away from it, and sometimes do neither (Fields et al., 2003a). Only one panel is analyzed for each country in the aforementioned paper. As in the case of studies of mobility in developed countries, we do not find in in the developing country studies a careful comparison of various panels over time, which is required in an analysis of changing earnings dynamics in growth and recession.

In the case of Latin America, to the extent that earnings gains and losses of different income groups have been studied for periods of growth and recession in the

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[6] Many macro-mobility concepts and measures are being used in the literature. The six concepts can be classified into six categories: (1) Time-independence, which asks how dependent current earnings are on past earnings; (2) Positional movement, which gauges how many quintiles, deciles, centiles, or ranks an individual moves; (3) Share movement, which measures changes in individuals' shares of total earnings; (4) Non-directional income movement, also called income flux, which measures the amplitude of earnings changes in absolute value; (5) Directional income movement, which measures the changes in earnings or log earnings in algebraic value; and (6) Mobility as an equalizer of longer term income, which compares the inequality of earnings over two or more periods with the inequality of base-year earnings.

region, the answers are based on comparable cross sections (IDB, 1999; Lustig and Székely, 1999; De Ferranti *et al.*, 2004; Bourguignon, Ferreira, and Lustig, 2004). Specifically for Argentina, earnings changes have been mostly analyzed in different macroeconomic conditions using cross-sectional data (Altimir and Beccaria, 2000 and 2001, Gasparini *et al.* 2001, Gasparini 2004, Damill *et al.*, 2002). In this way, researchers have looked at *anonymous* individuals and households: those in the poorest 20% of the income distribution versus others, men versus women, and so on. They have not, however, looked at *the same individuals and households*, following them and gauging changes in their economic circumstances over time. These studies can say nothing about the earnings changes of the initially poor or rich individuals.

To the best of our knowledge, no study comparing the patterns of earnings mobility in years of growth and recession has been done for Argentina or any other country, other than a parallel project in which we are participating (Fields et al., 2004). This study thus breaks new ground in the mobility literature as a whole.

B. Mobility, Poverty, and Inequality Are Three Distinct Concepts

The relationship between mobility, inequality, and poverty, merits some explanation. Our main point in the following paragraphs is that because these are logically distinct concepts, one does not imply anything about the other.

Consider first the relationship between mobility and inequality. Suppose we have an economy that consists of two individuals whose initial incomes are $1 and $5 respectively. Write this as the vector (1, 5). Suppose that the economy does not grow, so that later the anonymous income distribution remains (1, 5). Clearly, inequality is unchanged. But has there been mobility? With anonymous data, which typical cross-sections are, we simply cannot tell. There are, however, two underlying possibilities: denoting the two individuals by α and β, the underlying pattern for named individuals is either

I: (1, 5) → (1, 5)

α, β α, β

or it is

II: (1, 5) → (5, 1) .

α, β α, β

In Case I, there has been no income mobility, while in the second case there has been. Yet in both cases, inequality is unchanged. This exemplifies how mobility and inequality are distinct concepts.

Next, consider the relationship between mobility and poverty. The distributional changes

I: (1, 5) → (2, 5)

α, β α, β

and

III: (1, 5) → (1, 6)

α, β α, β

both exhibit upward mobility. If, as is reasonable in this example, we take the poverty line to be somewhere between \$1 and \$5, poverty measures that are sensitive to income gains among the poor such as the P_α class for $\alpha > 0$ (Foster, Greer, and Thorbecke, 1984) and the Sen poverty index (Sen, 1966) show a fall in poverty in Case I and not in Case III. This example demonstrates that mobility and poverty are distinct concepts.

Finally, consider the relationship between inequality and poverty. Suppose the pattern of distributional change is such that the poorer person's income doubles while the richer person's income triples:

IV: (1, 5) → (2, 15).

α, β α, β

Because the poor person's income has risen, poverty again falls (unless the poverty line is above \$2 and the poverty headcount is used). Yet, Lorenz curves and all Lorenz-

consistent inequality measures such as the Gini coefficient register an increase in inequality. This example shows that inequality and poverty are not the same thing.

C. Past Literature on Mobility, Poverty, and Inequality in the Case of Argentina

Turning now to the case of Argentina, inequality has been rising, sometimes slowly and sometimes rapidly, over a long period of time. Sánchez Puerta (2004) presents a detailed review of the relevant studies. The increase in inequality has been documented in a number of studies: Altimir and Beccaria (2000), Altimir and Beccaria (2001), Damill et al. (2002), Gasparini (2004), Gasparini et al. (2004), Gasparini and Walter Sosa Escudero (1999), De Ferranti et al. (2004). Our own calculations produce the following series on inequality as measured by the Gini coefficient: [7]

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

[7] These are the Gini coefficients of labor market earnings for panel individuals aged 25-60 when they are observed in the second year. The data are described further in Section 4.

For the earlier years, the underlying Lorenz curves are remarkably stable from one year to the next. As displayed in Figure 2, inequality changed so little in each year from 1996-1997 to 2000-2001 that we see only one Lorenz curve, 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 to 2002 and a substantial Lorenz-improvement from 2002 to 2003.

As for poverty, according to the official moderate poverty line, the poverty headcount ratio decreased in 1996-97 and stabilized until 1999. Then, it increased at an increasing rate for three years until it peaked in 2002. After that, it has been decreasing with the economic recovery. Sadly, the poverty headcount ratio has not yet fallen to the levels of the beginning of the 1990s nor the level of 1997.

The amount of research on mobility is starting to grow in the Argentina due to availability of new data from panel surveys. The major preceding studies are those by Wodon (2001), Gutierrez (2004), McKenzie (2004), Corbacho *et al.* (2003), and Menendez and Albornoz (2004).Wodon (2001) analyses income (wages and self-employment) macromobility and risk during the business cycle in Argentina and Mexico. He uses a new measure of mobility, namely the Gini index of mobility, which is a function of ranks of individuals in the distribution of income. In Argentina, mobility turns out to be higher during recessions and lower during growth compared to Mexico. Even though the author focuses on the different patterns of mobility in periods of growth and recession, he does not analyze the relationship between earnings changes and initial earnings or other measures of initial advantage of the individuals as explanatory variables of income dynamics in Argentina.

Gutierrez (2004) focuses on occupational and wage mobility in urban Argentina in the period 1998-2002. He constructs panels for all individuals (including the inactive)

using the EPH (Encuesta Permanente de Hogares)[8], which is also the data set that we use. He studies the determinants of wage mobility (using the concept of time independence, i.e., the correlation coefficient between wages at two different points in time) and the determinants of finding or losing a job. He finds 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 wage mobility.

In a very comprehensive paper about the 2002 financial crisis in Argentina, McKenzie (2004) constructs panels using data from the EPHs to assess the adjustments of household and individual incomes and the labor market response. He studies changes in nominal wages, entry into and exit from the workforce, hours worked, household labor supply and work program participation separately. The mobility analysis consists of an OLS regression of change in log income on individual characteristics and regions, with dummy variable for the period of crisis with interactions. His conclusions are that the larger income falls were for males, who were managers, or who changed jobs. Females in Cuyo did better than before, while females with tertiary education did worse. Corbacho *et al.* (2003) also use panel data from Argentina for the years 1999 to 2002 and analyze the determinants of changes in household income to draw inferences regarding socio-economic characteristics and vulnerability. They find 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 is 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 Menéndez and Albornoz (2004). The authors use the changes in logarithm of household income per capita to determine what

[8] EPH (Permanent Household Survey) conducted by INDEC (National Statistical Institute of Argentina)

are the principal observed socioeconomic factors driving income dynamics in Argentina. For this purpose, they perform 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 do not find any structural patterns for the determinants of income change and conclude that shocks affect different types of people over time. No special attention is given to the different patterns in periods of growth or periods of recession.

Our review of the literature for Argentina reveals that the studies that compare earnings gains and losses of different income groups in growth and recessionary periods focus only on inequality. These analyses are based on comparable cross sections (Altimir and Beccaria, 2000 and 2001; Gasparini et al., 2001; Damill et al., 2002; Gasparini, 2004). In no way does rising income inequality provide evidence that absolute economic conditions have worsened for the poor. Rising inequality indicates that the dispersion of income has widened, but contains no information on the movement of specific individuals within that distribution. If a sufficiently large number of poor and rich individuals swap incomes, the initially poor will gain more on average than the initially rich, even as the distribution of income grows more unequal.

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 any country, developed or developing. Some of the results of this paper appear in Fields, Duval, Freije, and Sánchez Puerta (2004), which compares earnings dynamics of Argentina, Mexico and Venezuela. We find that reported labor earnings in pesos consistently converge to the grand mean. Whether in good or bad times, the people at the bottom of the reported earnings distribution have the largest earnings gains and the people at the top the lowest ones. However, this finding does not always hold when other measures of initial well-being are taken into consideration. Our contributions in this

paper are to present the Argentine results from the Fields et al. (2004) study and to move beyond them in a number of important respects.

3. Theoretical Foundations: Divergence of Earnings and Symmetry of Mobility

We reported in Section 2 that although earnings inequality was noticeably higher in urban Argentina in 2003 than it had been in 1996, in some one-year periods, the changes in inequality were essentially nil. The small or zero changes in inequality in some years imply that each anonymous income group (e.g., bottom decile, second decile, etc.) had the same percentage change in income as every other. Of course, a given percentage change produces a larger change in pesos the higher is one's income. Therefore, the *anonymous* pattern of income changes is one where those who start with higher incomes gain the most pesos when the economy is growing and lose the most when the economy is contracting. From here, it is only a small step to hypothesize that *those particular individuals* who started with the highest initial incomes are those who gain the most pesos in periods of economic growth and lose the most pesos in periods of economic decline. And generalizing further, it might be hypothesized that those particular groups that gain the most when the economy is growing (men, for example) would be the ones that lose the most when the economy is contracting.

This idea is what we call the "symmetry of mobility" hypothesis. The symmetry of mobility hypothesis states that the groups which gain the most in periods of growth are the same ones which get hurt the most in recessions. However, as we showed in Section 2, mobility and inequality imply nothing about the other, so it is not evident that this hypothesis will be confirmed in the case of Argentina.

Other considerations lead to a different conjecture. The "divergent mobility hypothesis" holds that the initially-advantaged are the ones that gain the most and lose the least, whether in good times or in bad. Several theories underlie this hypothesis.

One theory is 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 (Rosenstein-Rodin, 1943; Nurkse, 1953; Nelson, 1956; Basu, 1997). 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. They act to produce a pattern which Nobel laureate James Meade (1976, p. 155) called "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 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 labor force survey conducted by Argentina's National Statistical Agency, INDEC. The survey is a rotating panel, with a quarter of the households rotated out each period, so that a given household can be followed 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 28 cities.[9] 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. The EPH is carried out via a two-stage random sample. Within each of the twenty-eight city areas, 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 micro-data for two consecutive years (May to May) to avoid capturing changes in earnings due to seasonality. The panels constructed for the periods of positive growth (1996-1997, 1997-1998 and 2002-2003) and negative growth (1998-1999, 1999-2000, 2000-2001, and 2001-2002) allow for the systematic comparison of the years of boom towards the end of last decade and the years of deep recession leading to the crisis of early 2002. We match dwellings by an identification code that uniquely characterizes each place that is surveyed. Due to the rotating nature of the EPH survey, around 50% of the original sample would be expected to not be present in the

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

second year. Indeed, this proportion is usually higher, since households that move and are not found at the time of the re-interview are not traced but replaced.

In order to avoid mismatching, additional matches of gender and date of birth of the individual are required. Then, 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% of the initial surveys, where 50% would correspond to zero attrition. Besides, not all the individuals selected to respond the EPH answer the questions about earnings. This phenomenon can bias the mobility estimations if (i) non-response depends on income, and (ii) if the percentage of non-response varies over time.[10] However, past researchers have not found attrition bias to be a serious issue.[11]

Sampling weights are provided which correct for non-response in the cross-section, and allow for population employment and unemployment numbers to be calculated. However, we chose to use the unweighted data for the following reasons. The weights can vary for the same household from one survey to the next and do not take account of attrition in the panel aspect. Furthermore, they need not be representative for group-level comparisons, such as comparing informal to formal workers.[12]

In the empirical work that follows, the dependent variable is the individual's change in labor market earnings. The reason for the choice of change in earnings as the variable of interest is that in developing countries including South Africa, Indonesia,

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[10]The number of people with incomplete household income reports was about 25% at the beginning and in the middle of the eighties and rose to 28% at the end of that decade. In the nineties the efforts of the INDEC to mitigate the problem of non-response succeeded: the percentages fell throughout the decade until they reached an 8% in the 1998 survey

[11] The first attempts to adjust for non-response in Argentina of which we are aware were done by Gasparini and Sosa Escudero (1999) in the context of measures of inequality. They use predictions of an income determination model to assign incomes to people who do not answer. In a study of mobility in Greater Buenos Aires, Menendez and Albornoz (2004) estimate longitudinal weights using a probit model for the probability of staying in the panels to correct for attrition and found that results were not significantly altered by non-systematic attrition. Cruces and Wodon (2002) also argue that attrition in the EPH panel does not seem to affect trends in income in a qualitatively important way.

[12] Results with weighted data do not alter the conclusions of the paper and are available from the authors upon request.

Spain and Venezuela, earnings have been shown to constitute the single most important source of variation of change in income, more so than all the other income sources combined (Fields et al., 2003b). The paramount role of changes in labor earnings in explaining changes in incomes points to the importance of understanding earnings dynamics and employment transitions 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 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. These restrictions might not allow the study of some interesting outcomes, such as the added-worker effect in times of recession, given that observations are dropped if participation in the labor force occurs in just one of the two periods of the panel. The focus of the paper is on individuals more permanently attached to the labor force.

The analyses are conducted using earnings changes in pesos, which measures absolute earnings gains. All earnings are expressed in 1999 pesos per month.[13] Nominal earnings are deflated by the April Consumer Price Indices for Greater Buenos Aires to obtain real earnings.[14] Earnings include wage or salary, self-employment income, and earnings as an 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). Moreover, we use both reported and predicted initial earnings as variables explaining earnings change.[15]

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

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

[15] The predictions are described below.

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. *Age* is grouped into three categories in the mobility profiles; it is entered linearly and quadratically in the regressions. Age is age in the first period of the panel; for example, age in the panel which combines the May 2002 and May 2003 waves of the EPH is the worker's age as of the May 2002 survey. *Education* is highest level of education reached. 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 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.

5. Hypotheses and Methods

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

> (H1) Divergence of Earnings, Unconditional Version: In any given year, those individuals for whom initial reported earnings level is highest are those who experience the largest earnings gains or the smallest earnings losses.

(H2) Divergence with Other Indicators, Unconditional Version: In any given year, those groups that earn the most are those that experience the largest earnings gains or the smallest earnings losses.

(H3) Symmetry of Gains and Losses, Unconditional Version: Comparing positive growth and negative growth years, those groups for whom earnings changes are the most positive when the economy is growing are those for whom earnings changes are most negative when the economy is contracting.

(H4) Symmetry of Gains and Losses, Conditional Version: Other things equal, comparing positive growth and negative growth years, those groups for whom earnings changes are the most positive when the economy is growing are those for whom earnings changes are 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 growth years and in recessionary years.

Figure 3 illustrates the relationship between these hypotheses. In these diagrams, a measure of welfare in the base year W_1 is plotted on the horizontal axis and income change ΔY is plotted on the vertical axis. The data would be consistent with unconditional divergence if the relationship between ΔY and W_1 is found to be positive

as in panel (a).[16] On the other hand, the data could be inconsistent with unconditional divergence in any number of ways. One of these is a pattern of unconditional convergence, which is illustrated in panel (b).

Figure 3 also illustrates the tests of symmetry of mobility. In these tests, we use alternate measures of W_1 as indicated by the following variables: initial reported earnings, initial predicted earnings, gender, age, years of education, initial economic sector, and region. We will conclude that symmetry holds if the groups that gain the most in positive growth years are those that lose the most in negative growth years. The diagram in panel (c) of Figure 3 illustrates a kind of symmetry in which it is those with the *highest* initial economic well-being who gain the most in positive growth years and lose the most in negative growth years. Symmetry could, however, be rejected in many ways. Two ways of rejecting symmetry are illustrated in panels (a) and (b). In panel (a), those who start in the *best* economic position are the ones who gain the most in both positive growth and negative growth years; in panel (b), it is those who start in the *worst* economic position who gain the most both when growth is positive and when it is negative.

Unconditional divergence will be said to hold if the relationship between ΔY and Y_1 is as in panel (a) *without* controls. Conditional divergence will be said to hold if the relationship between ΔY and Y_1 is as in panel (a) with controls. Similarly, unconditional symmetry will be said to hold if the relationship between ΔY and a welfare measure other than initial earnings is as in panel (c) *without* controls. Conditional symmetry will be said to hold if the relationship between ΔY and W_1 is as in panel (c) *with* controls.

Two methods are used to test the hypotheses. Starting with the unconditional analysis, we generate mobility profiles for years of growth and recession. These profiles

[16] The top line displays what a divergent relationship would look like in a positive growth year; the bottom line displays a a divergent relationship for a negative growth year.

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 percent 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. The method proposed by Fields (2003) decomposes the observed inequality in earnings and assigns weights to each factor. A variable is considered to be economically significant if its share in accounting for observed inequality is at least of one percent.

All of these analyses will be 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 data for one-year mobility are presented in two ways, depending on the hypothesis being tested. The tests of unconditional divergence involve a comparison of all years from 1996 to 2003. The tests of unconditional and conditional symmetry compare all positive growth years pooled together with all negative growth years pooled together.

The traditional way of analyzing 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 another measure of initial advantage: initial predicted earnings.

Throughout this analysis, we assume that there is 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:

$$\Delta y_{i,t+1} = \alpha + \beta y_{i,t} + u_{i,t+1} \qquad (1)$$

where

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

$y_{i,t}^{*P} + y_{i,t}^{*T}$ being true permanent and transitory earnings respectively,

and $\mu_{i,t}$ measurement error (orthogonal to true earnings)

The OLS estimator for this equation is

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

By running OLS, any reporting error 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_o 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_o 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

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

is consistent.

Earnings are predicted by instrumenting the permanent component of earnings, which generates a regressor that can be interpreted as a measure of long-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:[17]

Method 1 consists of predicting y_0 with a linear regression based on time-invariant characteristics and long-term income proxies. In the case of Argentina, 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 $P(y_0>0|X)*E(y_0|X, y_0>0)$, where the components are estimated by a Heckman selectivity correction method. The list of 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 $E(y_0|X, y_0>0)$ term.

[17] Throughout this paper, unless otherwise noted, when we mention initial predicted earnings, we refer to earnings predicted by Method 1.

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 initial 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. These explanatory variables were detailed in the previous subsection. Earnings variables are used in continuous forms. The regression equation is

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

where ΔX denotes sector transitions, Z denotes time-invariant characteristics like gender, age, education, and region, and $y_{i\,t-1}$ is initial reported income. Equation (2), which is a linear relationship among 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

A. Transition Matrices

As a first analysis of the data, Tables 1A-1G present quintile transition matrices year by year.[18] In most countries, the cells with the highest frequencies in quintile transition matrices are the 1-1 and 5-5 cells. Many times in Argentina, though, more people remain in the 2-2 cell than in the 1-1 cell. This is because the unemployment rates were so high (up to 23%) that all or nearly all of those who started in the lowest quintile initially had zero earnings, and the majority of them were found to be employed one year later. Otherwise, the quintile transition matrices in Argentina indicate substantial mobility between the three middle earnings quintiles.

A potentially important determinant of earnings change is sector change – that is, whether a worker started formally employed and moved to informal employment, etc. [19] Tables 2A-2G produce three patterns that hold for every year with one exception: (1) Most of the people who started formally employed remained formally employed. (2) Most of the people who started informally employed remained informally employed. (3) Most of the people who started unemployed were found to be employed one year later, the majority being found in the informal sector.[20]

[18] Because of heaping, the Argentina data do not produce quintiles containing exactly twenty percent of the people. ("Heaping" refers to the tendency of respondents to report incomes in round numbers: 0, 100 pesos, 200 pesos, etc.)

[19] The data set does not tell us whether those who remained employed in a given sector continued to work for the same employer or whether they changed employers.

[20] The one exception is that in Argentina's economic crisis (2001-2002), 54% of those who were unemployed in May 2001 were found to be unemployed in May 2002.

B. Tests of the Hypotheses

H1: Unconditional Divergence of Earnings

This hypothesis holds that in any given year, those individuals for whom initial reported earnings level is highest are those who experience the largest earnings gains and smallest earnings losses. We tested this hypothesis by looking at each of the seven panels from 1996-97 to 2002-03. The results year-by-year are summarized in Table 3; further details are given in the top blocks of Tables 4A-4G. Unconditional divergence of initial reported earnings, expressed in quintiles, is decisively rejected. Rather, what we find in each case is statistically significant *convergence.* Thus, when reported earnings are used, 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 perform several tests. First, we use median earnings changes in place of mean earnings changes; these results are in Table 4A-4G. Second, we use initial predicted earnings in place of initial reported earnings. In the previous section, we described the six different predictions of initial earnings we use. As an example, the prediction equations including gender, age, education, and dwelling characteristics for all individuals (Method 1) are reported in Appendix Table 1. Also, the relationships between earnings change and quintiles of predicted earnings, according to Method 1 and the analogous method for those with positive earnings (Method 5) are reported in Tables 3 and 4A-4G. The summary table below shows the results of univariate regressions of change in earnings on initial reported earnings and predicted earnings using all six methods.

Regressions of Earnings Change on Reported Earnings and Six Measures of Predicted Earnings, Entered in Quintiles and Linearly

	Quintiles	Linear
Initial Reported Earnings	Always significantly negative	Always significantly negative
Initial Predicted Earnings, Limited Predictors	3 out of 7 years significantly negative 4 years, not significant	5 out of 7 years significantly negative 2 years, not significant
Initial Predicted Earnings, All predictors	* 6 out of 7 years significantly negative 1 year not significant	Always significantly negative
Initial Predicted Earnings, Limited Predictors Heckman Correction	* 4 out of 7 years significantly negative 3 years, not significant *	5 out of 7 years significantly negative 2 years, not significant
Initial Predicted Earnings, All predictors Heckman Correction	3 out of 7 years significantly negative 4 years, not significant *	3 out of 7 years significantly negative 4 years, not significant
Initial Predicted Earnings, Limited Predictors Positive Earners Only	6 out of 7 years significantly negative 1 year, not significant *	Always significantly negative
Initial Predicted Earnings, All predictors Positive Earners Only	6 out of 7 years significantly negative 1 year, not significant *	Always significantly negative

*Non-monotonic pattern

The results for the robustness tests are similar to those for the base tests in some respects but not in others. The results are the same in that unconditional divergence is *never* found. Also, when the results are statistically significant, the pattern is one of unconditional *convergence*. However, unlike the results for reported earnings, the results for predicted earnings are sometimes statistically insignificant.

H2: Unconditional Divergence with Other Welfare 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. To know which groups of workers are those with the highest welfare indicators, Table 5 displays the reported earnings levels for workers in different categories. We see that in both positive growth and negative growth years: men earn significantly more than women; middle-aged workers earn significantly more than others; earnings rise significantly with education; formal sector workers earn significantly more than informal workers; and workers in Greater Buenos Aires are at or near the top of the earnings distribution compared to workers in other regions.

H2 would be confirmed for a given welfare indicator if the initially-high-earners are the ones with the most positive or least negative earnings changes. In general, though, this is *not* what we find when we look at the data in Tables 3 and 4A-4G. 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 welfare indicators other than initial reported earnings are used, we find *unconditional convergence or a statistically insignificant relationship;* unconditional divergence is *never* found for these other welfare indicators.

As we did for Hypothesis 1, we perform a robustness test of these results by analyzing median earnings changes. We find the same patterns using medians as we did using means and therefore reject unconditional divergence for all variables.

H3: Symmetry of Gains and Losses, Unconditional Version

This hypothesis holds that when positive and negative growth years are compared, those groups for whom earnings changes are the most positive when the economy is growing are those that experience the largest earnings losses 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" as opposed to "symmetric." A structural pattern could be further described as "convergent" or "divergent". If the groups with the initial advantage (e.g., the highest quintile) have the biggest losses in recession and the smallest gains in growth, we would refer to this pattern as "convergent." On the other hand, if the groups with the greatest initial advantage are getting ahead, we would consider this "divergent." However, if the hypothesis is rejected because the gains for the different groups are not significantly different from one another in booms and/or busts, this pattern will be referred to as "insignificant."

Comparing the positive growth and negative growth periods in Table 6, we find that the patterns for some variables are structural and for others are insignificant. First, taking mean changes in reported earnings as the criterion for comparison, the hypothesis of symmetry of gains and losses is overwhelmingly rejected. Rather, by initial reported earnings quintile, the pattern does not vary with macroeconomic conditions. In both

positive growth and negative growth years, earnings changes fall significantly as initial earnings quintile rises. Therefore, the earnings at the top of the distribution and those at the bottom converge to the grand mean.

We also test the hypothesis of symmetry using other measures of initial advantage. As already reported, in Argentina, men earn significantly more than women, prime-age individuals earn significantly more than others, earnings rise significantly with education, formal workers earn significantly more than informal sector workers, and the country displays significant regional differences. For these other indicators, the symmetry hypothesis also receives no support whatsoever. By *gender,* men do significantly worse than women in periods of negative growth, but the relationship is not significant in periods of positive growth. By *age* and *education*, we see a significant relationship with change in earnings only in negative growth periods. In those periods, young people and the less educated gain significantly more than their initially more advantaged counterparts (prime-age individuals and the more educated respectively).

The story changes when looking at *sector transitions*. For this variable, a strong and significant structural pattern appears. Those who started informal do significantly better than those who started formal in both positive growth and negative growth periods, furthering the evidence for convergence.

Finally, the pattern is insignificant by *region*. Even though Argentina exhibits significant differences among regional earnings *levels,* we find no association between *changes* in earnings and region either in positive growth or in negative growth periods.

To sum up, the main tests reveal no case of a symmetric relationship. Rather, all of the indicators, when statistically significant, exhibit structural relationships.

Four robustness checks are performed. First, we repeat the analysis based on comparisons of *median* earnings changes rather than means. Comparing the median columns of Table 6 with the mean columns of the same table, we find that the answers are essentially the same. That is, for the medians as for the means, those with higher

initial reported earnings and those who started formal had lower earnings changes, while no difference appears for the other variables.[21]

We also do the analysis for *initial predicted quintile* instead of initial reported quintile. Once again, the symmetry hypothesis is rejected. No significant pattern is found because earnings changes are not associated with this measure of more permanent earnings in periods of positive growth.[22]

We perform another robustness test by analyzing a subsample of workers, leaving aside the unemployed (Table 7). The results remain the same as with the whole sample, i.e., there is no symmetric pattern for any of the variables. The patterns are either insignificant (gender, age, education level, and region) or structural (initial reported earnings and sector transition.) The structural patterns are structural in the same way for this subsample as for the full sample, i.e., individuals in the lower quintiles and those who started informal have larger earnings changes than individuals in the higher quintiles and than those who started formal, respectively.

The last robustness test consists of analyzing formal sector workers and informal sector workers separately (Tables 8A-8B). Both for formal sector workers and for informal sector workers, the pattern is structural for initial reported earnings and insignificant for the remaining variables, which is what we found in the full sample.

In summary, we find *no evidence of unconditional symmetry* of mobility patterns for any of the groups, either in the main tests or in the robustness tests. The hypothesis is rejected using mean and median changes in earnings, as well as using different

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[21] No difference appears for variables such as gender, education level, age, and region. The median changes of each category of these variables are zero. This is because almost half of the changes are positive, almost half are negative and the remaining 7 % are zero, and the median change in earnings is included in this small percentage of earnings changes that are equal to zero. The zero earnings changes correspond mostly to individuals who are unemployed in both periods.

[22] Of course, the validity of these results hinges on the construction of the measure of permanent earnings, which might not be accurate given the limited data available with which to predict earnings in the survey. (There is no information about assets, consumption, etc.)

subsamples of the population. For initial reported earnings and sector transitions, the patterns are structural: the initially less advantaged individuals in those two groups get ahead in periods of growth as well as in periods of recession. The other variables show no significant patterns.

H4: Symmetry of Gains and Losses, Conditional Version

This hypothesis posits that, other things equal, when positive growth and negative growth years are compared, those groups for whom earnings changes are most positive when the economy is growing are those for whom earnings changes are the most negative when the economy is contracting. We test this hypothesis by comparing three panels covering periods of growth (1996-1998 and 2002-2003) pooled together and four panels in periods of recession (1998-2002) pooled together. Conditional tests of symmetry of gains and losses are 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 for growth years pooled and recessionary years pooled are shown in Table 9.[23] We also include the results of the OLS multiple regression for each of the seven years; see Table 10. The corresponding results for the median regressions with bootstrapped standard errors are presented in Tables 11 and 12. The general result is that 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.

Looking first at the OLS multiple regressions in Table 9, 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.,

[23] These are multiple regressions with OLS robust Huber-White correction for standard errors, allowing for heteroskedasticity of arbitrary form.

those with the highest initial reported earnings experience the worst changes in growth and in recession. Other things equal, *men* always have significantly higher earnings changes than women in both periods. In other words, being a male in urban Argentina leads to both higher earnings levels on average, and also to higher upward mobility, ceteris paribus. Other things equal, *age* has a positive and significant effect on earnings changes in both positive growth and negative growth years. The older the individual, the more positive earnings changes he/she experiences.

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 stayers (formal-formal and informal-informal) are always found to be significantly positive, ceteris paribus.[24] Also, among the movers, informal-formal and formal-informal are 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, in Table 9, the coefficients for *region* are significant. When comparing these panels, we reject the symmetry of mobility hypothesis once again. The pattern goes always in the same direction: earnings change in the region in question are less positive or more negative than in Greater Buenos Aires.

[24] Note that the informal sector is very heterogeneous, including informal salaried workers and different kinds of self-employed individuals.

When we run regressions year-by-year instead, the results are mostly the same as the ones just described for growth years pooled compared with recession years pooled; see Table 10. When significant, the structural patterns are the same as before with only one exception for sector transitions.

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 perform is to use median regressions (Tables 11 and 12). The median 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 restrict the sample of individuals with positive earnings in both periods. The results are reported in Table 13. As in the case of the main test, the conditional symmetry of mobility hypothesis is rejected when we analyze this sub-sample. For the most part, the patterns are the same as for the whole sample. We find structural patterns for initial reported earnings, gender, age, education, and region as before, but the pattern for sector transitions is insignificant in the subsample. (Sector transitions turn out not to be significant in growth years.)

The last robustness test consists of dividing the sample into initially formal and initially informal workers and comparing the results with the ones from the whole sample (Tables 14 and 15). Again, we reject the symmetry hypothesis for all of the variables in each of the sub-samples. 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 growth as well as in recessionary years.

In summary, contrary to the hypothesis of conditional symmetry of gains and losses, the results 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 analyzes whether the unconditional determinants of earnings changes are the same as the conditional ones in growth and recessionary years. First, we compare the statistical significance and sign of the variables in growth and recession. Second, we analyze their economic significance.

Regarding statistical significance and sign, the results are summarized in Table 16. 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, as follows. Gender, age, and education change signs and significance. Region changes from not significant unconditionally to significant conditionally. Sector change is always statistically significant but changes sign between the unconditional and the conditional analysis.

The statistically significant *unconditional* determinants of earnings changes are initial reported earnings and sector transitions in growth and recessionary years. Gender, age, and education are statistically significant in recession but not in growth. Region is not statistically significant in any period. When the variables are statistically significant, those with higher unconditional earnings changes were: the poor, women, the young, the less educated, and the ones who started informal.

Turning to the *conditional* results, all explanatory variables are statistically significant in growth and recessionary years. Those with higher conditional earnings changes are: the poor, men, older workers, the more educated, the ones who ended formal, and those in Greater Buenos Aires.

To sum up the results on statistical significance, initial reported earnings is the only variable which keeps its statistical significance and sign, in both the unconditional and the conditional analysis and in both periods. All the other variables flip signs or become significant when we go from the unconditional analysis to the full conditional regression.

To gain more insight about why and when the signs or the significance of the coefficients change, we add an intermediate step between the univariate and the full conditional regression. We run regressions with two explanatory variables and ask what the effect of X_j is when we control for X_k. For example, we analyze five different regressions of change in earnings on initial reported earnings (X_j) by adding different X_k's each time (gender, age, education, change in sector, or region) to a univariate regression. When we regress change in earnings on initial reported earnings and one other explanatory variable, we always get a significantly negative coefficient on initial reported earnings. However, all the other variables exhibit a change in sign or significance in the transition from the unconditional to the conditional analysis with initial reported earnings included. Most of the time, sign flips and changes in significance do not appear in the absence of initial reported earnings. The only exception is the case of sector transitions in periods of recession, which exhibit change in sign when we add education variables.

There are two important conclusions to draw regarding statistical significance. First, the coefficient for initial reported earnings is significantly negative in all of the regressions. The initially poor benefit the most in periods of growth and recession, whether conditionally or unconditionally. Secondly, 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.) This result arises because there are two offsetting effects of variables such as gender, age, and education. On the one hand, being a man, more experienced, or more educated raises base year earnings, and those

individuals with higher base year earnings have smaller earnings gains. On the other hand, once base year earnings are controlled for, men, the more experienced, or the more educated have more positive earnings gains. 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.

Turning from statistical to economic significance, the results are summarized in Table 17. 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. (This methodology was explained in Section 5.) 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 regression, only two variables turn out to be economically significant. They are initial reported earnings and sector transitions. In the conditional analysis, the weights are 0.16 in growth years and 0.33 in recessionary years for initial reported earnings, and 0.04 in growth and recession for sector transitions. In the unconditional analysis, the R-squareds were 0.13 in growth years and 0.27 in recessionary years on initial reported earnings, and 0.06 in growth years and 0.05 in recession for the regressions on sector transitions. The magnitude of the R-squareds show that initial reported earnings is much more important in explaining earnings changes than are sector transitions. Gender, age, education, and region are not economically significant in any of the analyses.

In summary, the conditional determinants of earnings changes are sometimes the same as the unconditional ones and sometimes not. One determinant (initial reported earnings) is always statistically and economically significant. For the other determinants, the results change sign and statistical significance. Turning from statistical significance to economic significance, initial reported earnings is always the most important determinant

of earnings change, sector change is always the second most important determinant, and all other determinants are economically insignificant.

C. Determinants of the Determinants

We have found that the most important determinant of earnings change is initial earnings level. Ample research on Argentina has shown that the variables we have used in our analysis (gender, age, education, sector, and region) are significant determinants of earnings levels (Beccaria and Orsatti, 1979; Cid and Paz, 2002; Monza,1989).

The other important determinant of earnings change in our analysis is sector change. We use ordered logits to analyze what are the determinants of sector change for initially unemployed, initially informal, and initially informal individuals. Ordered logit models are used to estimate relationships between an ordinal dependent variable and a set of independent variables. The ordinal dependent variable, which is ordered and categorical, is the sector of employment in the final year (unemployed, employed in the informal sector, or employed in the formal sector.) The independent variables we use are: gender, experience (age and age-squared), schooling (years of education and years of education-squared), region (Pampeana, Patagonica, Cuyo, Noreste, Noroeste, Greater Buenos Aires), and initial reported earnings (when applicable, i.e., initially employed individuals.) We have one regression for each of the three possible initial states: unemployed, formal sector, and informal sector. We do the analysis separately for periods of growth and for periods of recession.

The results are reported in Table 18. We find some statistically significant variables, but we do a poor job of explaining the variance of sector transitions using gender, age, education, and region. The pseudo R-squared values of the regressions range from half of one percent to four percent in growth and recessionary years.

7. Reconciling Mobility with Inequality Change: An Explanation

In this research, we have found that the pattern of income changes in Argentina was convergent in every period. Specifically, from one year to the next, those individuals who started with the highest incomes were found to have gained the fewest pesos or to have lost the most while those who started with the lowest incomes gained the most pesos. At the same time, our calculations, like those of others (e.g., Gasparini, 2004), show that income inequality was sometimes increasing, sometimes decreasing, and sometimes remaining unchanged. (Consistent with the literature, we are measuring inequality relatively, using Lorenz curves and Gini coefficients.)

The reader may be puzzled how convergent income changes are consistent with inequality that can be rising, remaining the same, or falling. We begin with some examples and then move on to the actual data.

A. A First Example

The first example is one presented earlier. Suppose that we have a two-person economy in which the anonymous distributions of income are (1, 5) in the base period and (1, 5) in the final period. Furthermore, suppose that the two constituent individuals swap incomes between the base and final periods. We shall adopt the notation that a vector of pairs of observations for the various individuals is written in square brackets. Thus, the swapping of incomes is denoted [1, 5], [5, 1]. In this example, the patterns of change are completely convergent, yet inequality is unchanged.

B. A Second Group of Examples

The second group of examples involves patterns in twelve-person economies in which some persons change incomes. In each case, the initial distribution of income is (1, 1, 1, 1, 2, 2, 2, 2, 3, 3, 3, 3).

In the first of these examples, the final distribution of income is exactly the same as the original distribution: (1, 1, 1, 1, 2, 2, 2, 2, 3, 3, 3, 3). However, there is movement of individuals within the distributions. The pairs of base year and final year income for the twelve constituent individuals are as follows:

[1, 1], [1, 1], [1, 2], [1, 3], [2, 1], [2, 2], [2, 2], [2, 3], [3, 1], [3, 2], [3, 3], [3, 3]. (1)

For the three initial thirds, the distribution of mean changes works out to be:

Lowest third: +0.75

Middle third: 0

Top third: -0.75

Thus, a convergent pattern is observed despite the fact that the anonymous distribution is unchanged.

Suppose instead that the anonymous income distribution had doubled between base year and final year, so that the final distribution became

(2, 2, 2, 2, 4, 4, 4, 4, 6, 6, 6, 6). Suppose that the pairs of base year and final year incomes followed a pattern similar to (1), but with all final year incomes doubled:

[1, 2], [1, 2], [1, 4], [1, 6], [2, 2], [2, 4], [2, 4], [2, 6], [3, 2], [3, 4], [3, 6], [3, 6]. (2)

For the three initial thirds, the distribution of mean changes is calculated as:

Lowest third: +2.5

Middle third: +2

Top third: +1.5

Once again, a convergent pattern is found despite unchanged inequality.

Finally, suppose that the economy had suffered a 50% recession, again spread proportionally across all incomes. The anonymous income distribution in the final year is then (0.5, 0.5, 0.5, 0.5, 1, 1, 1, 1, 1.5, 1.5, 1.5, 1.5). Assigning the panel people according to patterns analogous to (1) and (2), we have that the pairs of initial and final year incomes are:

[1, 0.5], [1, 0.5], [1, 1], [1, 1.5], [2, 0.5], [2, 1], [2, 1], [2, 1.5], [3, 0.5], [3, 1], [3, 1.5], [3, 1.5].

(3)

For the three initial thirds, the distribution of mean changes is:

Lowest third: -0.125

Middle third: -1

Top third: -1.875

All groups lose but the initially poor lose the least. In this case too, despite unchanged inequality, a convergent pattern is found.

The preceding examples show how it is possible for initial and final-year inequality to be identical and yet for the pattern of changes to be convergent, whereby the most positive or least negative changes are for the initially-poorest people and the least positive or most negative changes are for the initially-richest people.

C. Actual Data for Argentina, 2001-2002

The third application is for actual data from Argentina for the period 2001-2002. During that time, inequality increased sharply, both according to the Lorenz curve, which shifted outward (Figure 2), and according to the Gini coefficient, which rose from 0.53 to 0.58. Yet the pattern of changes was found to be convergent:

Initial Earnings Quintile (Quintile 1 = Lowest)	Mean Income Change of Those Who Started In That Quintile
Quintile 1	164
Quintile 2	-65
Quintile 3	-127
Quintile 4	-214
Quintile 5	-606

Let us now show explicitly how the rising Gini coefficient and the convergent pattern of changes are mutually compatible in the Argentine data for 2001-2002. To do this, we simulate the base and final year distributions for twenty-five illustrative individuals and show that the simulated Ginis are very close to the actual ones.

For the initial Gini, we selected individuals at the fifth, twenty-fifth, fiftieth, seventy-fifth, and ninety-fifth percentiles of each of the five quintiles in 2001. The calculated Gini for these twenty-five individuals is 0.52, quite close to the actual initial value of 0.53. The reason that we do not get exactly the same Gini is that the simulation is based on 25 people rather than 7,936.

The simulation of the final year Gini proceeds as follows. We assign five people the income at the 5%, 25%, 50%, 75%, and 95% points in the distribution of their initial quintile. We then assign these people the distributions of changes at the 1%, 25%, 50%, 75%, and 99% of the changes for their specific quintile, but in reverse order of magnitude, consistent with the convergent mobility patterns that we have encountered. For example, the income at the 5% point in the distribution of the first quintile is matched with the change at the 99% point in the distribution of the changes for that specific quintile. In the case of the first quintile, these levels and changes are, respectively:

Distribution of Earnings Level within Quintile 1	**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 Change 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

The simulated final year incomes are then:

Final Year Quintile 1	Simulated Final Year 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

Similarly, in the case of the second quintile, the five base levels, the five changes, and the simulated initial incomes are, respectively:

Distribution of Earnings Level within Quintile 2	Level
Fifth percentile of quintile 2	120
Twenty-fifth percentile of quintile 2	189
Fiftieth percentile of quintile 2	240
Seventy-fifth percentile of quintile2	300
Ninety-fifth percentile of quintile 2	300

Distribution of Earnings Change within Quintile 2	Change
First percentile of quintile 2	-300
Twenty-fifth percentile of quintile 2	-150
Fiftieth percentile of quintile 2	-47
Seventy-fifth percentile of quintile2	-4
Ninety-ninth percentile of quintile 2	311

Final Year Quintile 2	Final Year Income
Sixth simulated individual	120 + 311 = 431
Seventh simulated individual	189 - 4 = 185
Eighth simulated individual	240 – 47 = 193
Ninth simulated individual	300 – 150 = 150
Tenth simulated individual	300 – 300 = 0

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

Once we obtained these twenty-five simulated incomes, we calculated the Gini coefficient of the simulated final year distribution. This Gini was found to be 0.58, which is the same as the actual final year Gini. That is, when we take account of five values of the quintile-specific initial distribution and the quintile-specific distribution of changes, we arrive at a simulated income distribution for 2002 that is the same as the actual one.

Recall that for the base year (2001), the simulated distribution produced a Gini of 0.52, when the actual Gini was 0.53. Thus, using twenty-five individuals drawn from the actual Argentine income distribution for 2001 and twenty-five changes drawn from the actual distribution of changes between 2001 and 2002, we have come been able to reproduce both the rising inequality that took place and the convergent pattern of income 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 incomes of each of the five initial quintiles and applied the mean change for members of the respective quintile, the resulting distribution of income would have been

Quintile (Quintile 1 = Lowest)	**Simulated Income 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 final year value of 0.58. The primary reasons that this simpler simulation understates inequality are that: 1) it does not generate incomes that are sufficiently high at the top end, because it fails to recognize the inequality of changes

within the top income quintile, and 2) it does not generate zero incomes at the bottom end for those who became unemployed.

In summary, these examples show that when initial quintile mean incomes are combined with an appropriate distribution of initial-quintile-specific changes, the simulated final-year inequality values essentially match the actual ones. What this means is that the change in anonymous inequality is providing one type of information while the distribution of the changes in income for named individuals is providing another. Both pieces of information are true. They are, however, different.

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 rich were getting richer in growth periods and losing more in recessions than those who started poor. We performed unconditional and conditional tests for the years 1996-1997 to 2002-2003 in all urban Argentina, considering women and men aged 25-60 who participated in the labor 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 welfare 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 initial 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. We summarize these results in turn.

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 the economy is contracting. Specifically, convergence is found for initial reported earnings and sector transitions. For the rest of the variables, the pattern is insignificant in positive growth periods. 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 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 number of alternative specifications: using median regression in place of mean regression, using just the individuals employed in both periods, and analyzing 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.

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. We found some statistically significant variables, but did

a poor job explaining the variance of sector transitions using gender, age, education, and region.

After reporting these results, we explained in detail how convergent mobility is consistent with increasing inequality in the case of Argentina.

We have found that the use of panel data adds a whole new dimension to our understanding of winners and losers in Argentina. In the future, researchers would do well to perform both panel data analysis and cross-section analysis. It would be helpful if the data base were extended beyond urban Argentina to cover rural areas as well.

References

Agénor, Pierre-Richard (2002). "Why Crises Are Bad for the Poor," Development Outreach, Spring, 2002.

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

Altimir, O. and L. Beccaria (2000), "Distribucion del Ingreso en Argentina" in La Argentina de los noventa, Vol. I. Heyman and Kosacoff eds., Buenos Aires: EUDEBA-CEPAL.

Altimir, O. and L. Beccaria (2001), "El Persistente Deterioro de la Distribucion del Ingreso en Argentina". Desarrollo Economico, Vol. 40, 160.

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.

Baulch, Bob and Neil McCulloch (2000). "Tracking Pro-Poor Growth," Institute of Development Studies, University of Sussex.

Basu, Kaushik (1997). *Analytical Development Economics*. (Cambridge: MIT Press).

Beccaria, Luis and Alvaro Orsatti (1979)," Sobre el Tamaño del Desempleo Oculto en el Mercado de Trabajo Urbano de la Argentina", Desarrollo Económico, 74, Buenos Aires.

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).

Cid, Juan C. and Jorge Paz (2002), "El Transito por el Desempleo en la Argentina. Determinantes y Consecuencias sobre el Empleo", Anales de la AAEP, Argentina.

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.

Damill, M., Frenkel, R. and Roxana Maurizio (2002), "Argentina: A Decade of Currency Board. An Analysis of Growth, Employment, and Income Distribution", ILO Employment Paper 2002/42, Buenos Aires.

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

Duclos, Jean-Yves and Quentin Wodon (2004). "What Is 'Pro-Poor?" CIRPEE Working Paper 04-25.

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. (2003). "Accounting for Income Inequality and Its Change: A New Method, with Application to the Distribution of Earnings in the United States," in Solomon Polachek, ed., Research in Labor Economics, Volume 22 (Amsterdam: JAI Press).

Fields, Gary S., Maria Laura Sánchez Puerta, Robert Duval Hernandez and Samuel Freije (2004) "Earnings Mobility in Argentina, Mexico, and Venezuela: Testing the Divergence of Earnings and the Symmetry of Mobility Hypotheses", mimeo.

Fields, Gary S., Paul Cichello, Samuel Freije, Marta Menéndez and David Newhouse (2003a) "For Richer or For Poorer: Did Household Incomes Converge or Diverge in the 1990s?" *Journal of Economic Inequality*, 1:67-99.

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

Foster, James, Joel Greer and Erik Thorbecke (1984). "A Class of Decomposable Poverty Measures," Econometrica 52: 761-66.

Freije, Samuel (2001). *Household Income Dynamics in Venezuela.* Unpublished doctoral dissertation. Cornell University.

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. Marchionni, M. and Walter Sosa Escudero (2001), "La Distribucion del Ingreso en la Argentina. Perspectivas y Efectos sobre el Bienestar" Premio Fulvio Salvador Pagani, Fundacion Arcor.

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

Harberger, Arnold (1998). “Monetary and Fiscal Policy for Equitable Economic Growth,” in Vito Tanzi and Ke-Young Chu, eds., *Income Distribution and High-Quality Growth*. (Cambridge and London: MIT Press).

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).

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

Kakwani, Nanak (1993). "Poverty and Economic Growth with Application to Côte d'Ivoire," *Review of Income and Wealth* 39: 121-139.

Kraay, Aart (2003). “When Is Growth Pro-Poor? Cross-Country Evidence,” World Bank, processed.

Lopez-Calva, L.F and Maria F. Arce (2001). “Income Mobility and Political Choices in Mexico,” Unpublished working paper. Universidad de las Americas.

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.

Monza, A. (1989), "La Cuestión Ocupacional Argentina", Mimeo, CGI, Buenos Aires.

Nelson, Richard R. (1956). "A Theory of the Low-Level Equilibrium Trap in Underdeveloped Economies," *American Economic Review,* 46: 894-908.

Nurkse, Ragnar (1953). *Problems of Capital Formation in Underdeveloped Countries.* (New York: Oxford University Press).

Ravallion, Martin (2004). "Pro-Poor Growth: A Primer," World Bank Policy Research Working Paper 3242, March.

Ravallion, M. and Shaohua Chen (2004), "Measuring pro-poor growth", Development Research Group, World Bank.

Rosenstein-Rodin, Paul N. (1943). "Problems of Industrialisation in Eastern and South-Eastern Europe," *Economic Journal* 53: 202-211.

Sanchez Puerta, M.L. (2004). "Stylized Facts on Poverty, Inequality and Economic Growth," Paper Prepared for the Seminar "Poverty, Inequality, and Economic Growth in Argentina," Buenos Aires, December, 2004.

Sen, Amartya K. (1976). "Poverty: An Ordinal Approach to Measurement," Econometrica 219-231.

Summers, Lawrence (1998). "Comment," in Vito Tanzi and Ke-Young Chu, eds., *IncomeDistribution and High-Quality Growth*. (Cambridge and London: MIT Press).

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

Winters, L. Alan, Neil McCulloch, and Andrew McKay (2004). "Trade Liberalization and Poverty: The Evidence So Far," *Journal of Economic Literature* XLII: 72-115.

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

Table 1-A
Quintile transition matrix, 1996-1997

Quintile 1996	Quintile 1997					
	Quintile 1	**Quintile 2**	**Quintile 3**	**Quintile 4**	**Quintile 5**	**Total**
Quintile 1						
Number	1077	366	198	117	84	1842
Row percentage	58.47	19.87	10.75	6.35	4.56	100
Column percentage	60.92	24.19	11.59	7.48	5.32	22.65
Table percentage	13.24	4.5	2.43	1.44	1.03	22.65
Quintile 2						
Number	316	709	346	96	20	1487
Row percentage	21.25	47.68	23.27	6.46	1.34	100
Column percentage	17.87	46.86	20.25	6.14	1.27	18.29
Table percentage	3.89	8.72	4.25	1.18	0.25	18.29
Quintile 3						
Number	187	322	741	336	77	1663
Row percentage	11.24	19.36	44.56	20.2	4.63	100
Column percentage	10.58	21.28	43.36	21.48	4.88	20.45
Table percentage	2.3	3.96	9.11	4.13	0.95	20.45
Quintile 4						
Number	105	100	334	715	267	1521
Row percentage	6.9	6.57	21.96	47.01	17.55	100
Column percentage	5.94	6.61	19.54	45.72	16.92	18.7
Table percentage	1.29	1.23	4.11	8.79	3.28	18.7
Quintile 5						
Number	83	16	90	300	1130	1619
Row percentage	5.13	0.99	5.56	18.53	69.8	100
Column percentage	4.69	1.06	5.27	19.18	71.61	19.91
Table percentage	1.02	0.2	1.11	3.69	13.9	19.91
Total	1768	1513	1709	1564	1578	8132
Row percentage	21.74	18.61	21.02	19.23	19.4	100
Column percentage	100	100	100	100	100	100
Table percentage	21.74	18.61	21.02	19.23	19.4	100

Table 1-B
Quintile transition matrix, 1997-1998

Quintile 1997	Quintile 1998					
	Quintile 1	**Quintile 2**	**Quintile 3**	**Quintile 4**	**Quintile 5**	**Total**
Quintile 1						
Number	1019	298	211	151	117	1796
Row percentage	56.74	16.59	11.75	8.41	6.51	100
Column percentage	47.91	19.75	11.85	8.17	7.2	20.21
Table percentage	11.46	3.35	2.37	1.7	1.32	20.21
Quintile 2						
Number	565	787	412	172	26	1962
Row percentage	28.8	40.11	21	8.77	1.33	100
Column percentage	26.56	52.15	23.15	9.31	1.6	22.07
Table percentage	6.36	8.85	4.64	1.94	0.29	22.07
Quintile 3						
Number	243	306	784	383	91	1807
Row percentage	13.45	16.93	43.39	21.2	5.04	100
Column percentage	11.42	20.28	44.04	20.73	5.6	20.33
Table percentage	2.73	3.44	8.82	4.31	1.02	20.33
Quintile 4						
Number	160	88	294	825	214	1581
Row percentage	10.12	5.57	18.6	52.18	13.54	100
Column percentage	7.52	5.83	16.52	44.64	13.18	17.79
Table percentage	1.8	0.99	3.31	9.28	2.41	17.79
Quintile 5						
Number	140	30	79	317	1176	1742
Row percentage	8.04	1.72	4.54	18.2	67.51	100
Column percentage	6.58	1.99	4.44	17.15	72.41	19.6
Table percentage	1.58	0.34	0.89	3.57	13.23	19.6
Total	2127	1509	1780	1848	1624	8888
Row percentage	23.93	16.98	20.03	20.79	18.27	100
Column percentage	100	100	100	100	100	100
Table percentage	23.93	16.98	20.03	20.79	18.27	100

Table 1-C
Quintile transition matrix, 1998-1999

Quintile 1998	Quintile 1999					
	Quintile 1	**Quintile 2**	**Quintile 3**	**Quintile 4**	**Quintile 5**	**Total**
Quintile 1						
Number	800	390	156	114	100	1560
Row percentage	51.28	25	10	7.31	6.41	100
Column percentage	51.22	22.11	9.61	8.18	6.98	20.06
Table percentage	10.29	5.01	2.01	1.47	1.29	20.06
Quintile 2						
Number	343	811	372	90	27	1643
Row percentage	20.88	49.36	22.64	5.48	1.64	100
Column percentage	21.96	45.98	22.91	6.46	1.88	21.13
Table percentage	4.41	10.43	4.78	1.16	0.35	21.13
Quintile 3						
Number	191	394	704	290	67	1646
Row percentage	11.6	23.94	42.77	17.62	4.07	100
Column percentage	12.23	22.34	43.35	20.8	4.68	21.16
Table percentage	2.46	5.07	9.05	3.73	0.86	21.16
Quintile 4						
Number	102	129	313	654	237	1435
Row percentage	7.11	8.99	21.81	45.57	16.52	100
Column percentage	6.53	7.31	19.27	46.92	16.54	18.45
Table percentage	1.31	1.66	4.02	8.41	3.05	18.45
Quintile 5						
Number	126	40	79	246	1002	1493
Row percentage	8.44	2.68	5.29	16.48	67.11	100
Column percentage	8.07	2.27	4.86	17.65	69.92	19.2
Table percentage	1.62	0.51	1.02	3.16	12.88	19.2
Total	1562	1764	1624	1394	1433	7777
Row percentage	20.08	22.68	20.88	17.92	18.43	100
Column percentage	100	100	100	100	100	100
Table percentage	20.08	22.68	20.88	17.92	18.43	100

Table 1-D
Quintile transition matrix, 1999-2000

Quintile 1999	Quintile 2000					
	Quintile 1	**Quintile 2**	**Quintile 3**	**Quintile 4**	**Quintile 5**	**Total**
Quintile 1						
Number	758	472	213	106	107	1656
Row percentage	45.77	28.5	12.86	6.4	6.46	100
Column percentage	48.19	28.61	11.74	7.76	7.56	21.18
Table percentage	9.7	6.04	2.72	1.36	1.37	21.18
Quintile 2						
Number	312	753	344	56	15	1480
Row percentage	21.08	50.88	23.24	3.78	1.01	100
Column percentage	19.83	45.64	18.96	4.1	1.06	18.93
Table percentage	3.99	9.63	4.4	0.72	0.19	18.93
Quintile 3						
Number	226	306	884	324	64	1804
Row percentage	12.53	16.96	49	17.96	3.55	100
Column percentage	14.37	18.55	48.73	23.72	4.52	23.07
Table percentage	2.89	3.91	11.31	4.14	0.82	23.07
Quintile 4						
Number	119	96	295	642	196	1348
Row percentage	8.83	7.12	21.88	47.63	14.54	100
Column percentage	7.57	5.82	16.26	47	13.85	17.24
Table percentage	1.52	1.23	3.77	8.21	2.51	17.24
Quintile 5						
Number	158	23	78	238	1033	1530
Row percentage	10.33	1.5	5.1	15.56	67.52	100
Column percentage	10.04	1.39	4.3	17.42	73	19.57
Table percentage	2.02	0.29	1	3.04	13.21	19.57
Total	1573	1650	1814	1366	1415	7818
Row percentage	20.12	21.11	23.2	17.47	18.1	100
Column percentage	100	100	100	100	100	100
Table percentage	20.12	21.11	23.2	17.47	18.1	100

Table 1-E
Quintile transition matrix, 2000-2001

Quintile 2000	Quintile 2001					
	Quintile 1	**Quintile 2**	**Quintile 3**	**Quintile 4**	**Quintile 5**	**Total**
Quintile 1						
Number	762	389	121	118	112	1502
Row percentage	50.73	25.9	8.06	7.86	7.46	100
Column percentage	48.78	23.41	9.97	7.97	7.58	20.31
Table percentage	10.3	5.26	1.64	1.6	1.51	20.31
Quintile 2						
Number	364	871	242	113	29	1619
Row percentage	22.48	53.8	14.95	6.98	1.79	100
Column percentage	23.3	52.41	19.93	7.63	1.96	21.89
Table percentage	4.92	11.78	3.27	1.53	0.39	21.89
Quintile 3						
Number	147	274	580	271	46	1318
Row percentage	11.15	20.79	44.01	20.56	3.49	100
Column percentage	9.41	16.49	47.78	18.3	3.11	17.82
Table percentage	1.99	3.7	7.84	3.66	0.62	17.82
Quintile 4						
Number	174	111	234	786	383	1688
Row percentage	10.31	6.58	13.86	46.56	22.69	100
Column percentage	11.14	6.68	19.28	53.07	25.93	22.82
Table percentage	2.35	1.5	3.16	10.63	5.18	22.82
Quintile 5						
Number	115	17	37	193	907	1269
Row percentage	9.06	1.34	2.92	15.21	71.47	100
Column percentage	7.36	1.02	3.05	13.03	61.41	17.16
Table percentage	1.55	0.23	0.5	2.61	12.26	17.16
Total	1562	1662	1214	1481	1477	7396
Row percentage	21.12	22.47	16.41	20.02	19.97	100
Column percentage	100	100	100	100	100	100
Table percentage	21.12	22.47	16.41	20.02	19.97	100

Table 1-F
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 1-G
Quintile transition matrix, 2002-2003

Quintile 2002	Quintile 2003					
	Quintile 1	**Quintile 2**	**Quintile 3**	**Quintile 4**	**Quintile 5**	**Total**
Quintile 1						
Number	488	371	140	124	119	1242
Row percentage	39.29	29.87	11.27	9.98	9.58	100
Column percentage	44.48	26.2	16.77	12.55	11.16	22.99
Table percentage	9.03	6.87	2.59	2.3	2.2	22.99
Quintile 2						
Number	254	562	92	39	9	956
Row percentage	26.57	58.79	9.62	4.08	0.94	100
Column percentage	23.15	39.69	11.02	3.95	0.84	17.7
Table percentage	4.7	10.4	1.7	0.72	0.17	17.7
Quintile 3						
Number	170	403	386	212	49	1220
Row percentage	13.93	33.03	31.64	17.38	4.02	100
Column percentage	15.5	28.46	46.23	21.46	4.6	22.58
Table percentage	3.15	7.46	7.15	3.92	0.91	22.58
Quintile 4						
Number	84	60	192	472	213	1021
Row percentage	8.23	5.88	18.81	46.23	20.86	100
Column percentage	7.66	4.24	22.99	47.77	19.98	18.9
Table percentage	1.55	1.11	3.55	8.74	3.94	18.9
Quintile 5						
Number	101	20	25	141	676	963
Row percentage	10.49	2.08	2.6	14.64	70.2	100
Column percentage	9.21	1.41	2.99	14.27	63.41	17.83
Table percentage	1.87	0.37	0.46	2.61	12.51	17.83
Total	1097	1416	835	988	1066	5402
Row percentage	20.31	26.21	15.46	18.29	19.73	100
Column percentage	100	100	100	100	100	100
Table percentage	20.31	26.21	15.46	18.29	19.73	100

Table 2-A
Intersectoral transition matrix, 1996-1997

Sector in 1996	Sector in 1997			
	Formally employed	**Informally employed**	**Unemployed**	**Total**
Formally employed				
Number	3448	785	131	4364
Row percentage	79.01	17.99	3	100
Column percentage	80.92	24.98	17.99	53.66
Table percentage	42.4	9.65	1.61	53.66
Informally employed				
Number	698	1906	231	2835
Row percentage	24.62	67.23	8.15	100
Column percentage	16.38	60.64	31.73	34.86
Table percentage	8.58	23.44	2.84	34.86
Unemployed				
Number	115	452	366	933
Row percentage	12.33	48.45	39.23	100
Column percentage	2.7	14.38	50.27	11.47
Table percentage	1.41	5.56	4.5	11.47
Total	4261	3143	728	8132
Row percentage	52.4	38.65	8.95	100
Column percentage	100	100	100	100
Table percentage	52.4	38.65	8.95	100

Table 2-B
Intersectoral transition matrix, 1997-1998

Sector in1997	Sector in 1998			
	Formally employed	**Informally employed**	**Unemployed**	**Total**
Formally employed				
Number	3032	857	116	4005
Row percentage	75.71	21.4	2.9	100
Column percentage	78.71	19.61	17.42	45.06
Table percentage	34.11	9.64	1.31	45.06
Informally employed				
Number	720	3076	288	4084
Row percentage	17.63	75.32	7.05	100
Column percentage	18.69	70.39	43.24	45.95
Table percentage	8.1	34.61	3.24	45.95
Unemployed				
Number	100	437	262	799
Row percentage	12.52	54.69	32.79	100
Column percentage	2.6	10	39.34	8.99
Table percentage	1.13	4.92	2.95	8.99
Total	3852	4370	666	8888
Row percentage	43.34	49.17	7.49	100
Column percentage	100	100	100	100
Table percentage	43.34	49.17	7.49	100

Table 2-C
Intersectoral transition matrix, 1998-1999

Sector in 1998	Sector in 1999			
	Formally employed	Informally employed	Unemployed	Total
Formally employed				
Number	2558	734	87	3379
Row percentage	75.7	21.72	2.57	100
Column percentage	74.45	19.72	14.08	43.45
Table percentage	32.89	9.44	1.12	43.45
Informally employed				
Number	801	2696	312	3809
Row percentage	21.03	70.78	8.19	100
Column percentage	23.31	72.41	50.49	48.98
Table percentage	10.3	34.67	4.01	48.98
Unemployed				
Number	77	293	219	589
Row percentage	13.07	49.75	37.18	100
Column percentage	2.24	7.87	35.44	7.57
Table percentage	0.99	3.77	2.82	7.57
Total	3436	3723	618	7777
Row percentage	44.18	47.87	7.95	100
Column percentage	100	100	100	100
Table percentage	44.18	47.87	7.95	100

Table 2-D
Intersectoral transition matrix, 1999- 2000

Sector in 1999	Sector in 2000			
	Formally employed	Informally employed	Unemployed	Total
Formally employed				
Number	2770	621	133	3524
Row percentage	78.6	17.62	3.77	100
Column percentage	78.45	17.83	16.54	45.08
Table percentage	35.43	7.94	1.7	45.08
Informally employed				
Number	676	2536	386	3598
Row percentage	18.79	70.48	10.73	100
Column percentage	19.14	72.81	48.01	46.02
Table percentage	8.65	32.44	4.94	46.02
Unemployed				
Number	85	326	285	696
Row percentage	12.21	46.84	40.95	100
Column percentage	2.41	9.36	35.45	8.9
Table percentage	1.09	4.17	3.65	8.9
Total	3531	3483	804	7818
Row percentage	45.17	44.55	10.28	100
Column percentage	100	100	100	100
Table percentage	45.17	44.55	10.28	100

Table 2-E
Intersectoral transition matrix, 2000- 2001

Sector in 2000	Sector in 2001			
	Formally employed	Informally employed	Unemployed	Total
Formally employed				
Number	2579	520	127	3226
Row percentage	79.94	16.12	3.94	100
Column percentage	79.01	15.4	16.8	43.62
Table percentage	34.87	7.03	1.72	43.62
Informally employed				
Number	616	2510	370	3496
Row percentage	17.62	71.8	10.58	100
Column percentage	18.87	74.35	48.94	47.27
Table percentage	8.33	33.94	5	47.27
Unemployed				
Number	69	346	259	674
Row percentage	10.24	51.34	38.43	100
Column percentage	2.11	10.25	34.26	9.11
Table percentage	0.93	4.68	3.5	9.11
Total	3264	3376	756	7396
Row percentage	44.13	45.65	10.22	100
Column percentage	100	100	100	100
Table percentage	44.13	45.65	10.22	100

Table 2-F
Intersectoral transition matrix, 2001- 2002

Sector in 2001	Sector in 2002			
	Formally employed	Informally employed	Unemployed	Total
Formally employed				
Number	2603	688	199	3490
Row percentage	74.58	19.71	5.7	100
Column percentage	81.09	19.45	16.76	43.99
Table percentage	32.81	8.67	2.51	43.99
Informally employed				
Number	539	2549	559	3647
Row percentage	14.78	69.89	15.33	100
Column percentage	16.79	72.07	47.09	45.97
Table percentage	6.79	32.13	7.05	45.97
Unemployed				
Number	68	300	429	797
Row percentage	8.53	37.64	53.83	100
Column percentage	2.12	8.48	36.14	10.05
Table percentage	0.86	3.78	5.41	10.05
Total	3210	3537	1187	7934
Row percentage	40.46	44.58	14.96	100
Column percentage	100	100	100	100
Table percentage	40.46	44.58	14.96	100

Table 2-G
Intersectoral transition matrix, 2002- 2003

Sector in 2002	Sector in 2003			
	Formally employed	**Informally employed**	**Unemployed**	**Total**
Formally employed				
Number	1698	373	66	2137
Row percentage	79.46	17.45	3.09	100
Column percentage	76.28	13.83	13.81	39.56
Table percentage	31.43	6.9	1.22	39.56
Informally employed				
Number	453	1855	163	2471
Row percentage	18.33	75.07	6.6	100
Column percentage	20.35	68.75	34.1	45.74
Table percentage	8.39	34.34	3.02	45.74
Unemployed				
Number	75	470	249	794
Row percentage	9.45	59.19	31.36	100
Column percentage	3.37	17.42	52.09	14.7
Table percentage	1.39	8.7	4.61	14.7
Total	2226	2698	478	5402
Row percentage	41.21	49.94	8.85	100
Column percentage	100	100	100	100
Table percentage	41.21	49.94	8.85	100

Table 3
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		
	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 Initial 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 Initial Predicted Quintile (without zeroes)	H_{02}: **			H_{02}:			H_{02}: ***			H_{02}: ***			H_{02}: ***			H_{02}: ***			H_{02}: ***		
Quintile 1	-13.2	184.3	1338	5.8	226.5	1461	-15.6	195.7	1285	-9.8	182.8	1239	-18.9	176.4	1168	-94.2	235.3	1196	-33.5	137.7	803
Quintile 2	-4.8	332.2	1331	-2.0	293.3	1451	-33.9	257.9	1272	-25.5	263.8	1228	-37.4	306.0	1162	-133.7	240.0	1195	-48.3	196.5	782
Quintile 3	-16.7	359.9	1320	-10.2	335.3	1459	-32.7	327.3	1280	-37.4	315.1	1231	-43.8	303.6	1160	-167.7	375.5	1197	-56.4	232.9	793
Quintile 4	-26.4	382.5	1333	-26.0	508.0	1454	-58.5	536.7	1271	-43.4	376.7	1233	-98.8	547.7	1164	-222.5	454.5	1198	-86.1	325.9	791
Quintile 5	-57.3	806.9	1326	-28.7	1006.5	1453	-123.5	1029.6	1276	-177.8	906.5	1231	-97.0	877.9	1161	-381.2	798.3	1189	-169.2	618.3	789
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_0 rejected at 99, 95, 90% of significance

H_{01}: mean equal to zero.
H_{02} : equality of means by groups

Table 4-A
Unweighted Reported Earnings Changes by Initial Position
Dependent Variable: Change in Reported Earnings

	1996-1997				
	Mean	Std.Dev.	H_{01}	Median	Obs.
Total Population	2.0	496.7	**	-1.6	8130
By Initial Reported	H_{02}: ***				
Quintile					
Lowest Quintile	207.2	494.7	***	64.8	1840
Quintile 2	22.2	207.6	***	-1.6	1487
Quintile 3	7.7	262.5		-2.9	1663
Quintile 4	-25.4	376.0	***	-8.2	1521
Highest Quintile	-230.1	784.4	***	-144.5	1619
By Initial Predicted	H_{02}:				
Quintile					
Quintile 1	-1.2	212.9		-1.3	1627
Quintile 2	3.3	325.8		-1.3	1646
Quintile 3	6.4	384.4		-1.3	1611
Quintile 4	8.1	500.2		-2.3	1639
Quintile 5	-6.9	831.1		-3.0	1607
By Initial Predicted	H_{02}: **				
Quintile (without zeroes)					
Quintile 1	-13.2	184.3	***	-2.4	1338
Quintile 2	-4.8	332.2		-2.9	1331
Quintile 3	-16.7	359.9	*	-3.2	1320
Quintile 4	-26.4	382.5	**	-3.9	1333
Quintile 5	-57.3	806.9	***	-6.4	1326
By Gender	H_{02}: *				
Men	-0.8	574.0		-1.9	5012
Women	6.3	337.3	**	-1.3	3118
By Age	H_{02}: *				
25-36 yrs	2.3	397.5		-0.4	3415
37-48 yrs	-4.5	482.9		-2.4	3200
49-60 yrs	15.0	689.4		-1.5	1515
By Education Level	H_{02}:				
Primary or less	2.1	354.7		0.0	2829
Secondary	53.4	547.8	**	0.0	3026
Higher	70.1	939.9		0.0	1804
By Sector					
Transition	H_{02}: ***				
Unemployed to Informal	317.0	324.2		248.2	451
Unemployed to Formal	486.4	498.6		397.1	115
Informal to Formal	21.4	441.7		-1.0	699
Informal to Informal	19.1	413.7	**	-1.6	1904
Informal to Unemployed	-336.2	388.0		-249.8	231
Formal to Formal	-28.5	518.7	***	-3.9	3448
Formal to Informal	23.4	635.1		-5.8	785
Formal to Unemployed	-584.4	569.1		-449.6	131
By Region	H_{02}: ***				
GBA	60.6	692.7	***	0.0	973
Pampeana	1.0	452.3		-1.3	2436
Patagonica	-15.8	545.6		-3.2	1067
Noreste	-9.6	498.6		-1.9	1289
Noroeste	6.4	397.3		-1.3	1312
Cuyo	-23.5	427.0		-2.5	1053

***, **, * H_{0j} rejected at 99, 95, 90% of significance
H_{01}: mean equal to zero
H_{02} : equality of means by groups

Table 4-B
Unweighted Reported Earnings Changes by Initial Position
Dependent Variable: Change in Reported Earnings

	1997-1998				
	Mean	Std.Dev.	H_{01}	Median	Obs.
Total Population	21.1	570.7	***	-2.3	8889
By Initial Reported	H_{02}: ***				
Quintile					
Lowest Quintile	264.9	501.7	***	126.4	1796
Quintile 2	33.3	207.0	***	-2.3	1963
Quintile 3	13.8	301.1	*	-5.2	1807
Quintile 4	-39.1	368.0	***	-9.2	1581
Highest Quintile	-181.8	1016.0	***	-60.6	1742
By Initial Predicted	H_{02}:				
Quintile					
Quintile 1	21.3	254.0	***	-2.1	1779
Quintile 2	18.6	325.2	**	0.0	1783
Quintile 3	12.8	350.2		-0.9	1781
Quintile 4	6.5	556.6		-3.4	1769
Quintile 5	46.1	1013.5	*	-3.4	1777
By Initial Predicted	H_{02}:				
Quintile (without zeroes)					
Quintile 1	5.8	226.5		-3.4	1461
Quintile 2	-2.0	293.3		-4.4	1451
Quintile 3	-10.2	335.3		-4.6	1459
Quintile 4	-26.0	508.0	*	-5.7	1454
Quintile 5	-28.7	1006.5		-11.5	1453
By Gender	H_{02}:				
Men	18.6	662.1	**	-2.3	5609
Women	25.4	364.8	***	-1.8	3280
By Age	H_{02}:				
25-36 yrs	25.8	427.4	***	-1.0	3540
37-48 yrs	28.2	643.8	***	-2.3	3559
49-60 yrs	-2.3	657.1		-2.3	1790
By Education Level	H_{02}: *				
Primary or less	7.1	327.7	***	-2.3	3002
Secondary	-9.8	599.8	**	-3.4	3032
Higher	92.2	1052.9	**	0.0	1986
By Sector					
Transition	H_{02}: ***				
Unemployed to Informal	316.5	304.1	***	245.3	437
Unemployed to Formal	611.3	681.1	***	441.6	101
Informal to Formal	56.8	592.0	**	0.0	720
Informal to Informal	21.3	520.8	**	-2.3	3076
Informal to Unemployed	-318.2	329.1	***	-248.2	288
Formal to Formal	14.3	648.1		-4.6	3032
Formal to Informal	-5.5	529.2		-5.7	857
Formal to Unemployed	-565.0	507.9	***	-476.5	117
By Region	H_{02}:				
GBA	21.0	756.7		0.0	971
Pampeana	27.6	612.2	***	-2.3	3246
Patagonica	17.7	447.4	*	0.0	957
Noreste	13.1	523.7		-1.7	933
Noroeste	4.6	424.0		-2.3	1593
Cuyo	34.6	572.5	*	0.0	1189

***, **, * H_{0j} rejected at 99, 95, 90% of significance
H_{01}: mean equal to zero
H_{02} : equality of means by groups

Table 4-C
Unweighted Reported Earnings Changes by Initial Position
Dependent Variable: Change in Reported Earnings

	1998-1999				
	Mean	Std.Dev.	H_{01}	Median	Obs.
Total Population	-18.6	577.7	***	2.2	7777
By Initial Reported	H_{02}: ***				
Quintile					
Lowest Quintile	243.4	479.2	***	94.5	1560
Quintile 2	20.8	200.2	***	2.2	1643
Quintile 3	-18.1	238.1	***	2.9	1646
Quintile 4	-36.1	345.7	***	-35.6	1435
Highest Quintile	-319.7	1055.3	***	-149.8	1493
By Initial Predicted	H_{02}:				
Quintile					
Quintile 1	-5.1	218.5		1.5	1570
Quintile 2	-22.1	356.7	**	1.5	1541
Quintile 3	-12.4	355.3		1.8	1577
Quintile 4	-15.0	563.7		3.7	1536
Quintile 5	-38.8	1027.0		5.9	1553
By Initial Predicted	H_{02}: ***				
Quintile (without zeroes)					
Quintile 1	-15.6	195.7	***	2.1	1285
Quintile 2	-33.9	257.9	***	2.2	1272
Quintile 3	-32.7	327.3	***	2.2	1280
Quintile 4	-58.5	536.7	***	3.7	1271
Quintile 5	-123.5	1029.6	***	5.9	1276
By Gender	H_{02}: ***				
Men	-29.8	661.7	***	2.2	4891
Women	0.2	396.3		2.6	2886
By Age	H_{02}: **				
25-36 yrs	0.2	424.7		2.9	3019
37-48 yrs	-24.1	688.6	*	2.3	3071
49-60 yrs	-42.4	593.2	***	0.0	1687
By Education Level	H_{02}:				
Primary or less	-25.3	306.1	***	1.5	2430
Secondary	-17.9	466.5	**	2.9	2498
Higher	21.1	917.0		7.4	1744
By Sector					
Transition	H_{02}: ***				
Unemployed to Informal	302.5	331.7	***	197.7	293
Unemployed to Formal	490.6	408.8	***	395.5	77
Informal to Formal	5.9	696.8		5.9	801
Informal to Informal	-20.5	442.7	**	1.5	2696
Informal to Unemployed	-358.0	530.8	***	-279.7	312
Formal to Formal	-8.5	661.1		5.9	2558
Formal to Informal	-60.1	651.1	**	0.0	734
Formal to Unemployed	-497.1	341.5	***	-412.1	87
By Region	H_{02}:				
GBA	1.1	546.0		2.9	1204
Pampeana	-19.0	617.6	*	1.8	2522
Patagonica	9.6	504.5		2.9	970
Noreste	-44.9	538.8	**	1.5	864
Noroeste	-19.7	560.4		3.0	1338
Cuyo	-48.3	636.4	**	1.3	879

***, **, * H_{0j} rejected at 99, 95, 90% of significance
H_{01}: mean equal to zero
H_{02} : equality of means by groups

Table 4-D
Unweighted Reported Earnings Changes by Initial Position
Dependent Variable: Change in Reported Earnings

	1999-2000				
	Mean	Std.Dev.	H_{01}	Median	Obs.
Total Population	-23.1	531.5	***	2.1	7818
By Initial Reported	H_{02}: ***				
Quintile					
Lowest Quintile	249.3	536.3	***	70.8	1656
Quintile 2	2.2	184.8		2.7	1480
Quintile 3	-18.4	232.4	***	3.7	1804
Quintile 4	-61.2	322.0	***	-42.2	1348
Highest Quintile	-314.2	882.0	***	-180.2	1530
By Initial Predicted	H_{02}: ***				
Quintile					
Quintile 1	-4.0	202.3		2.1	1567
Quintile 2	-3.9	308.9		3.2	1561
Quintile 3	-19.5	346.0	**	0.0	1569
Quintile 4	-6.0	472.6		4.3	1558
Quintile 5	-82.0	964.5	***	0.0	1563
By Initial Predicted	H_{02}: ***				
Quintile (without zeroes)					
Quintile 1	-9.8	182.8	*	3.2	1239
Quintile 2	-25.5	263.8	***	3.2	1228
Quintile 3	-37.4	315.1	***	3.2	1231
Quintile 4	-43.4	376.7	***	5.3	1233
Quintile 5	-177.8	906.5	***	0.3	1231
By Gender	H_{02}: ***				
Men	-34.2	585.6	***	0.0	4929
Women	-4.1	423.1		3.2	2889
By Age	H_{02}: **				
25-36 yrs	-7.9	434.3		2.7	3039
37-48 yrs	-35.7	575.4	***	1.3	3094
49-60 yrs	-27.4	601.9	*	2.1	1685
By Education Level	H_{02}: ***				
Primary or less	-17.3	284.2	***	1.6	2730
Secondary	-4.8	405.4		2.7	3016
Higher	-57.2	848.0	***	3.2	2072
By Sector					
Transition	H_{02}: ***				
Unemployed to Informal	259.2	221.8	***	199.9	326
Unemployed to Formal	522.7	665.0	***	399.7	85
Informal to Formal	-34.8	605.4		5.5	676
Informal to Informal	-4.5	449.6		3.0	2536
Informal to Unemployed	-332.2	347.3	***	-281.8	386
Formal to Formal	-9.4	601.9		6.4	2770
Formal to Informal	-70.4	534.6	***	-36.3	621
Formal to Unemployed	-574.7	530.9	***	-425.1	133
By Region	H_{02}:				
GBA	-27.4	515.1		3.2	1403
Pampeana	-3.2	560.8		1.6	2381
Patagonica	-45.4	566.0	*	2.9	897
Noreste	-23.5	493.4	*	3.2	969
Noroeste	-34.5	476.9	**	1.4	1324
Cuyo	-29.8	558.4	*	1.6	844

***, **, * H_{0j} rejected at 99, 95, 90% of significance
H_{01}: mean equal to zero
H_{02} : equality of means by groups

Table 4-E
Unweighted Reported Earnings Changes by Initial Position
Dependent Variable: Change in Reported Earnings

	2000-2001				
	Mean	Std.Dev.	H_{01}	Median	Obs.
Total Population	-23.5	542.3	***	0.5	7396
By Initial Reported	H_{02}: ***				
Quintile					
Lowest Quintile	238.1	552.8	***	60.3	1502
Quintile 2	2.7	183.4		0.5	1619
Quintile 3	-23.8	196.4	***	0.8	1318
Quintile 4	-49.4	315.0	***	-16.0	1688
Highest Quintile	-331.7	980.0	***	-196.9	1269
By Initial Predicted	H_{02}: *				
Quintile					
Quintile 1	-6.6	206.2		0.2	1481
Quintile 2	-10.4	434.8		0.2	1479
Quintile 3	-15.3	348.6	*	0.5	1482
Quintile 4	-57.6	550.3	***	0.5	1475
Quintile 5	-27.6	902.3		1.2	1479
By Initial Predicted	H_{02}: ***				
Quintile (without zeroes)					
Quintile 1	-18.9	176.4	***	0.5	1168
Quintile 2	-37.4	306.0	***	0.6	1162
Quintile 3	-43.8	303.6	***	0.7	1160
Quintile 4	-98.8	547.7	***	0.7	1164
Quintile 5	-97.0	877.9	***	1.4	1161
By Gender	H_{02}: *				
Men	-32.5	583.4	***	0.0	4563
Women	-9.0	468.2		0.7	2833
By Age	H_{02}: **				
25-36 yrs	-8.8	437.5		0.5	2869
37-48 yrs	-32.5	502.3	***	0.5	2846
49-60 yrs	-33.2	734.7	*	0.0	1681
By Education Level	H_{02}:				
Primary or less	-15.9	349.3	**	0.0	2316
Secondary	-18.6	500.8	***	0.7	2484
Higher	0.4	789.7		1.6	1686
By Sector					
Transition	H_{02}: ***				
Unemployed to Informal	228.7	217.2	***	200.3	346
Unemployed to Formal	400.9	326.8	***	360.6	69
Informal to Formal	-3.1	660.9		1.8	616
Informal to Informal	-26.8	430.3	***	0.5	2510
Informal to Unemployed	-260.7	236.8	***	-199.9	370
Formal to Formal	-16.3	615.4		1.2	2579
Formal to Informal	0.4	750.4		0.8	520
Formal to Unemployed	-575.1	518.3	***	-449.7	127
By Region	H_{02}:				
GBA	-3.5	508.9		0.7	1318
Pampeana	-24.5	590.3	**	0.5	2269
Patagonica	-28.9	448.6	**	0.5	853
Noreste	-31.1	586.6		0.3	830
Noroeste	-23.0	462.6		0.4	1323
Cuyo	-40.6	614.4	*	0.0	803

***, **, * H_{0j} rejected at 99, 95, 90% of significance
H_{01}: mean equal to zero
H_{02} : equality of means by groups

Table 4-F
Unweighted Reported Earnings Changes by Initial Position
Dependent Variable: Change in Reported Earnings

	2001-2002				
	Mean	Std.Dev.	H_{01}	Median	Obs.
Total Population	-154.8	501.2	***	-80.1	7935
By Initial Reported	H_{02}: ***				
Quintile					
Lowest Quintile	163.6	410.4	***	0.0	1614
Quintile 2	-65.5	139.3	***	-47.5	1807
Quintile 3	-126.9	204.1	***	-96.7	1778
Quintile 4	-213.7	287.7	***	-177.8	1300
Highest Quintile	-606.3	846.3	***	-433.4	1436
By Initial Predicted	H_{02}: ***				
Quintile					
Quintile 1	-83.5	234.5	***	-46.6	1589
Quintile 2	-110.5	310.2	***	-66.6	1597
Quintile 3	-135.6	386.5	***	-78.7	1575
Quintile 4	-174.4	463.1	***	-112.2	1587
Quintile 5	-270.3	848.9	***	-155.4	1587
By Initial Predicted	H_{02}: ***				
Quintile (without zeroes)					
Quintile 1	-94.2	235.3	***	-58.7	1196
Quintile 2	-133.7	240.0	***	-82.2	1195
Quintile 3	-167.7	375.5	***	-104.5	1197
Quintile 4	-222.5	454.5	***	-135.5	1198
Quintile 5	-381.2	798.3	***	-208.9	1189
By Gender	H_{02}: ***				
Men	-176.3	568.0	***	-96.7	4898
Women	-120.2	366.0	***	-64.9	3037
By Age	H_{02}: ***				
25-36 yrs	-140.5	426.7	***	-73.4	3035
37-48 yrs	-159.8	505.5	***	-88.9	3066
49-60 yrs	-170.1	598.2	***	-82.4	1834
By Education Level	H_{02}: ***				
Primary or less	-102.7	274.9	***	-62.1	2289
Secondary	-147.9	431.9	***	-88.9	2713
Higher	-229.6	717.8	***	-115.6	1952
By Sector					
Transition	H_{02}: ***				
Unemployed to Informal	161.4	165.0	***	126.9	300
Unemployed to Formal	331.3	314.0	***	253.9	68
Informal to Formal	-136.5	518.8	***	-73.2	539
Informal to Informal	-119.6	417.9	***	-71.1	2549
Informal to Unemployed	-297.3	383.5	***	-200.3	559
Formal to Formal	-182.7	564.0	***	-101.0	2603
Formal to Informal	-226.1	642.4	***	-141.2	689
Formal to Unemployed	-620.1	614.9	***	-480.8	199
By Region	H_{02}:				
GBA	-149.7	465.2	***	-85.4	1350
Pampeana	-168.1	499.2	***	-79.1	2448
Patagonica	-170.1	595.7	***	-96.7	995
Noreste	-134.3	449.3	***	-78.3	874
Noroeste	-152.5	521.3	***	-74.3	1506
Cuyo	-129.2	446.2	***	-81.2	762

***, **, * H_{0j} rejected at 99, 95, 90% of significance
H_{01}: mean equal to zero
H_{02} : equality of means by groups

Table 4-G
Unweighted Reported Earnings Changes by Initial Position
Dependent Variable: Change in Reported Earnings

	2002-2003				
	Mean	Std.Dev.	H_{01}	Median	Obs.
Total Population	-19.7	386.4	***	0.0	5402
By Initial Reported	H_{02}: ***				
Quintile					
Lowest Quintile	216.8	401.0	***	401.0	1241
Quintile 2	28.2	204.5	***	8.0	956
Quintile 3	-31.4	165.6	***	-41.2	1220
Quintile 4	-72.2	212.1	***	-68.7	1022
Highest Quintile	-301.3	591.7	***	-206.1	963
By Initial Predicted	H_{02}: ***				
Quintile					
Quintile 1	4.0	165.8		0.0	1108
Quintile 2	3.2	236.3		0.0	1055
Quintile 3	-18.0	249.9	**	-6.8	1084
Quintile 4	-25.5	355.4	***	-12.6	1075
Quintile 5	-62.0	688.0	***	-30.1	1080
By Initial Predicted	H_{02}: ***				
Quintile (without zeroes)					
Quintile 1	-33.5	137.7	***	-22.5	803
Quintile 2	-48.3	196.5	***	-34.3	782
Quintile 3	-56.4	232.9	***	-38.0	793
Quintile 4	-86.1	325.9	***	-54.9	791
Quintile 5	-169.2	618.3	***	-81.8	789
By Gender	H_{02}:				
Men	-20.0	447.4	**	0.0	3350
Women	-19.1	257.5	***	-10.0	2052
By Age	H_{02}: ***				
25-36 yrs	-5.8	316.3		0.0	2042
37-48 yrs	-30.7	389.7	***	-12.3	2150
49-60 yrs	-23.3	477.0	*	-4.5	1210
By Education Level	H_{02}: ***				
Primary or less	9.0	221.4		0.0	1523
Secondary	-5.8	270.1		0.0	1898
Higher	-49.1	850.1	***	-5.8	1280
By Sector					
Transition	H_{02}: ***				
Unemployed to Informal	162.3	131.4	***	127.6	469
Unemployed to Formal	307.6	250.7	***	283.5	75
Informal to Formal	-36.9	321.9	**	-29.4	453
Informal to Informal	-4.4	260.0		-13.5	1855
Informal to Unemployed	-200.3	211.5	***	-139.6	164
Formal to Formal	-57.3	531.9	***	-41.2	1698
Formal to Informal	-50.5	444.0	**	-48.08	373
Formal to Unemployed	-476.5	475.7	***	-330.0	66
By Region	H_{02}:				
GBA	-22.4	578.2		0.0	746
Pampeana	-21.5	320.5	**	-8.7	1686
Patagonica	-28.7	317.6	**	-5.8	705
Noreste	-28.7	401.4		-12.1	661
Noroeste	-12.5	397.4		0.0	1040
Cuyo	-1.7	274.5		-6.8	564

***, **, * H_{0j} rejected at 99, 95, 90% of significance
H_{01}: mean equal to zero
H_{02} : equality of means by groups

Table 5

Unweighted Average of Reported Earnings Levels by Initial Position

Dependent Variable: Reported Earnings Levels in Base Period

	Positive Growth			Negative Growth		
	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.
Total Population	528.5	627.3	22421	556.4	682.4	30925
By Initial Reported Quintile	***			***		
Quintile 1	34.9	64.9	4877	26.4	47.6	6332
Quintile 2	247.7	84.1	4406	247.4	56.0	6548
Quintile 3	394.5	85.5	4690	419.9	53.2	6546
Quintile 4	617.2	118.1	4124	652.6	95.3	5771
Quintile 5	1431.85	899.43	4324	1554.9	1024.0	5728
By Gender	***			***		
Men	584.3	700.0	13971	612.4	744.9	19281
Women	436.1	469.3	8450	463.8	551.5	11644
By Age	***			***		
25-36 yrs	463.8	499.3	8997	481.9	556.4	11962
37-48 yrs	581.8	653.2	8909	607.5	708.6	12077
49-60 yrs	552.0	775.2	4515	596.3	810.8	6886
By Education Level	***			***		
Primary or less	342.2	331.5	7969	341.5	326.4	10675
Secondary	507.3	502.9	8751	513.2	509.1	11904
Higher	821.4	933.2	5701	893.0	1022.1	8346
By Sector	***			***		
Unemployed	0	0	2524	0	0	2756
Informal	472.5	555.0	9390	474.1	576.3	14551
Formal	705.5	680.5	10507	757.0	769.8	13618
By Region	***			***		
GBA	576.6	779.0	2690	571.5	663.7	5192
Pampeana	513.1	592.7	7368	539.5	690.1	9660
Patagonica	546.0	592.8	2729	575.5	686.5	3677
Noreste	526.9	623.9	2883	565.6	689.3	3548
Noroeste	499.3	559.5	3945	552.0	680.3	5577
Cuyo	548.1	673.8	2806	558.7	679.6	3271

***H_0: equality of means by group rejected at 99% of significance

Table 6
Unweighted Reported Earnings Changes by Initial Position
Dependent Variable: Change in Reported Earnings

	Positive Growth						Negative Growth					
	Mean	Std.Dev.	H_{01}	Median	Obs.	R-sq^	Mean	Std.Dev.	H_{01}	Median	Obs.	R-sq^
Total Population	4.33	504.77		-1.69	22421		-55.84	541.75	***	0	30925	
By Initial Reported Quintile	H_{02}: ***					0.13	H_{02}: ***					0.27
Lowest Quintile	230.89	475.94	***	106.33	4877		223.33	498.32	***	50.20	6332	
Quintile 2	28.47	206.69	***	0.44	4406		-11.65	180.52	***	-9.44	6548	
Quintile 3	-0.13	258.46		-5.75	4690		-48.84	224.66	***	-44.53	6546	
Quintile 4	-42.28	339.83	***	-34.65	4124		-85.86	326.15	***	-91.39	5771	
Highest Quintile	-226.48	852.01	***	-134.52	4324		-392.74	951.45	***	-237.02	5728	
By Initial Predicted Quintile	H_{02}:					0	H_{02}: ***					0
Quintile 1	9.28	218.76	***	-0.39	4313		-27.71	220.42	***	0	5989	
Quintile 2	6.48	306.00		0	4330		-33.35	345.92	***	0	5996	
Quintile 3	6.96	365.60		-1.42	4297		-53.20	384.78	***	-2.05	5981	
Quintile 4	1.20	477.57		-2.30	4321		-65.15	569.63	***	0	5984	
Quintile 5	-3.87	865.25		-4.51	4291		-104.97	890.83	***	0	5985	
By Gender	H_{02}:					0	H_{02}: ***					0
Men	2.39	585.12		-1.29	13971		-68.76	604.26	***	0	19281	
Women	7.56	331.69	**	-1.93	8450		-34.45	417.32	***	0	11644	
By Age	H_{02}:					0	H_{02}: ***					0
25-36 yrs	9.69	393.30	**	0	9973		-39.70	434.69	***	0	11962	
37-48 yrs	2.21	535.27		0	9830		-63.47	576.91	***	-3.11	12077	
49-60 yrs	-2.14	625.87		0	4992		-70.49	636.72	***	0	6886	
By Education Level	H_{02}:					0	H_{02}: ***					0
Primary or less	5.76	287.31	*	-0.97	7969		-36.37	315.40	***	0	10675	
Secondary	5.10	426.47		-1.93	8751		-50.59	433.89	***	0	11904	
Higher	1.16	779.49		-2.90	5701		-88.24	830.81	***	0	8346	
By Sector Transition^^	H_{02}: ***					0.06	H_{02}: ***					0.05
Informal to Formal	20.91	483.54	*	-2.30	1872		-35.77	633.67	***	2.21	2633	
Informal to Informal	13.71	433.77	***	-2.30	6835		-42.63	437.63	***	-15.54	10291	
Formal to Formal	-18.64	573.22	***	-5.39	8178		-53.78	615.62	***	0	10509	
Formal to Informal	-2.56	559.61		-9.20	2015		-94.88	649.82	***	-47.59	2563	
By Region	H_{02}:					0	H_{02}:					0
GBA	23.28	688.29	*	0	2690		-47.02	514.91	***	0	5192	
Pampeana	7.56	506.53		-1.93	7368		-54.78	569.48	***	0	9660	
Patagonica	-7.40	461.41		-2.58	2729		-60.18	535.20	***	0	3677	
Noreste	-6.62	486.78		-1.93	2883		-63.02	564.87	***	0	3548	
Noroeste	0.68	408.29		-1.55	3945		-57.43	488.04		0	5577	
Cuyo	5.49	472.22		-1.93	2806		-57.59	567.65		-5.16	3271	

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

^ R-squared from simple regression of change in earnings on each variable

^^ Transitions involving unemployment are not reported

H_{01}: mean equal to zero

H_{02} : equality of means by groups

Table 7

Unweighted Reported Earnings Changes by Initial Position, without the Unemployed

Dependent Variable: Change in Reported Earnings												
	Positive Growth						Negative Growth					
	Mean	Std.Dev.	H_{01}	Median	Obs.	R-sq^	Mean	Std.Dev.	H_{01}	Median	Obs.	R-sq^
Total Population	-31.20	480.47	***	-5.77	17883		-91.86	513.41	***	-27.45	24337	
By Initial Reported												
Quintile	H_{02}: ***					0.11	H_{02}: ***					0.27
Quintile 1	106.64	304.21	***	48.67	1082		79.99	201.40	***	40.20	1421	
Quintile 2	46.34	200.57	***	14.84	4117		18.54	170.21	***	1.47	5763	
Quintile 3	20.64	247.78	***	-4.60	4453		-21.94	208.31	***	-21.28	6098	
Quintile 4	-23.59	328.10	***	-25.46	3994		-58.73	308.64	***	-63.87	5503	
Quintile 5	-203.40	838.19	***	-116.77	4237		-360.04	935.13	***	-209.28	5552	
By Initial Predicted												
Quintile	H_{02}:					0	H_{02}: ***					0.01
Quintile 1	-11.93	195.16	***	-3.45	3260		-37.48	203.77	***	-15.72	4566	
Quintile 2	-13.20	289.83	***	-4.60	3393		-54.33	261.24	***	-24.13	4534	
Quintile 3	-21.81	321.59	***	-5.77	3338		-74.97	351.83	***	-36.98	4570	
Quintile 4	-37.24	419.83	***	-6.45	3564		-107.13	538.24	***	-37.29	4841	
Quintile 5	-69.40	827.71	***	-13.79	3610		-179.83	835.81	***	-45.75	5006	
By Gender	H_{02}:					0	H_{02}: ***					0
Men	-39.43	560.10	***	-6.90	11007		-111.17	579.17	***	-39.67	14882	
Women	-18.04	312.97	***	-4.51	6876		-61.46	386.03	***	-15.54	9455	
By Age	H_{02}:					0	H_{02}: ***					0
25-36 yrs	-18.72	366.49	***	-4.02	7105		-58.65	417.06	***	-15.54	9291	
37-48 yrs	-31.77	524.67	***	-6.90	7265		-101.76	549.13	***	-32.48	9716	
49-60 yrs	-55.26	577.44	***	-11.54	3513		-131.67	589.17	***	-39.60	5330	
By Education Level	H_{02}:					0	H_{02}: ***					0
Primary or less	-17.87	269.61	***	-4.60	6105		-53.03	263.13	***	-22.08	7987	
Secondary	-24.50	380.51	***	-5.75	7000		-80.68	402.97	***	-29.17	9409	
Higher	-58.05	747.06	***	-10.35	4778		-151.67	786.78	***	-32.50	6941	
By Sector												
Transition	H_{02}: ***					0	H_{02}: ***					0.01
Informal to Formal	-12.10	448.75		-3.45	1760		-89.66	585.70	***	1.15	2443	
Informal to Informal	-16.77	389.65	***	-4.60	6363		-80.11	395.72	***	-31.07	9499	
Formal to Formal	-45.47	539.48	***	-6.90	7850		-91.14	579.19	***	-16.68	9987	
Formal to Informal	-38.25	521.80	***	-15.85	1910		-143.38	551.47	***	-69.19	2408	
By Region	H_{02}:					0	H_{02}:					0
GBA	-39.52	665.99	***	-6.90	1931		-91.67	471.46	***	-31.07	3882	
Pampeana	-27.62	502.19	***	-6.90	5850		-91.75	561.23	***	-27.41	7618	
Patagonica	-36.57	449.46	***	-7.76	2211		-95.72	514.82	***	-27.97	2973	
Noreste	-48.13	408.34	***	-4.60	2388		-88.81	500.60	***	-22.00	2844	
Noroeste	-23.78	379.92	***	-5.16	3179		-92.92	479.27	***	-25.57	4342	
Cuyo	-20.97	460.36	**	-4.60	2324		-89.63	494.85	***	-29.88	2678	

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

^ R-squared from simple regression of change in earnings on each variable

H_{01}: mean equal to zero

H_{02} : equality of means by groups

Table 8-A

Unweighted Reported Earnings Changes by Initial Position, Informal and Formal Workers Separately

Dependent Variable: Change in Reported Earnings in Growth Years												
	Informal						Formal					
	Mean	Std.Dev.	H_{01}	Median	Obs.	R-sq^	Mean	Std.Dev.	H_{01}	Median	Obs.	R-sq^
Total Population	-7.38	445.06		-3.68	9390		-31.57	576.66	***	-6.90	10507	
By Initial Reported												
Quintile	H_{02}: ***					0.12	H_{02}: ***					0.12
Quintile 1	188.72	468.31	***	67.94	1740		488.56	834.55	***	283.55	613	
Quintile 2	18.05	181.87	***	-2.14	2798		46.59	242.93	***	17.63	1608	
Quintile 3	-15.04	273.60	**	-29.62	2018		11.13	245.87	**	-4.60	2672	
Quintile 4	-65.06	335.13	***	-61.82	1399		-30.58	341.69	***	-25.27	2725	
Quintile 5	-227.75	807.32	***	-123.63	1435		-225.85	873.49	***	-137.37	2889	
By Initial Predicted												
Quintile	H_{02}:					0	H_{02}:					0
Quintile 1	-8.05	207.37	*	-2.58	2435		-34.35	221.53	***	-7.93	1210	
Quintile 2	-10.68	319.92		-4.60	1857		-23.83	303.96	***	-5.16	1895	
Quintile 3	-10.27	404.94		-4.60	1845		-29.09	328.77	***	-8.05	1912	
Quintile 4	3.51	488.42		-3.68	1734		-41.84	480.02	***	-6.90	2200	
Quintile 5	-12.68	756.75		-9.20	1146		-31.81	920.80	*	-9.20	2869	
By Gender	H_{02}:					0	H_{02}:					0
Men	-5.78	519.97		-4.60	5750		-43.22	670.47	***	-9.20	6581	
Women	-9.90	289.66	**	-3.22	3640		-12.04	368.63	**	-5.16	3926	
By Age	H_{02}:					0	H_{02}:					0
25-36 yrs	-2.33	347.66		-3.22	3736		-29.83	445.11	***	-5.17	4142	
37-48 yrs	-8.46	453.18		-4.60	3641		-29.34	617.94	**	-8.05	4383	
49-60 yrs	-14.81	572.96		-5.16	2013		-40.11	710.42	***	-11.49	1982	
By Education Level	H_{02}:					0	H_{02}:					0
Primary or less	-10.43	295.26	**	-3.45	4090		-39.30	276.12	***	-8.05	2710	
Secondary	-1.13	439.62		-3.90	3772		-32.06	430.78	***	-6.45	4035	
Higher	-14.64	712.03		-5.76	1528		-25.47	821.51	*	-6.58	3762	
By Sector						0.03						0.03
Transition	H_{02}: ***						H_{02}: ***					
into Formal	20.91	483.54	*	-2.30	1872		-18.64	573.22	***	-5.39	8178	
into Informal	13.71	433.77	***	-2.30	6835		-2.56	559.61		-9.20	2015	
into Unemployment	-295.96	331.65	***	-203.10	683		-554.51	528.00	***	-423.12	314	
By Region	H_{02}:					0	H_{02}:					0
GBA	2.01	640.87		-5.75	1064		-17.40	782.97		-6.38	1232	
Pampeana	-0.52	411.24		-3.87	3054		-36.22	603.06	***	-10.35	3415	
Patagonica	-18.50	355.91	*	-4.60	1201		-48.31	556.48	***	-11.16	1236	
Noreste	-7.24	439.48		-3.06	1238		-41.88	551.27	***	-5.75	1380	
Noroeste	-24.16	354.27	***	-4.38	1646		-13.67	469.87		-5.17	1884	
Cuyo	0.93	510.02		-2.76	1187		-31.82	452.92	***	-5.75	1360	

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

H_{01}: mean equal to zero

^ R-squared from simple regression of change in earnings on each variable

H_{02} : equality of means by groups

Table 8-B

Unweighted Reported Earnings Changes by Initial Position, Informal and Formal Workers Separately

Dependent Variable: Change in Reported Earnings in Recessionary Years												
	Informal						Formal					
	Mean	Std.Dev.	H_{01}	Median	Obs.	R-sq^	Mean	Std.Dev.	H_{01}	Median	Obs.	R-sq^
Total Population	-71.17	481.28	***	-31.07	14550		-82.58	627.63	***	-22.16	13620	
By Initial Reported	H_{02}: ***						H_{02}: ***					
Quintile						0.32						0.24
Quintile 1	188.54	462.79	***	50.17	2737		554.27	898.01	***	300.48	839	
Quintile 2	-25.87	176.84	***	-31.07	4817		27.79	184.80	***	9.73	1732	
Quintile 3	-80.46	231.54	***	-69.91	2931		-23.24	215.57	***	-15.50	3615	
Quintile 4	-120.98	352.81	***	-98.78	2138		-65.19	307.57	***	-50.91	3633	
Quintile 5	-483.90	934.50	***	-324.61	1927		-346.52	956.74	***	-196.41	3801	
By Initial Predicted	H_{02}: ***						H_{02}: ***					
Quintile						0						0
Quintile 1	-37.25	204.26	***	-19.99	3846		-61.30	261.70	***	-21.24	1486	
Quintile 2	-53.64	320.47	***	-39.28	3066		-57.97	399.69	***	-25.95	2276	
Quintile 3	-81.99	410.51	***	-46.61	2976		-65.04	355.80	***	-26.89	2384	
Quintile 4	-100.79	599.84	***	-45.72	2636		-77.59	564.66	***	-21.04	2885	
Quintile 5	-133.41	922.91	***	-20.37	1535		-119.18	894.02	***	-25.12	4172	
By Gender	H_{02}: ***					0	H_{02}: ***					0
Men	-84.03	536.96	***	-46.61	9035		-102.95	703.16	***	-36.45	8483	
Women	-50.10	371.56	***	-18.64	5515		-48.95	475.58	***	-7.31	5137	
By Age	H_{02}: *						H_{02}: **					0
25-36 yrs	-59.46	377.98	***	-25.01	5527		-65.95	504.87	***	-15.84	5215	
37-48 yrs	-75.59	515.52	***	-37.33	5600		-53.78	615.59	***	0.00	10510	
49-60 yrs	-82.84	564.67	***	-34.58	3423		-94.93	649.69	***	-47.61	2564	
By Education Level	H_{02}: ***					0	H_{02}: ***					0
Primary or less	-49.57	281.36	***	-30.05	6426		-71.67	396.61	***	-31.07	3061	
Secondary	-78.23	479.82	***	-39.67	5833		-65.13	393.25	***	-19.30	4985	
Higher	-113.79	812.35	***	-18.65	2291		-104.19	858.58	***	-17.48	5574	
By Sector	H_{02}: ***						H_{02}: ***					
Transition						0.03						0.03
into Formal	-35.81	633.78	***	2.21	2632		-53.78	615.59	***	0.00	10510	
into Informal	-42.63	437.63	***	-15.54	10291		-94.93	649.69	***	-47.61	2564	
into Unemployment	-308.89	383.18	***	-240.38	1627		-578.97	536.49	***	-449.69	546	
By Region	H_{02}:					0	H_{02}:					0
GBA	-68.63	456.12	***	-39.60	2294		-80.70	591.18	***	-16.45	2359	
Pampeana	-67.24	441.86	***	-30.05	4479		-80.51	707.67	***	-22.29	4328	
Patagonica	-61.50	483.63	***	-31.07	1793		-103.75	622.75	***	-27.82	1597	
Noreste	-76.33	484.21	***	-29.27	1738		-77.19	583.34	***	-16.82	1515	
Noroeste	-71.18	491.77	***	-31.07	2623		-86.38	557.89	***	-19.11	2413	
Cuyo	-90.76	586.12	***	-31.07	1623		-67.39	588.74	***	-39.02	1408	

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

H_{01}: mean equal to zero

^ R-squared from simple regression of change in earnings on each variable

H_{02} : equality of means by groups

Table 9
OLS Regressions
Dependent Variable: Change in Reported Earnings

	Positive Growth	Negative Growth
Initial Reported Earnings	-0.35	-0.5
	[0.03]***	[0.02]***
Male	75.83	79.65
	[6.91]***	[6.35]***
Age	H_{02}: ***	H_{02}: ***
Linear	14.02	14.12
	[2.97]***	[2.56]***
Squared	-0.14	-0.14
	[0.04]***	[0.03]***
Years of Education	H_{02}: ***	H_{02}: ***
Linear	-9.89	-15.64
	[3.31]***	[2.69]***
Squared	1.32	1.67
	[0.20]***	[0.16]***
Sector Transition	H_{02}: ***	H_{02}: ***
Unemployed-Unemployed	omitted	omitted
Unemployed- Informal	275.38	251.73
	[7.85]***	[7.09]***
Unemployed- Formal	431.08	391.14
	[30.66]***	[26.87]***
Informal- Unemployed	-182.4	-142.38
	[12.59]***	[9.59]***
Informal- Informal	183.02	193.07
	[13.20]***	[11.62]***
Informal- Formal	195.15	256.81
	[17.08]***	[16.21]***
Formal- Unemployed	-389.24	-333.95
	[24.95]***	[17.60]***
Formal- Informal	190.01	208.21
	[19.75]***	[17.85]***
Formal- Formal	194.97	282.74
	[16.28]***	[14.78]***
Region	H_{02}: ***	H_{02}: ***
Greater Buenos Aires	omitted	omitted
Pampeana	-49.65	-39.04
	[13.20]***	[8.04]***
Patagonica	-48.79	-32.09
	[13.91]***	[9.28]***
Noreste	-58.2	-35.19
	[13.98]***	[9.23]***
Noroeste	-56.03	-39.65
	[13.01]***	[8.31]***
Cuyo	-35.84	-36.7
	[13.89]***	[10.28]***
Constant	-353.12	-359.89
	[61.17]***	[53.31]***
Number of Observations	22421	30926
R^2	0.2	0.35

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

H_{02} : equality of coefficients by groups

Table 10
OLS Regressions, Year by Year
Dependent Variable: Change in Reported Earnings

	Growth Years			Recessionary 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 11
Median Regression
Dependent Variable: Change in Reported Earnings

	Positive Growth	Negative Growth
Initial Reported Earnings	-0.24	-0.34
	[0.01]***	[0.01]***
Male	25.32	20.97
	[1.60]***	[2.64]***
Age	H_{02}: ***	H_{02}: ***
Linear	3.51	3.62
	[0.60]***	[0.77]***
Squared	-0.04	-0.04
	[0.01]***	[0.01]***
Years of Education	H_{02}: ***	H_{02}: ***
Linear	-3.38	-5.74
	[1.33]**	[1.47]***
Squared	0.41	0.54
	[0.08]***	[0.08]***
Sector Transition	H_{02}: ***	H_{02}: ***
Unemployed- Unemployed	omitted	omitted
Unemployed- Informal	203.35	193.47
	[3.50]***	[3.59]***
Unemployed- Formal	357.03	356.99
	[17.23]***	[17.73]***
Informal- Unemployed	-166.18	-151.51
	[9.67]***	[5.91]***
Informal- Informal	79.26	80.46
	[4.26]***	[3.97]***
Informal- Formal	111.32	154.38
	[4.56]***	[7.52]***
Formal- Unemployed	-337.63	-299.55
	[9.92]***	[9.67]***
Formal- Informal	80.6	98.52
	[5.20]***	[7.06]***
Formal- Formal	108.24	154.66
	[5.43]***	[5.94]***
Region	H_{02}: ***	H_{02}: ***
Greater Buenos Aires	omitted	omitted
Pampeana	-14.3	-10.96
	[3.37]***	[2.34]***
Patagonica	-13.59	-6.3
	[4.30]***	[3.16]**
Noreste	-15.96	-9.62
	[3.38]***	[2.77]***
Noroeste	-18.6	-10.31
	[4.46]***	[3.22]***
Cuyo	-7.42	-10.24
	[3.83]*	[4.65]**
Constant	-80.06	-76.05
	[15.31]***	[18.69]***
Number of Observations	22421	30926
Pseudo R^2	0.11	0.15

***, **, * H_{0j} rejected at 99, 95, 90% of significance
Bootstrap Std. Errors in brackets
H_{02} : equality of coefficients by groups

Table 12
Median Regressions, Year by Year
Dependent Variable: Change in Reported Earnings

	Growth Years			Recessionary Years			
	1996-97	**1997-98**	**2002-03**	**1998-99**	**1999-2000**	**2000-01**	**2001-02**
Initial Reported Earnings	-0.25	-0.22	-0.37	-0.33	-0.28	-0.3	-0.43
	[0.02]***	[0.01]***	[0.02]***	[0.02]***	[0.01]***	[0.03]***	[0.01]***
Male	35.1	31.76	24.16	37.62	16.4	19.07	5.45
	[4.48]***	[4.41]***	[3.80]***	[5.34]***	[3.13]***	[3.69]***	[3.51]
Age	H_{02}: **	H_{02}: **	H_{02}:	H_{02}: ***	H_{02}: **	H_{02}:	H_{02}:
Linear	9.41	4.18	1.45	5.38	2.4	5.09	1.03
	[1.33]***	[1.28]***	[1.42]	[2.14]**	[2.41]	[1.52]***	[0.83]
Squared	-0.11	-0.05	-0.01	-0.06	-0.02	-0.06	-0.01
	[0.02]***	[0.02]***	[0.02]	[0.03]**	[0.03]	[0.02]***	[0.01]
Years of Education	H_{02}: **	H_{02}: ***	H_{02}: ***	H_{02}: ***	H_{02}: ***	H_{02}: ***	H_{02}: ***
Linear	2.37	-6.41	-3.86	-9.45	-4.48	-7.25	-4.66
	[1.70]	[2.45]***	[2.62]	[1.93]***	[2.20]**	[2.52]***	[1.70]***
Squared	0.24	0.66	0.41	0.9	0.49	0.71	0.36
	[0.11]**	[0.16]***	[0.17]**	[0.12]***	[0.13]***	[0.16]***	[0.11]***
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	251.5	255.72	138.56	224.36	215.26	179.92	128.17
	[8.85]***	[11.33]***	[4.95]***	[10.06]***	[14.15]***	[10.33]***	[6.43]***
Unemployed- Formal	372.75	409.19	275.58	389.53	382.57	354.23	255.51
	[23.40]**	[43.74]***	[25.27]***	[45.43]***	[27.85]***	[39.15]***	[32.00]***
Informal- Unemployed	-183.64	-196.04	-87.35	-165.64	-195.64	-143.96	-118.31
	[15.61]**	[8.54]***	[12.11]***	[16.18]***	[10.69]***	[13.64]***	[3.68]***
Informal- Informal	96.63	92.59	75.1	108.02	87.81	77.52	49.65
	[8.00]***	[7.27]***	[6.16]***	[9.66]***	[6.00]***	[8.63]***	[5.30]***
Informal- Formal	137.03	117.56	111.39	172.69	138.01	142.8	110.86
	[10.53]**	[11.30]***	[11.21]***	[12.96]***	[8.43]***	[13.72]***	[10.31]***
Formal- Unemployed	-339.94	-366.23	-222.83	-284.88	-326.06	-324.02	-275.23
	[19.84]**	[21.29]***	[22.69]***	[14.78]***	[17.86]***	[18.70]***	[14.39]***
Formal- Informal	91.18	92.32	69.23	133	85.91	114.01	70.29
	[9.59]***	[8.99]***	[10.97]***	[14.22]***	[7.49]***	[15.83]***	[10.88]***
Formal- Formal	116.36	114.42	115.08	184.53	152.65	140.96	119.95
	[7.44]***	[8.40]***	[9.47]***	[14.33]***	[8.99]***	[13.05]***	[8.45]***
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	-26.96	-16.3	-13.21	-33.65	-16.34	-15.62	0.79
	[6.74]***	[6.42]**	[5.90]**	[9.02]***	[5.02]***	[5.20]***	[2.42]
Patagonica	-26.8	-7.53	-6.75	-28.47	-13.41	-8.32	3.32
	[7.65]***	[9.21]	[5.86]	[8.58]***	[6.64]**	[5.24]	[3.49]
Noreste	-25.37	-22.72	-10.1	-25.84	-10.38	-19.88	4.49
	[6.12]***	[7.19]***	[5.57]*	[10.11]**	[7.08]	[7.42]***	[5.08]
Noroeste	-26.58	-21.31	-11.13	-19.67	-14.26	-19.29	0.82
	[7.73]***	[6.10]***	[6.01]*	[9.84]**	[5.38]***	[5.17]***	[2.99]
Cuyo	-22.57	-5.32	0.23	-40.04	-14.41	-17.24	6.39
	[7.07]***	[7.79]	[5.96]	[10.15]***	[8.10]*	[6.59]***	[4.95]
Constant	-228.06	-91.86	-47.66	-112.37	-57.25	-100.57	-15.52
	[26.54]**	[30.85]***	[28.95]*	[47.29]**	[51.17]	[30.67]***	[22.80]
Number of Observations	8130	8889	5402	7777	7818	7396	7935
Pseudo R^2	0.1284	0.0977	0.2008	0.122	0.1313	0.1243	0.276

***, **, * H_{0j} rejected at 99, 95, 90% of significance
H_{02} : equality of coefficients by groups
Bootstrap Std. Errors in brackets

Table 13
OLS Regressions, Without the Unemployed
Dependent Variable: Change in Reported Earnings

	Positive Growth	Negative Growth
Initial Reported Earnings	-0.30	-0.44
	[0.01]***	[0.00]***
Male	56.6	63.57
	[7.23]***	[5.89]***
Age	H_{02}: ***	H_{02}: ***
Linear	15.08	14.29
	[3.28]***	[2.64]***
Squared	-0.17	-0.16
	[0.04]***	[0.03]***
Years of Education	H_{02}: ***	H_{02}: ***
Linear	-6.88	-9.25
	[3.29]**	[2.76]***
Squared	0.96	1.2
	[0.16]***	[0.13]***
Sector Transition	H_{02}:	H_{02}: ***
Formal- Informal	omitted	omitted
Formal- Formal	7.91	80.34
	[11.49]	[9.76]
Informal- Informal	-4.44	-4.62
	[11.90]	[9.98]
Informal- Formal	10.02	45.71
	[14.86]	[12.34]***
Region	H_{02}: **	H_{02}: ***
Greater Buenos Aires	omitted	omitted
Pampeana	-28.84	-35.46
	[11.85]**	[8.49]***
Patagonica	-26.86	-26.96
	[14.05]*	[10.48]***
Noreste	-47.1	-29.13
	[13.80]***	[10.62]***
Noroeste	-30.49	-32.59
	[13.03]**	[9.51]***
Cuyo	-14.52	-29.71
	[69.01]	[10.81]***
Constant	-213.55	-194.97
	[69.01]***	[55.90]***
Number of Observations	17883	24337
R^2	0.125	0.3

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

Table 14
OLS Regressions, Formal Sector Workers
Dependent Variable: Change in Reported Earnings

	Positive Growth	Negative Growth
Initial Reported Earnings	-0.35	-0.46
	[0.01]***	[0.01]***
Male	82.21	82.71
	[11.21]***	[9.75]***
Age	H_{02}:	H_{02}: ***
Linear	16.69	11.91
	[5.07]**	[4.40]***
Squared	-0.17	-0.11
	[0.06]***	[0.05]***
Years of Education	H_{02}:	H_{02}: ***
Linear	-11.22	-10.78
	[5.21]**	[4.68]***
Squared	1.38	1.41
	[0.24]***	[0.21]***
Sector Transition	H_{02}: ***	H_{02}: ***
Formal- Unemployed	-580	-538
	[31.96]***	[24.82]***
Formal- Informal	omitted	omitted
Formal- Formal	4.52	71.77
	[13.11]	[11.60]***
Region	H_{02}:	H_{02}:
Greater Buenos Aires	omitted	omitted
Pampeana	-64.83	-45.89
	[17.52]***	[13.49]***
Patagonica	-66.17	-48.67
	[21.23]***	[17.05]***
Noreste	-70.61	-37.67
	[20.66]***	[17.32]**
Noroeste	-51.86	-56.86
	[19.32]***	[15.25]***
Cuyo	-44.57	-162.01
	[20.72]**	[93.06]*
Constant	-218.9	-162.01
	[106.96]**	[93.06]*
Number of Observations	10507	13620
R^2	0.1714	0.3

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

Table 15
OLS Regressions, Informal Sector Workers
Dependent Variable: Change in Reported Earnings

	Positive Growth	Negative Growth
Initial Reported Earnings	-0.36	-0.58
	[0.01]***	[0.01]***
Male	75.74	86.82
	[8.66]***	[6.45]***
Age	H_{02}:	H_{02}: *
Linear	15.26	18.2
	[3.90]***	[2.84]***
Squared	-0.16	-0.19
	[0.05]***	[0.03]***
Years of Education	H_{02}:	H_{02}: ***
Linear	-8.59	-20.57
	[4.06]**	[3.11]***
Squared	1.33	2.12
	[0.21]***	[0.16]***
Sector Transition	H_{02}: ***	H_{02}: ***
Informal- Unemployed	-375	omitted
	[18.15]***	
Informal- Informal	-9.02	345.41
	[10.81]	[9.87]***
Informal- Formal	omitted	412.25
		[11.97]***
Region	H_{02}:	H_{02}:
Greater Buenos Aires	omitted	omitted
Pampeana	-39.61	-40.38
	[14.23]***	[9.46]***
Patagonica	-39.05	-22.71
	[16.82]**	[11.60]***
Noreste	-48.08	-36.88
	[16.70]***	[11.71]***
Noroeste	-62.9	-27.62
	[15.72]**	[10.53]***
Cuyo	-34.9	-44.77
	[16.87]	[11.94]***
Constant	-186.63	-557.94
	[81.03]***	[59.57]***
Number of Observations	9390	14550
R^2	0.2014	0.4171

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

H_{02} : equality of coefficients by groups

Table 16
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	***

Table 17
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 18
Ordered Logit Estimation
Dependent Variable: Final year sector of employment

Positive Growth

Independent Variables	Initially Unemployed			Initially Informal Sector			Initially Formal Sector		
	Coefficient	Std.Error		Coefficient	Std.Error		Coefficient	Std.Error	
Male	0.330	0.084	***	0.148	0.048	***	-0.104	0.051	**
Experience									
Age	0.083	0.035	**	0.028	0.022		0.101	0.023	***
Age-Squared	-0.001	0.000	***	0.000	0.000		-0.001	0.000	***
Schooling									
Years of Education	-0.254	0.042	***	-0.067	0.023	***	0.090	0.024	***
Years of Education-Sq	0.017	0.002	***	0.010	0.001	***	-0.003	0.001	***
Region *									
Pampeana	0.344	0.119	***	0.470	0.083	***	-0.168	0.083	**
Patagonica	0.290	0.152	*	0.410	0.097	***	-0.204	0.099	**
Noreste	0.344	0.155	**	0.478	0.096	***	-0.097	0.098	
Noroeste	0.130	0.139		0.482	0.091	***	-0.161	0.091	*
Cuyo	0.182	0.158		0.499	0.097	***	-0.236	0.096	**
Pseudo R-squared	0.027			0.044			0.004		
Observations	2524			9390			10507		
* GBA omitted									

Negative Growth

Independent Variables	Initially Unemployed			Initially Informal Sector			Initially Formal Sector		
	Coefficient	Std.Error		Coefficient	Std.Error		Coefficient	Std.Error	
Male	0.202	0.08	**	-0.086	0.04	**	-0.186	0.04	***
Experience									
Age	0.069	0.03	**	0.034	0.02	**	0.051	0.02	**
Age-Squared	-0.001	0.00	**	0.000	0.00	*	-0.001	0.00	**
Schooling									
Years of Education	-0.086	0.04	**	-0.035	0.02	*	0.072	0.02	***
Years of Education-Sq	0.006	0.00	***	0.008	0.00	***	-0.002	0.00	**
Region *									
Pampeana	-0.016	0.10		0.243	0.06	***	-0.083	0.06	
Patagonica	-0.079	0.13		0.219	0.07	***	-0.035	0.08	
Noreste	0.039	0.14		0.238	0.07	***	-0.032	0.08	
Noroeste	-0.115	0.12		0.159	0.06	**	-0.085	0.07	
Cuyo	0.326	0.14	**	0.258	0.07	***	-0.242	0.08	***
Pseudo R-squared	0.010			0.044			0.005		
Observations	2756			14550			13620		
* GBA omitted									

Figure 1

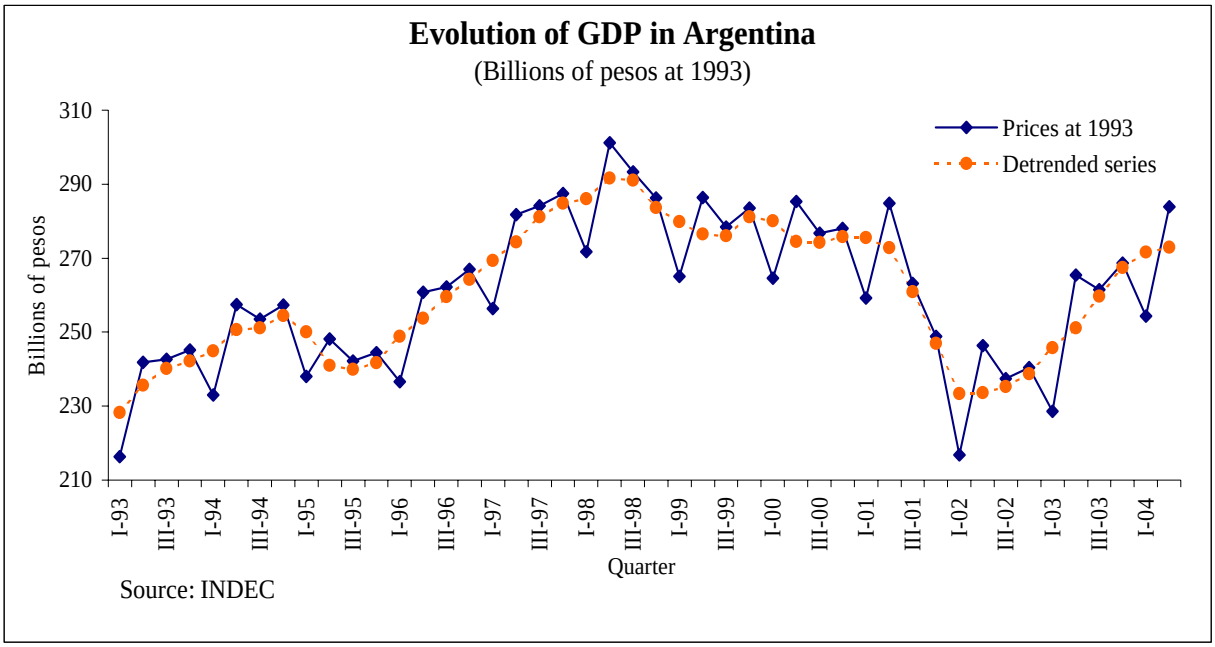
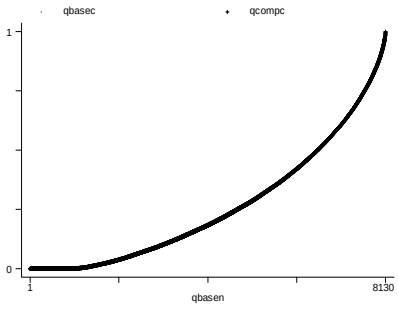
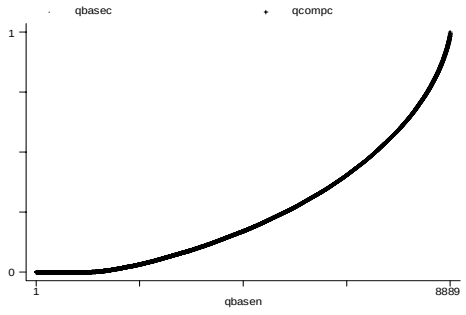

Evolution of GDP in Argentina
(Billions of pesos at 1993)
Billions of pesos
310
290
270
250
230
210
Prices at 1993
Detrended series
I-93
III-93
I-94
III-94
I-95
III-95
I-96
III-96
I-97
III-97
I-98
III-98
I-99
III-99
I-00
III-00
I-01
III-01
I-02
III-02
I-03
III-03
I-04
Quarter
Source: INDEC

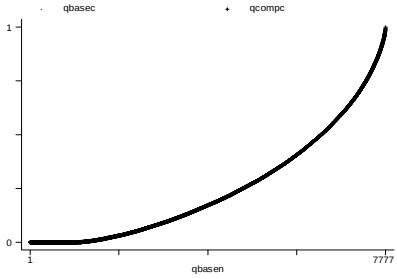
Figure 2.
Year-to-Year Comparisons of Lorenz Curves for Earnings of Individuals Aged 25-60 in the Labor Force in Two Successive Periods in All Urban Argentina*



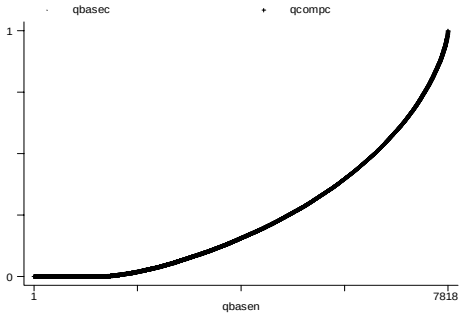
96-97



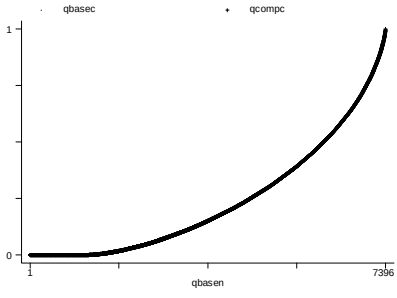
97-8



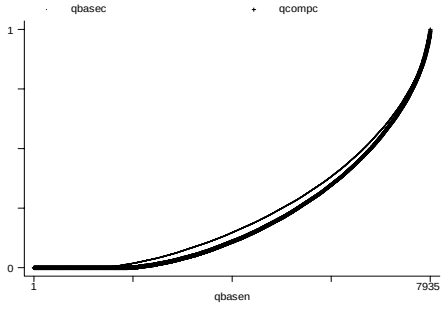
98-99



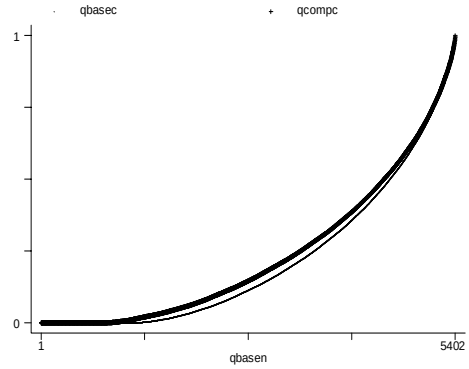
99-00



00-01



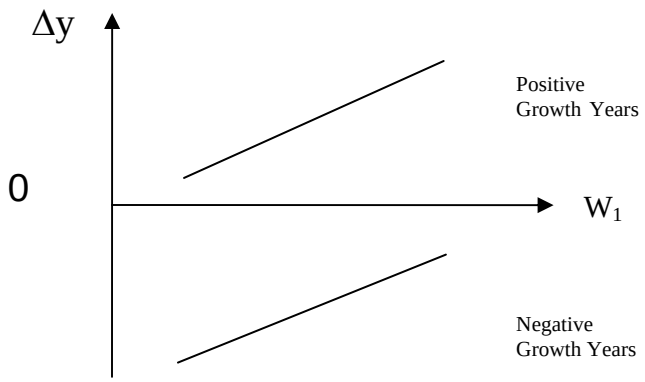
01-02



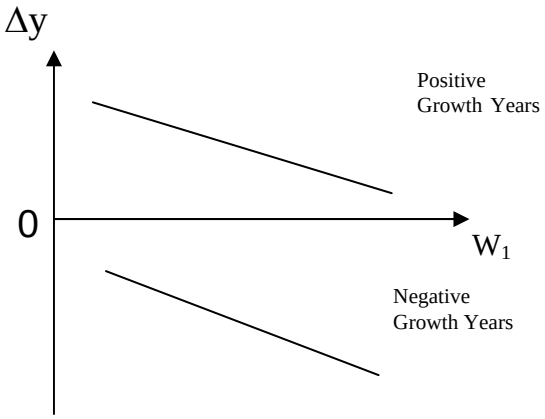
02-03

*Solid lines correspond to final year

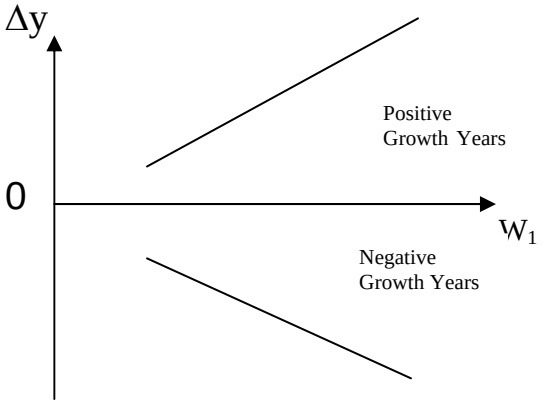
Figure 3
Illustrations of Divergent, Convergent, and Symmetric Growth Patterns



(a)
Divergence



(b)
Convergence



(c)
Symmetry

Appendix

Table A-1
OLS Regressions (first stage for predicted earnings)
Dependent Variable: Reported Earnings

	Growth Years			Recessionary Years			
	1996-97	**1997-98**	**2002-03**	**1998-99**	**1999-2000**	**2000-01**	**2001-02**
Male	257.84	259.75	137.99	288.31	232.14	209.74	221.51
	[13.95]**	[13.14]**	[11.99]***	[15.41]**	[13.96]**	[15.00]	[13.91]***
Age							
Linear	67.82	52.32	41.4	55.69	57.53	52.89	45.31
	[6.38]***	[5.97]***	[5.43]***	[6.94]***	[6.24]***	[6.79]*	[6.18]***
Squared	-0.72	-0.51	-0.41	-0.55	-0.59	-0.53	-0.44
	[0.08]***	[0.07]***	[0.07]***	[0.08]***	[0.08]***	[0.08]*	[0.07]***
Years of Education							
Linear	-19.42	-12.02	-20.06	-42.07	-33.27	-18.41	-35.79
	[6.28]***	[6.22]*	[5.81]***	[7.34]***	[6.60]***	[7.23]*	[6.56]***
Squared	3.83	3.31	3.03	5.14	4.46	3.64	4.54
	[0.31]***	[0.30]***	[0.28]***	[0.35]***	[0.32]***	[0.35]*	[0.31]***
House owner	-34.37	-13.17	8.86	3.87	3.82	18.17	-12.86
	[16.12]**	[15.34]	[14.22]	[17.75]	[16.29]	[17.32]	[16.17]
Dwelling character							
More than 2 rooms	33.34	21.86	18.44	5.2	34.27	31.92	21.63
	[15.14]**	[13.96]	[12.83]	[15.97]	[14.45]**	[15.88]	[14.60]
Comfort	25.87	13.02	16.52	34.83	-4.18	4.1	11.71
	[19.04]	[17.36]	[18.31]	[20.82]*	[20.23]	[21.30]	[20.49]
Number of Observations	8130	8889	5402	7777	7818	7396	7935
Pseudo R^2	0.1934	0.1892	0.1946	0.2039	0.2075	0.1697	0.1994

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

H_{01}: mean equal to zero

H_{02} : equality of means by groups