ESCUELA DE ECONOMIA EMPRESARIAL
Universidad Torcuato Di Tella

CIF
Centro de Investigación en Finanzas

Documento de Trabajo 01/2002

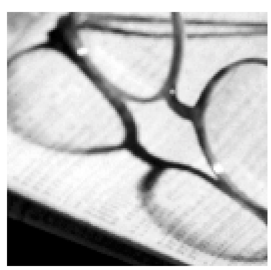
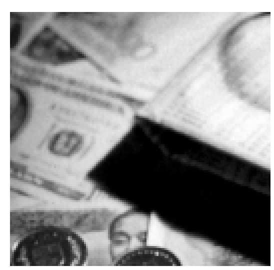
Why have poverty and income inequality increased so much? Argentina 1991-2002

Martín González-Rozada
Universidad Torcuato Di Tella

and

Alicia Menendez
Princeton University



Miñones 2177, C1428ATG Buenos Aires • Tel: 4784.0080 interno 181 y 4787.9394 • Web site: www.utdt.edu/departamentos/empresarial/cif/cif.htm

Why have poverty and income inequality increased so much? Argentina 1991-2002

Martín González-Rozada
Universidad Torcuato Di Tella
Email: mrozada@utdt.edu

Alicia Menendez*
Princeton University
Email: menendez@princeton.edu

September 2002

Abstract: This paper analyzes the sources of changes in poverty and income inequality among Argentine households during the 1991-2001 period. We assess the effect of changes in labor market participation, unemployment, education levels, and returns to human capital on income inequality and poverty by using a micro-simulation approach. This procedure allows us to evaluate the impact of each one of those changes on several measures of income inequality and poverty during the nineties. We found that unemployment accounts for a large part of the increase in income inequality and poverty that this country experienced in the last decade.

In January 2002, Argentina declared the default on its external debt and devaluated the peso 40% ending the convertibility period. Since then, a growing inflation is affecting the purchasing power of Argentine households for the first time in more than ten years. Using our methodology we estimate the effect of the emerging inflation on poverty among households. Our findings indicate that inflation increases poverty significantly at least in the short run.

Key-Words: Income inequality, Micro-simulations, Poverty, Sequential Poisson sampling, Unemployment.
JEL Classification: D31, I32

*We thank participants at the Princeton University Development Seminar, the 2nd LACEA/IDB/WB Conference on Poverty and Inequality, and especially François Bourguignon, Francisco Ferreira, and Gary Fields for their comments on a previous version of this paper. Alicia Menendez thankfully acknowledges financial support from the John D. and Catherine T. MacArthur Foundation through its Network on Poverty and Inequality in Broader Perspective. Correspondence: Alicia Menendez, 343 Wallace Hall, Princeton University, Princeton, NJ, 08544. menendez@princeton.edu.

1 Introduction

Recently, there has been a renewed and growing concern about increasing income inequality and poverty and their negative implications for both economic growth and social peace (see for instance, Bourguignon, Fournier and Gurgand (1998) for Taiwan and Bouillon, Legovini and Lustig (1999) for Mexico). During the nineties, several Latin American countries witnessed an impressive process of market-friendly reforms, centered on the privatization of a large proportion of the state-owned enterprises, as well as commercial and financial liberalization and fiscal and monetary discipline. However, income inequality in the region -the highest in the world- was not reduced and it even increased in many cases, like in Mexico or Argentina.

In Argentina during the first part of the decade, capital inflows lead the economic growth. Between 1991 and 1995 the GDP per capita grew approximately at an average annual rate of 5%. However, the performance regarding labor markets during the same period has been very disappointing. Although the rate of growth has been positive during the period, the rate of job creation decelerated, unemployment rates increased, mainly due to an increase in labor supply, and income distribution became more unequal. Measured by the Gini coefficient, inequality increased more that 6% between 1991 and 1996. More shocking was the fact that besides the economic growth, poverty has increased from 16% of the households below the poverty line in 1991 to more than 20% in 1996. After a year of recession associated to the "tequila crisis" in 1995, economic growth returned to Argentina during the second part of the decade. In this second period unemployment continued its growing path. Poverty increased and the distribution of income became more unequal. (see Altimir and Beccaria, (1998)).

In this paper we try to understand how the behavior of the labor market during the nineties affected income inequality and poverty in Argentina. In particular, we assess the impact of changes in the rate of returns to individual socio-demographic characteristics, changes in labor force participation and in the rate of unemployment and changes in the formal education of the participants in the labor force, on the income inequality and poverty observed in Argentina during the nineties. Understanding these changes over time becomes very relevant in order to design economic policies to reduce the observed inequality and poverty.

We use a micro-simulation approach which builds on previous methods for decomposing changes in the distribution of individual earnings (see Juhn, Murphy and Pierce (1993) for the US and Almeida dos Reis and Paes de Barros (1991) for Brazil) that has been proposed by

Bourguignon et al. (1998) as a way to identify the sources of changes in observed inequality. However, this methodology has been developed for labor markets that are at full employment. That is, it does not include the effects of unemployment -a feature observed not only in Latin America but also in many countries in Western Europe- on income inequality and/or poverty.

We extend this methodology in two ways. First, by taking into account explicitly the disequilibrium in labor markets we can address the question of how changes in unemployment affect the observed inequality and poverty. Second, in any micro-simulation exercise the magnitude of the changes are path dependent. For example, in our case modifying first labor force participation and then unemployment will affect poverty differently that if first the unemployment rate and then the labor force participation are modified. To deal with this path dependence, we construct statistical confidence intervals using a sequential Poisson sampling to evaluate each modification.

Using this approach we found that unemployment accounts for a large part of the increase in inequality between 1991 and 1996, with a small contribution from the change in the returns to the individual social-demographic characteristics of the workers. For the second part of the decade, the rise in the labor force participation implies an increment of about 6% in the Gini coefficient. The effect of the unemployment is less clear than in the first period. If we divide the last part of the decade in two periods, unemployment has an equalizing effect on the Gini coefficient from 1996 to 1998 but increase the inequality from 1998 to 2001. The small effect of the returns to individual socio-demographic characteristics disappears through time by the end of the decade.

With respect to poverty, unemployment and participation have similar effects that with inequality. That is, unemployment affects negatively the proportion of households below the poverty line from 1991 to 1996. It reduces the percentage of households below the poverty line more than 10% between 1996 and 1998 but increase that percentage 14% from 1998 to 2001. Meanwhile, labor force participation has no effects on the households below the poverty line between 1991 and 1996, and it has a negative effect, i.e. increasing the number of households below the poverty line more than 17%, during the second part of the decade.

The rest of the paper is organized as follows. In Section 2 we present the methodology used to trace the impact of changes in labor force participation, unemployment, structure of formal education and returns to individual socio-demographic characteristics on the income distribution and poverty. In Section 3, we analyze the characteristics of the argentine labor market using household survey data. Section 4 presents a brief summary of the individual participation and wage equation estimations for Argentina. Section 5 discusses the main empirical results of the paper and the conclusions are found in Section 6.

2 Methodology

The main objective of this section is to describe a methodology that allows us to evaluate quantitatively the causes behind the increasing income inequality and poverty among Argentine households during the nineties. In particular, we want to study how changes in labor force participation and unemployment, the formal education structure of the active population, and the returns to individual socio-demographic characteristics, affect inequality and poverty.

Our basic approach will be the following. We begin by considering household income per capita, YT_t^h, as the sum of household labor income, YL_t^h, and household non-labor income YNL_t^h in per capita terms. We treat non-labor income as given and attached to each household in the population and therefore we will not model it. The household labor income will be modeled through the individual labor income of each of their members. In particular we will work with the labor income distribution as a function of participation, unemployment, education, and returns to individual characteristics. We will consider modifications to these arguments and see how these changes affect the labor income of the members of the household. After these modifications are made, we will compute the household labor income per capita and by adding the non-labor income we will reconstruct the total household income per capita. Computing and comparing the household income distribution before any change is made and after the modifications take place will give us a measure of the impact on the income distribution.

2.1 General Strategy

We specify the distribution of labor income per capita at time t (YL_t) as a function of participation (P_t) and unemployment (U_t) rates, formal education structure of the active population (E_t) and returns to individual socio-demographic characteristics (R_t). That is, $YL_t = f(P_t, U_t, E_t, R_t)$ represents the actual labor income distribution in period t. Next, we reproduce this labor income distribution but replacing the actual arguments of the function with counterfactual ones. This new function will try to capture how the labor income distribution would have been if the actual arguments of the YL_t function were replaced with counterfactual arguments of the function, i.e. $YL_t^* = f(P^*, U^*, E^*, R^*)$. We will use as counterfactual arguments for the function at time t, the actual arguments at time, say $t + l$ $(l > 0)$. In this way, the resulting counterfactual labor income distribution, $YL_t^* = f(P_{t+l}, U_{t+l}, E_{t+l}, R_{t+l})$, would represent the actual distribution at time $t + l$ $(l > 0)$ except for a residual that would capture any other effects not present as arguments of the function. A particular exercise could be, for example, replacing in YL_t, the participation rate at time t by the participation rate at time $t+l$, such that $YL_t^* = f(P_{t+l}, U_t, E_t, R_t)$. After this change is made, we will compute, first, the counterfactual household labor income per capita, $YL_t^{h^*}$, and then, by adding the per capita household non-labor income YNL_t^h, we will find the total counterfactual household income $YT_t^{h^*}$ in per capita terms. Using actual and counterfactual household incomes we can compute the actual, YT_t, and counterfactual, YT_t^*, household income distributions. By comparing both distributions we could measure the effect of the change in the participation rate between t and $t + l$.

This exercise could be generalized by changing all arguments in the labor income distribution function such that, after the reconstruction of actual and counterfactual household income, the comparison between YT_t and YT_t^*, will show the variation in the income distribution due to changes in participation and unemployment rates, formal education structure of the active population and returns to socio-demographic characteristics between t and $t + l$. Furthermore, the difference between YT_{t+l} and YT_t^* will show the unexplained change in the income distribution between years t and $t + l$.

Once the counterfactual income distribution (YT_t^*) is determined, the comparison with the actual one (YT_t) will be made by computing income inequality and poverty measures. In this way, by comparing actual and counterfactual figures, we can measure how changes in the labor market conditions between two given years affect inequality and poverty.

2.2 Micro-simulations

At this point we need to answer two questions. The first one is how to implement the replacement of actual for counterfactual arguments in the labor income distribution function. The second is how to evaluate statistically the effects of these replacements on the overall distribution function. To answer these questions we use a micro-simulation approach based on a sequential Poisson sampling (see Ohlsson, 1998) as explained below. We simulate the counterfactual arguments (P^*, U^*, and E^*) of the labor income distribution function by estimating some probabilities for each individual in the sample. First, we estimate individual working status probabilities using three mutually exclusive alternatives. These alternatives are (1) employed, (2) unemployed and, (3) out of the labor force. Using the conditional logit model (see McFadden, 1974), the estimated probability that individual k will be in category s ($s = 1, 2, 3$) is given by the following expression,

$$P_{s,k} = \frac{e^{\hat{\delta}_s' X}}{\sum_{j=1}^{3} e^{\hat{\delta}_j' X}},$$

where X is a vector of explanatory variables that captures socio-demographic characteristics of the individual and $\hat{\delta}_j$ ($j = 1, 2, 3$) are estimations of the parameter vectors.

Then, for each individual k in the population we estimate a probability of labor force participation i.e. $P_{p,k} = P_{1,k} + P_{2,k}$, and a probability of being unemployed, $P_{u,k} = P_{2,k}$.

Using the same conditional logit model approach, we estimate for each individual in the population probabilities of having (i) incomplete primary education, P_{pi}, (ii) complete primary education, P_{pc}, (iii) incomplete high school education, P_{hi}, (iv) complete high school education, P_{hc}, (v) incomplete university education, P_{ui}, and (vi) complete university education, P_{uc}.[1]

After these computations are made, each individual k in the population will have attached a set of eight probabilities ($P_{p,k}$, $P_{u,k}$, $P_{pi,k}$, $P_{pc,k}$, $P_{hi,k}$, $P_{hc,k}$, $P_{ui,k}$, $P_{uc,k}$).

With these probabilities, and using a sequential Poisson sampling, we reproduce the counterfactual arguments of the labor income distribution function in the following way. Working with our microdata for year t, we modify the arguments of the YL_t function, one at a time accumulatively, beginning with the participation rate, $YL_t^*(P_{t+l}) = f(P_{t+l}, U_t, E_t, R_t)$. For this modification, first, we apply the estimated coefficients for year $t + l$, $\hat{\delta}_j$ ($j = 1, 2, 3$), to the characteristics of the individuals in the population at time t, such that we reproduce a probability, ($P^*_{p,k}$), of participating in the labor force "as if" the individual were deciding to participate in year $t + l$. Then, we obtain the number of people that would be participating in the labor force at time t, in order to reproduce the actual number of people participating

[1] We do not present these results here. They are available from the authors upon request.

in year $t+l$. That is $N_p^* = N_t \times P_{t+l}$, where N_t is the total population at time t, and P_{t+l} is the actual labor force participation rate at $t+l$. Second, a sequential Poisson sampling is implemented by generating a random number, $\xi_{p,k}$, for each individual k, from a uniform distribution and computing $\epsilon_{p,k} = \xi_{p,k}/P_{p,k}^*$. Then, individuals are sorted according to $\epsilon_{p,k}$ such that the first individuals in the new arranged population will be those with greater probability of participating in the labor force. Once the individuals are sorted in this way, the first N_p^* individuals are assigned to the counterfactual labor force. This means that from the total population of N_t at time t, N_p^* now does belong to the counterfactual labor force and $N_t - N_p^*$ does not. To complete the process, the sequential Poisson sampling is repeated but this time using $N_u^* = N_p^* \times U_t$ as the number of unemployed people and generating a random number from a uniform distribution, $\xi_{u,k}$ for each individual k belonging to the counterfactual labor force. Then, individuals are sorted according to $\epsilon_{u,k} = \xi_{u,k}/P_{u,k}$ (where $P_{u,k}$ is the probability of being unemployed at time t) such that the first individuals in the counterfactual labor force population will be those with greater probability of being unemployed. Once the individuals are arranged in this way, the first N_u^* individuals are assigned to the counterfactual unemployed population. After this procedure is finished, the counterfactual participating population will be composed by N_p^* individuals, N_u^* of which are unemployed. Notice that in this counterfactual population, $N_p^*/N_t \cong P_{t+l}$ and $N_u^*/N_p^* \cong U_t$ are the labor force participation rate at time $t+l$ and the unemployment rate at time t, respectively. Therefore we are modifying the labor force participation rate in the labor income distribution function from P_t to P_{t+l}.

Once the counterfactual population is obtained, we need to assign labor earnings to the $N_e^* = N_p^* - N_u^*$ individuals employed. In the N_e^* population there are at most three kind of individuals: those that were employed, those that were unemployed, and those that were out of the labor force in the original population. Those who were employed in the original population will maintain their labor income. For those either unemployed or out of the labor force in the original population but employed in the counterfactual population we need to impute them a labor income. This is done using a random regression imputation. That is, for those individuals employed in the original population, the labor income (in logs) is given by:

$$W_{1,k} = \beta_1' Z_{1,k} + \epsilon_{1,k}, \quad k = 1, 2, \cdots, N_1 \tag{1}$$

where the subscript k refers to the k-th individual, $Z_{1,k}$ is a vector of exogenous socio-demographic variables including the number of years of formal schooling, and $\epsilon_{1,k}$ is a disturbance term. Selectivity bias occurs in equation (1) if the disturbances $\epsilon_{1,k}$ are correlated with those of the working status model. We correct for this problem by using a two-stage method proposed by Lee (1983) (see Appendix).

Using equation (1) we do a random regression imputation in the following way. First, we generate a residual term for those individuals, either unemployed or out of the labor force in the original population that are employed in the counterfactual population. Since the residual term of the labor income equation is not observed for those individuals, it was necessary to draw it conditionally on the observation that was available. This was done by drawing appropriately random numbers from a standard normal distribution with variance equal to the empirical variance of the residuals obtained by least squares estimation of the labor income equation. Second, using the estimated coefficients of the labor income equation, $\hat{\beta}_1$, and the socio-demographic characteristics of the individuals employed in the counterfactual population, $Z_{1,k}$, for year t, plus the residual term generated before, we impute labor earnings to the counterfactual employed population.

Once each individual in the counterfactual employed population has income earnings, the final step consists in reconstruct, first, the per capita household labor income $YL_t^{h^*}(P_{t+l})$ and, then by adding the non-labor income, the total per capita household income $YT_t^{h^*}(P_{t+l})$. Using the actual and counterfactual per capita household income distributions at time t, we compute measures of income inequality and poverty. The comparison between them will give us a measure of the impact on inequality and poverty due to the labor force participation dynamics between t and $t+l$. This is what we will call the "participation effect".

The procedure to modify the unemployment rate in the labor income distribution of period t, $YL_t^*(P_{t+l}, U_{t+l}) = f(P_{t+l}, U_{t+l}, E_t, R_t)$ is similar to the one we use to compute the "participation effect". However, in this case when we apply the estimated coefficients for year $t+l$, $\hat{\delta}_j$ $(j = 1, 2, 3)$, to the socio-demographic characteristics of the individuals in the population at time t, we reproduce a probability of being unemployed "as if" the individual were unemployed in year $t+l$, $(P^*_{u,k})$. The number of unemployed individuals in the counterfactual population is computed then by using $N_u^* = N_p^* \times U_{t+h}$, where U_{t+h}, is the unemployment rate in period $t+h$. In the second stage, after performing the sequential Poisson sampling for the counterfactual participation rate, a new sequential Poisson sampling is made but this time individuals are sorted according to $\epsilon^*_{u,k} = \xi_{u,k}/P^*_{u,k}$. The rest of the procedure is the same.

Again, as it was the case with the participation effect, the comparison between some measure of income inequality and poverty, computed using counterfactual household incomes $YT^{h^*}_t(P_{t+l})$ and $YT^{h^*}_t(P_{t+l},\, U_{t+l})$ will give us a quantitative measure of the effect of unemployment on labor income distribution. This is what we will call the "unemployment effect". Notice that the comparison between the distributions $YT^*_t(P_{t+l},\, U_{t+l})$ and YT_t will give us a measure of the effect on inequality and poverty due to the change in participation and unemployment from t to $t+l$.

Next, we change the formal education structure of the active population in the labor income distribution function at time t, $YL^*_t(P_{t+l},\, U_{t+l},\, E_{t+l}) = f(P_{t+l},\, U_{t+l},\, E_{t+l},\, R_t)$. This procedure is similar to the one described to modify the unemployment rate except that a new sequential Poisson sampling is performed after the one used to reproduce the counterfactual unemployment rate above. This new re-sampling uses the formal education probabilities, estimated for period $t+l$, plus the total number of people (classified as having formal education in one of the six categories in which the structure of education was divided) participating in the counterfactual labor force.

With these elements we compute the fixed counterfactual number of active people with formal education in each one of these categories. Drawing appropriately uniform random numbers and sorting the individuals according to the formal education probabilities a new counterfactual population is obtained. Once this sequential Poisson sampling is performed, each person in the counterfactual active population will have a new number of years of formal education assigned according to probabilities trying to reproduce the education structure of the active population in year $t+l$. Next, labor income is assigned to each person in the counterfactual employed population following the same random imputation regression procedure described above. The only change is that for each person in the counterfactual employed population $Z_{1,k}$ includes an explanatory variable containing the counterfactual number of years of formal education instead of the actual number of years of schooling in period t.

Then, computing and comparing some measures of income inequality and poverty on the distributions $YT^*_t(P_{t+l}, U_{t+l})$ and $YT^*_t(P_{t+l},\, U_{t+l},\, E_{t+l})$ will measure of how the change in formal education of the active population between t and $t+l$ affects the household income distribution. This will be called the "education structure effect". As before, the comparison between $YT_t^*(P_{t+l},\, U_{t+l},\, E_{t+l})$ and YT_t will give us a measure of the effect on inequality and poverty due to the change in participation, unemployment and education structure from t to $t+l$.

Finally, we need to consider the effect of changes in returns to individual socio-demographic characteristics between period t and $t{+}l$ on the labor income distribution, i.e. $YL_t^*(P_{t+l},\, U_{t+l},\, E_{t+l},\, R_{t+l}) = f(P_{t+l}, U_{t+l}, E_{t+l}, R_{t+l})$. In order to compute the "returns effect", we repeat the procedure described above but in its last stage the estimated coefficients of the labor earnings equation in period t are replaced by the same estimated coefficients, $\hat{\beta}_1$, but for period $t+l$. Comparing the distribution $YT_t^*(P_{t+l},\, U_{t+l},\, E_{t+l})$ with $YT_t^*(P_{t+l},\, U_{t+l},\, E_{t+l},\, R_{t+l})$ we estimate the impact of changes in returns between t and $t+l$.

The overall effect can be computed by comparing the original household income distribution at time t, YT_t, with the counterfactual household income distribution that accumulates the effects of the participation and unemployment rates, the changing structure of formal education and returns to individual socio-demographic characteristics, $YT_t^*(P_{t+l},\, U_{t+l},\, E_{t+l},\, R_{t+l})$.

In any micro-simulation approach the magnitude of the impact of changes, in this case in the arguments of the labor income distribution, is path dependent. For example, modifying first labor force participation and then unemployment rate will give us an impact on the labor income distribution that is going to differ from the impact given by modifying first the unemployment rate and then the labor force participation. One possible solution frequently used in the literature (see Boullion, C et al. 1998), is to assume monotonicity and to compute the effect both ways and consider the average of both effects as the result. We follow another approach (see Frenkel and González-Rozada (1999, 2000)) based on constructing statistical confidence intervals for the impact of different effects on labor income distribution. These confidence intervals for the estimated effects are constructed by replicating the micro-simulations a large number of times, say 1000 times, and then to compute empirical confidence intervals. Therefore, our approach will consist in replicate each modification 1000 times and then computing 95% empirical confidence intervals for the counterfactual measures of income inequality and poverty we use.

3 Participation, Unemployment and Labor Earnings

We begin our discussion with an examination of the evolution of unemployment, labor income, and poverty in Greater Buenos Aires (GBA). We use the Permanent Household Survey (EPH) from the National Statistical Institute (INDEC) for 1991 through 2001. The data cover the city of Buenos Aires and the Greater Buenos Aires region. This area is exclusively urban, and comprises forty percent of the total population in the country; its contribution to total GDP is more than sixty percent. These surveys are conducted twice a year, in May and October, and provide information on employment status, occupation, earnings, hours worked, education, age, and other characteristics of individuals and characteristics of their jobs and sector of activity.

Although the analysis is restricted to GBA, the similitud between this area and the rest of the main cities in the country, with respect to average income evolution, income distribution and labor market indicators allow us to believe that the characteristics of poverty and its evolution for other urban areas of the country would not be much different from those analyzed in this paper.

The unemployment rate increased dramatically during the 1990s . At the beginning of the decade the unemployment rate was around 6%. In the subsequent years it increased rapidly, exceeding 20% in May 1995. After that maximum was reached, it began to decrease very slowly although it stayed well above the historical level of 4%. By October 1998 the unemployment rate was over 13%. The deep recession at the end of the decade push it up again reaching 18.3% in 2001 .

Figure 1 about here

Figure 1 shows this evolution in detail. During this period, participation rates increased 4 percentage points while the employment ratio remained stable (see Table 1). In terms of gender, most of the change in participation is due to females. Male participation has remained stable around 55% while the participation for women has increased from 39 to 45%. Participation rates for teenagers have been decreasing in absolute values and relative to the overall participation rate. In 1991, the group between 16 and 19 years old had a participation rate of 41%; by 1998 that figure went down to 35%. All other age groups are participating more, particular those 50 and older.

Table 1 about here

Unemployment rates vary substantially across groups of workers. Table 2 presents unemployment rates by sex, age and schooling. Women tend to have higher unemployment rates than men during most of the period. This is true even when we control by schooling attainment. However in October 2001 the male unemployment rate reached a record high and surpassed the female rate.

Table 2 about here

In terms of age, workers younger than 35 years old are more likely to be unemployed. The rates of unemployment are particularly high for teenagers. Workers under 20 have an unemployment rate well above of any other age group, and it is more than three times the unemployment rate of workers over 35. Older workers -50 years old or more- have higher rates of unemployment than prime age workers do, although the difference is not as streaking as in the case of young workers. Table 2 shows unemployment rates for six schooling groups. In general, education reduces the probability of being unemployed. In 1998, for example, the unemployment rate for workers with primary complete education was above 16% while it was only 5% for those with college degree. Degree completion is important. High school dropouts tend to show higher unemployment rates than workers with primary school degree. In some years, unemployment rates are lower for high school graduates than for workers with some college education. Overall, the structure of unemployment based on workers' characteristics appears similar to that in developed countries. Women, young and less educated workers are more likely to be unemployed. In terms of age and education the differences in unemployment rates are very similar to those found in the US. Although female, young and less educated workers are more likely to be unemployed, it is interesting to note that when unemployment is very high, like in 1996, unemployment rates for other groups of workers -like prime age or highly educated workers- go up sharply and sometimes even more than proportionally.

In Table 3, we show the change in real monthly labor earnings by percentile. The evolution between 1991 and 2001 was not homogeneous across groups. The bottom 40% of the distribution suffered a reduction while the rest increased their real earnings. From 1991 to 1994, real monthly wages increased for all groups of workers. From 1994 to 1996 all groups but the 90th percentile experienced a contraction of their real wages. In some cases, like the bottom 10th of the distribution, the reduction was larger than 20%. The second half of the decade shows additional reductions in labor income for most income groups. The very bottom of the distribution was severely affected, in particular, during the final years of the period. In sum, over the 1991-01 interval, the bottom tail of the distribution experienced a serious decrease of real labor earnings; the middle group had a modest increase around 5 to 10%, while those in a more privileged position enjoyed important increments.

Table 3 about here

In this context of high unemployment and increasing differences in earnings between workers, capturing their impact on poverty and income inequality becomes more than relevant. In order to outline the effect of these tendencies of the labor market on household income inequality and poverty we take 1991 as our base year. We will simulate alternative distributions using counterfactual arguments on participation, unemployment, individual socio-demographic characteristics and their market returns, for 1996, 1998, and 2001. The choice of 1991 as our base year is not arbitrary. In March 1991, the most important legal instrument of the Argentine stabilization process, the Convertibility Law, established a fixed peso-dollar parity. Therefore, the conditions of the labor market in 1991 corresponds to the beginning of the convertibility period. Our study ends in 2001, the last year of the convertibility.

4 Estimation of Individual Participation and Wage Equations

As was mentioned in the methodology section, before the sequential Poisson sampling can be performed we need to characterize the labor market through the probabilities that each individual has of being unemployed, employed or out of the labor force. Therefore, our first step is to estimate a working status model using the logit maximum likelihood method.

The dependent variable takes values 1, 2 or 3, depending on the individual being employed, unemployed, or out of the labor force respectively. As independent variables, we have included: age and its square, sex, education, a dummy to indicate if married, interaction between gender and marital status, dummies for head of household and having children younger than twelve years old, interaction term between gender and having children, and spouse's employment status.

Estimation results are as expected and we present them in Table 4.[2] The first panel shows the results for employed workers versus non-participants and the second panel presents the estimates for unemployed workers relative to non-participants.

Table 4 about here

Education increases the odds of participating in the labor force, and it significantly raises the chances of being employed. As expected, those currently attending school tend not to be active. Participation in the labor market also increases with age. Conditional on participating, the probability of being unemployed is higher for younger workers. The effect of being male is positive too. Being head of household has a positive effect on employment but it doesn't seem to distinguish the unemployed from the non-participants. The coefficients on marital status and its interaction with sex show that being married tends to have a strong negative effect on women's participation and a positive one on men's. Having children younger than 12 years old reduces the odds of being in the labor force in the case of women but not in the case of men. Finally, the chances of participating are higher for those whose spouse is unemployed. This effect is stronger for the group of unemployed.

From these estimations we compute the necessary probabilities to perform the various sequential Poisson sampling described above.

Using the working status polychotomous estimated coefficients, we also construct a sample selection bias correction as described in the appendix, ϕ/F, to be used in the wage equation estimations. This sample bias correction term tries to capture the probability of being employed given the worker's sociodemographic characteristics. Therefore, it provides a measure of the unobserved difference between employed and unemployed people, and between those employed and those out of the labor force.

After the participation and unemployment sequential Poisson sampling are performed we get the individuals employed in the counterfactual population. We need to assign them a labor income using a random regression imputation. In order to do that, we proceed to estimate a wage function for the employed workers (employees, self-employed and proprietors). The

[2] We also estimate a sequential working status model were the decision, of the members of the household, to enter the labor force depend on the decision of the head of the household. Since we got similar results, those regressions are not presented here but they are available from the authors upon request.

explanatory variables in this wage function are age and its square, education, and a dummy variable for sex (male = 1). We have also included the estimated sample selectivity correction for working status based on our prior estimates.

As the results in Table 5 show, all these variables have the expected sign. The coefficient on education is positive and significant, and it is increasing from 7% to more than 10% during the period under study. We use age as a proxy for experience. Its effect is positive and concave. Being male has a positive and significant effect too. Later, we will return to analyze the changes in the returns to the workers characteristics and its relation with changes in inequality in more detail.

Table 5 about here

Using these wage equation estimations, and following the procedure described in the methodology section we assigned to each member of the counterfactual employed population a labor income.

5 Results

5.1 The Convertibility Period: 1991-2001.

Tables 6 through 9 show actual and estimated measures of household income inequality and poverty. We use the Gini coefficient to measure inequality and three different measures of poverty. Our measures of poverty are calculated on a household basis and are equal to: $P_\alpha = N^{-1} \sum (1 - x_i/z)^\alpha 1(x_i \leq z)$, where x_i is the total household income, z is the poverty line and α can be equal to 0, 1, or 2. When α equals 0 our poverty measure is the headcount ratio (P_0), which indicates the percentage of households that are below the poverty line. In the case that α is 1, we obtain the poverty gap measure (P_1). This measure conveys an idea of the degree of poverty. The farther household i is from the poverty line, the larger is its contribution to total poverty, and the larger the gap. Finally, we construct a third measure of poverty using α equal to 2 (P_2). This measure is similar to the povery gap but put more weight on poorest households.[3]

[3]For a more detailed explanation on poverty measures see Deaton (1997).

The poverty line, z, is computed using the methodology established by the INDEC in its official estimations. The procedure consists in estimating the value of a basic food basket (BFB) that takes into account consumption habits and covers during a month the protein and calories requirements for an adult man between 30 and 59 years old. From this BFB a total basic basket (TBB) is constructed by adding non-food goods and services. This is done through an expansion of the BFB using the inverse of the Engel's coefficient which is defined as the relationship between food expenditures and total expenditures (see INDEC, (1990)).

In each table the first row shows actual values for poverty levels and income inequality between households in year t. The following rows show how these measures would have been under different conditions present in year $t+l$. That is, the effect on these measures of changes in: the participation rate, the unemployment rate, the new distribution of education among active workers and the returns to worker's personal characteristics. Finally, the last row in each table shows the actual inequality and poverty measures for the end years, $t+l$.

Table 6 about here

We note immediately the very severe increase in both, poverty and inequality among households. All measures increased substantially between 1991 and 2001. The Gini coefficient went up more than 5 points between 1991 and 2001, around 11 percent. The number of families with total income below the poverty threshold went from 16 to 26 percent in the same period and the poverty gap more than double its 1991 level.

We start by analyzing the effect of changes in participation. Overall the period, participation keep inequality between households unaffected. However, when we focus on shorter periods we see that the participation effect has increased inequality in a significant way in the second part of the decade, 1996-2001. Simulating 1994 participation rates in the household income distribution of 1991 decreases the Gini coefficient in around two points. Increasing participation has no effects between 1991 and 1996 and raises income inequality between 1996 and 1998 and between 1998 and 2001 (see figure 2 and table 6). Regarding poverty, changes in participation have increased all measures in the second part of the decade. Between 1991 and 1996, participation does not affect the number of households below the poverty line but it increases the poverty gap and P2 due to the worsening of the income distribution among the poorer.

Figure 2 about here

The unemployment effect was very important during the 1991-2001 period. The raise in unemployment implied an increase in income inequality and poverty from 1991 to 1996 and from 1998 to 2001. During 1996 to 1998, the unemployment rate was reduced and, as a consequence, poverty and income inequality among households went down too.

Changes in the education of the labor force were not very pronounced and therefore the effects on income inequality and poverty are modest. For income inequality there is a small increase from 1996 to 1998 due to this effect, for the rest of the periods, changes are not statistically significant. The tendency is a little more robust when considering poverty. During the second part of the decade, from 1996 on, changes in the structure of education of active workers increase slightly the number of households below the poverty line. However the effect is larger for the other poverty measures and also for the 1991-1996 period. This could be saying that changes in the structure of formal education of the labor force influence negatively the income distribution of the poorer.

Tables 7, 8 and 9 about here

Finally, we considered the changes in returns to individual socio-demographic characteristics. These changes have a small effect in the sense of increasing inequality among households between 1991 and 1996. For the rest of the decade changes in the returns to individual socio-demographic characteristics are not statistically significant. Similar results are obtained with poverty. Changes in returns have a slight tendency to increase the three measures of poverty between 1998 and 2001, but overall these changes do not affect significantly neither inequality nor poverty.

5.2 The Post-Convertibility Period

In January 2002, Argentina declared the default on its external debt and devaluated the peso 40% ending the convertibility period. Since then, growing inflation is affecting the purchasing power of Argentine families for the first time in more than ten years. Between December 2001 and April 2002 the prices of the items in the BFB that determines the poverty line increased more than 35%. Unemployment is still growing and labor force participation is decreasing. To alleviate the current situation, the government launched a social program to give a subsidy of 150 pesos to all heads of the household that are unemployed.

Using our methodology, we add to our analysis the effects on income inequality and poverty among households of the emerging inflation ("Inflation effect"), and the subsidy implemented for the government ("Subsidy effect").

In order to do this exercise we use data from the May 2002 EPH . Since the official poverty line is computed by multiplying the value of a BFB by the inverse of the Engel's coefficient, we compute the effects of inflation taking into account a "price effect" and a "substitution effect" . The price effect is given by the difference between the value of the BFB in April 2002 and September 2001 which reflects the inflation in the food items included in that basket. An additional effect due to inflation -the substitution effect- is the change in the percentage of the total budget devoted to food consumption. As many households devote a larger percentage of their total expenditure to food, the Engel's coefficient changed. According to official figures, the BFB increased 34% between September 2001 and April 2002,while the the percentage of household expenditures dedicated to food, that was 40.6% in September 2001, increased to 42.2% in April 2002. The combination of both effects will give us the impact of the increase in the price level on poverty among households.

Table 10 shows the results of this exercise. Labor force participation has an unequalizing effect on the distribution of income. It also increases marginally the number of households below the poverty line but it deteriorates much more the other measures of poverty. The 15% increase in unemployment between September 2001 and April 2002, and the change in the structure of formal education both have a small worsening impact in the household income distribution and the poverty measures. As it was expected the inflation effect on the income distribution is null by construction.

Regarding poverty, the largest effect for the period corresponds to inflation which increased the number of households below poverty line by about 22%. This effect is composed by a 25% increase due to the price effect and a negative 3% due to the change in the household budget share dedicated to food (substitution effect). We also observe a major effect of inflation on the other poverty measures.

The social subsidy implemented for the government decreases inequality by about 4%, and has about the same effect on the number of households falling below poverty line. However the social subsidy to the head of the household clearly reduces the poverty gap by improving the income distribution among the poorer.

Table 10 about here

6 Conclusions

In this paper we proposed a methodology to trace the impact of labor force participation, unemployment, education structure and returns to individual socio-demographic characteristics on the observed income inequality and poverty in Argentina during the nineties. Based on estimations of a labor wage equation conditional on a working status polychotomous model, we apply a micro-simulation approach that uses a sequential Poisson sampling to reproduce counterfactual changes in the household income distribution between 1991 and 2002. We applied our procedure to the Argentine labor market finding that unemployment accounts for a large part of the increasing inequality during nineties. Labor force participation has a unequalizing effect on the income distribution from 1996 on. Regarding poverty, changes in participation have increased all measures in the second part of the decade. After Argentina abandoned the convertibility regime in January 2001, the emerging inflation accounts for much of the deterioration observed in the poverty measures.

Appendix

The polychotomous model can be transformed into a binary decision problem as follows. For each of the three alternatives there is a utility as in (1). The individual selects alternative s ($s = 1, 2, 3$) if and only if it provides the highest utility, i.e.,

$$V_s > \max_{j \neq s} V_j$$

Now define

$$\pi_s = \max_{j \neq s} V_j - u_s \tag{2}$$

It follows that the individual will select alternative s if and only if $\delta_s' x_s > \pi_s$. Since u_{ij} is independently and identically Gumbel distributed and if X is a vector of exogenous variables ($X = [x_1', x_2', \cdots, x_N']'$) the distribution $F(\pi_s)$ of π_s is

$$F(\pi_s) = \frac{e^{\pi_s}}{e^{\pi_s} + \sum_{j \neq s} e^{\delta_j' x}}, \tag{3}$$

and the probability that the individual is in state s is

$$P_s = \frac{e^{\delta_s' x}}{\sum_{j=1}^{3} e^{\delta_j' x}}, \tag{4}$$

which is the conditional logit model (see McFadden, 1974). Let Φ denote the standard normal distribution function. The transformation $J = \Phi^{-1} F$ is strictly increasing, and the transformed random variable π_s^* where $\pi_s^* = J(\pi_s)$ will be a standard normal variate. Therefore, the individual will be in alternative s if and only if $J(\delta_s' X) > \pi_s^*$. This specification implies that, conditional on the individual being in state s,

$$W_s = \beta_s' Z_s - \rho_s \frac{\phi(J(\delta_s' X))}{F(\delta_s' X)} + \xi_s = \beta_s' Z_s + \omega_s, \tag{5}$$

where $E(\xi_s | \text{individual is in } s) = 0$, ϕ is the standard normal density function and X_s is a partition of X (see Lee, 1983). Therefore, in the first step of our approach, equation (5) can be consistently estimated, for $s = 1$, in two stages. In the first stage a working status polychotomous model is estimated by the logit maximum likelihood method and estimators of d are obtained. Replacing these estimators into (5), in the second stage we estimate the following equation,

$$W_1 = \beta_1' Z_1 - \rho_1 \frac{\phi(J(\delta_1' X))}{F(\delta_1' X)} + \tilde{\xi}_s. \tag{6}$$

The disturbances of equation (6) are heteroskedastic and correlated across different sample observations. We construct the correct asymptotic variance-covariance matrix following Lee, Maddala and Trost (1980).

Define two diagonal matrices: Λ an $N \times N$ matrix given by,

$$\Lambda = \text{diag}\left[\frac{\phi^2(J(\hat{\delta}' X))}{F(\hat{\delta}' X)(1 - F(\hat{\delta}' X)}\right] \tag{7}$$

and an $N_1 \times N_1$ matrix defined as,

$$A = \text{diag}\left[J(\hat{\delta}' X_1)\frac{\phi(J(\delta_1' X))}{F(\delta_1' X)} + \left(\frac{\phi(J(\delta_1' X))}{F(\delta_1' X)}\right)^2\right]. \tag{8}$$

Next, define the vector,

$$Y_1 = \left[Z_1, \ \frac{\phi(J(\delta_s' X_s))}{F(\delta_s' X_s)}\right] \tag{9}$$

Then, the asymptotic covariance matrix of estimators in model (6) is

$$\text{Var}\begin{pmatrix} \hat{\beta}_1 \\ \hat{\rho}_1 \end{pmatrix} = \sigma_1^2 (Y_1' Y_1)^{-1} - \hat{\rho}_1 (Y_1' Y_1)^{-1} Y_1' (A - A X_1 (X' \Lambda X)^{-1} X_1' A) Y_1 (Y_1' Y_1)^{-1} \tag{10}$$

References

Almeida dos Reis, J. and R. Paes de Barros, (1991), "Wage inequality and the distribution of education: A study of the evolution of regional differences in inequality in metropolitan Brazil," *Journal of Development Economics*, 36, pp. 117-143.

Altimir, O. and L. Beccaria, (1998), "Efectos de los cambios macroeconómicos y de las reformas sobre la pobreza urbana en Argentina," in *Política macroeconómica y pobreza en America Latina y el Caribe* PNUD, Santiago de Chile.

Bouillon, C., A. Legovini and N. Lustig, (1998), "Rising inequality in Mexico: Returns to household characteristics and the 'Chiapas effect'," Inter-American Development Bank, mimeo.

Bourguignon F., M. Fournier, and M. Gurgand, (1998), "Distribution, development and education: Taiwan, 1979-1994," World Bank, mimeo.

Deaton, A. (1997), "The analysis of household surveys. A micoreconometric approach to development policy," *Johns Hopkins University Press*

Frenkel, R. and M. González-Rozada, (1999), "Liberalizacin del balance de pagos. Efectos sobre el crecimiento, el empleo y los ingresos en Argentina," Universidad de Palermo-CEDES Working Paper (in Spanish).

Frenkel, R. and M. González-Rozada, (2000), "Comportamiento macroeconómico, empleo y distribución de ingresos. Argentina en los años noventa," in *Liberalización, desigualdad y pobreza: América Latina y el Caribe en los 90* Enrique Ganuza et al. editors. Eudeba, 151-199.

INDEC (1990), "La pobreza urbana en Argentina," Buenos Aires.

Juhn, C., K. Murphy, and B. Pierce, (1993), "Wage inequality and the rise in returns to skill," *Journal of Political Economy*, 101 (3), pp. 410-442.

Lee, Lung-Fei, (1983), "Generalized econometric models with selectivity," *Econometrica*, 51, pp. 507-512.

Lee, L-F., G. S. Maddala, and R. P. Trost, (1980), "Asymptotic covariance matrices of two-stage Tobit methods for simultaneous equation models with selectivity," *Econometrica*, 48, pp. 491-503.

McFadden, Daniel, (1974), "Conditional logit analysis of qualitative choice behavior," In Paul Zarembka (ed.), *Frontiers in Econometrics*, New York, Academic Press.

Ohlsson, E. (1998), "Sequential Poisson sampling," *Journal of Official Statistics*, Vol. 14, No. 2, pp. 149-162.

Ros, J. and N. Lustig, (1999), "Trade and financial liberalization with volatile capital inflows: Macroeconomic consequences and social impacts in Mexico during the 1990s, " mimeo.

Table 1: Employment, Unemployment and Participation Rates

	1991	1996	1998	2001
Employment Rate	38.1%	36.3%	39.0%	35.5%
Unemployment Rate	5.3%	18.9%	13.5%	19.0%
Participation Rate	40.6%	44.7%	45.1%	44.7%

Note: computations using population 14 years old and older.

Table 2: Unemployment Rates

	1991	1996	1998	2001
Unemployment rates by gender				
Female	5.9%	22.0%	15.8%	18.3%
Male	4.9%	16.9%	11.9%	19.6%
Unemployment rates by age				
less than 20	16.6%	46.8%	34.9%	39.1%
between 20 and 34	5.5%	19.1%	13.5%	22.5%
between 35 and 49	3.7%	14.5%	10.4%	14.4%
more than 49	3.1%	15.7%	11.8%	16.9%
Unemployment rates by education				
Primary Incomplete	5.0%	21.8%	19.0%	24.7%
Primary Complete	5.4%	21.2%	16.4%	21.8%
Secondary Incomplete	6.4%	23.0%	16.6%	23.2%
Secondary Complete	6.0%	16.3%	10.8%	20.5%
University Incomplete	3.6%	20.2%	11.0%	18.4%
University Complete	3.5%	8.2%	5.0%	7.0%

Table 3. Evolution of Monthly Labor Earnings

Real Labor Income	1991	1996	1998	2001
centile				
5	164	121	104	101
10	218	202	200	152
20	273	302	300	253
30	341	403	400	304
40	409	454	450	405
50	477	504	530	506
60	545	605	600	607
70	682	756	800	709
80	818	1008	1000	962
90	1091	1512	1500	1518
95	1636	2016	2120	2126
Percentage Change	1991 – 1996	1996 – 1998	1998 – 2001	1991 – 2001
centile				
5	−26%	−14%	−3%	−38%
10	−7%	−1%	−24%	−30%
20	11%	−1%	−16%	−7%
30	18%	−1%	−24%	−11%
40	11%	−1%	−10%	−1%
50	6%	5%	−5%	6%
60	11%	−1%	1%	11%
70	11%	6%	−11%	4%
80	23%	−1%	−4%	18%
90	39%	−1%	1%	39%
95	23%	5%	0%	30%

Note: monthly labor income presented in constant prices of October 1998.

Table 4: Working Status Polychotomous Model

Panel 1: Employed compared to Out of the Labor Force:				
	1991	1996	1998	2001
Intercept	−3.953	−5.676	−5.787	−6.653
	(−15.27)	(−21.06)	(−21.88)	(−23.79)
Age	0.248	0.364	0.338	0.368
	(19.19)	(25.85)	(−29.84)	(26.90)
Age^2	−0.003	−0.005	−0.004	−0.005
	(−23.79)	(−29.76)	(−29.84)	(−30.49)
Education	0.144	0.129	0.162	0.166
	(14.95)	(13.35)	(17.31)	(17.59)
Attending School	−2.506	−2.367	−2.155	−2.152
	(−22.25)	(−21.43)	(−21.08)	(−20.56)
Male	0.515	0.396	0.496	0.475
	(4.74)	(3.80)	(5.06)	(4.74)
Married	−1.498	−1.866	−1.593	−1.590
	(−13.55)	(−16.23)	(−14.44)	(−14.32)
Married*Male	2.146	2.532	1.968	2.225
	(11.78)	(14.17)	(11.63)	(12.67)
Head	0.517	0.274	0.589	0.386
	(4.15)	(2.28)	(5.07)	(3.36)
Child	−0.663	−0.729	−0.861	−0.688
	(−7.64)	(−8.09)	(−9.91)	(−7.66)
Male*Child	1.095	0.953	1.152	0.916
	(7.46)	(6.25)	(7.91)	(6.18)
Spouse Unemployed	0.591	0.794	0.608	0.594
	(1.95)	(4.97)	(3.44)	(4.23)

Panel 2: Unemployed compared to Out of the Labor Force:				
	1991	1996	1998	2001
Intercept	−4.565	−4.009	−3.933	−5.147
	(−8.05)	(−12.07)	(−10.48)	(−14.31)
Age	0.179	0.261	0.238	0.296
	(5.85)	(14.47)	(−12.24)	(16.23)
Age^2	−0.003	−0.004	−0.003	−0.004
	(−7.59)	(−17.37)	(−14.92)	(−18.95)
Education	0.112	0.047	0.046	0.070
	(5.08)	(3.62)	(3.23)	(5.50)
Attending School	−2.956	−2.181	−2.453	−2.170
	(−10.91)	(−15.83)	(−15.52)	(−15.88)
Male	0.609	0.407	0.190	0.482
	(2.83)	(3.23)	(1.38)	(3.87)
Married	−2.331	−2.082	−2.068	−2.161
	(−8.48)	(−13.87)	(−12.69)	(−13.93)
Married*Male	2.606	2.251	2.194	2.878
	(6.64)	(10.04)	(9.15)	(12.82)
Head	−0.187	−0.033	0.103	−0.153
	(−0.69)	(−0.22)	(0.63)	(−1.04)
Child	−0.330	−0.474	−0.669	−0.629
	(−1.37)	(−3.80)	(−4.82)	(−4.64)
Male*Child	0.707	0.534	0.951	0.619
	(2.25)	(2.84)	(4.70)	(3.25)
Spouse Unemployed	n.a.	1.035	1.361	0.660
	n.a.	(5.20)	(6.21)	(3.33)
Sample Size	7988	8623	9059	8911
$\chi^2(22)$	4573.93	5128.93	5251.39	5384.01
p-value	0.0000	0.0000	0.0000	0.0000

Note: t-statistics in parentheses. Robust standard errors are computed assuming observations are independent only between households.

Table 5: Wage Estimation

Dependent Variable: Logarithm of Monthly Wages				
	1991	1996	1998	2001
Intercept	3.858	4.296	3.557	3.294
	(28.81)	(23.28)	(19.33)	(14.91)
Age	0.063	0.046	0.069	0.070
	(10.67)	(5.83)	(9.15)	(8.00)
Age^2	−0.0007	−0.0004	−0.0007	−0.0007
	(−8.71)	(−4.27)	(−7.35)	(−6.23)
Education	0.071	0.092	0.103	0.111
	(21.59)	(27.74)	(29.84)	(26.94)
Male	0.244	0.290	0.398	0.373
	(7.71)	(8.79)	(12.38)	(10.53)
ϕ/F	−0.225	−0.442	−0.252	−0.334
	(−5.29)	(−7.69)	(−4.65)	(−5.15)
Sample Size	3029	3471	4010	3480
Adjusted R^2	0.2945	0.3652	0.3524	0.3662

Note: t-statistics in parentheses. Heteroskedasticity and autocorrelation robust standard errors were computed using equation (A5).

Table 6: Inequality Measures of Total Household Income Per Capita[4]

Gini Coefficient

	1991-1996	1996-1998	1998-2001	1991-2001
Actual Gini begin of period	0.4716	0.5013	0.5072	0.4716
P. Effect	0.4742	0.5312	0.5308	0.4763
	(0.467, 0.481)	(0.522, 0.540)	(0.524, 0.538)	(0.470, 0.483)
P. and U. Effects	0.5083	0.5204	0.5475	0.5161
	(0.500, 0.516)	(0.513, 0.528)	(0.539, 0.555)	(0.508, 0.524)
P., U. and E. Effects	0.5074	0.5283	0.5537	0.5177
	(0.499, 0.516)	(0.520, 0.536)	(0.546, 0.562)	(0.509, 0.525)
P., U., E. and R. Effects	0.5167	0.5304	0.5571	0.5325
	(0.507, 0.526)	(0.522, 0.538)	(0.549, 0.565)	(0.523, 0.543)
Actual Gini end of period	0.5013	0.5072	0.5245	0.5245

Note: Figures in parentheses are 95% Monte Carlo confidence intervals computed using 1000 simulations.

Table 7: Poverty Measures of Total Household Income: P_0

	1991-1996	1996-1998	1998-2001	1991-2001
Actual P_0 begin of period	16.318	20.600	19.254	16.318
P. Effect	16.174	24.048	23.377	16.345
	(15.16, 17.16)	(23.06, 25.05)	(22.43, 24.31)	(15.30, 17.34)
P. and U. Effects	22.655	21.552	26.737	23.616
	(21.48, 23.88)	(20.57, 22.56)	(25.82, 27.66)	(22.50, 24.72)
P., U. and E. Effects	23.648	23.247	27.970	23.742
	(22.50, 24.81)	(22.32, 24.24)	(26.99, 28.96)	(22.59, 24.94)
P., U., E. and R. Effects	23.083	23.242	28.673	23.911
	(22.10, 24.14)	(22.22, 24.34)	(27.66, 29.64)	(22.72, 25.08)
Actual P_0 end of period	20.600	19.254	26.304	26.304

Note: Figures in parentheses are 95% Monte Carlo confidence intervals computed using 1000 simulations.

[4]Definitions for tables 6 through 10. $P \equiv$ Participation effect; $U \equiv$ Unemployment effect; $E \equiv$ Education structure effect; $R \equiv$ Returns effect; $I \equiv$ Price effect; $G \equiv$ Substitution effect ($I + G \equiv$ Inflation effect) and $S \equiv$ Subsidy effect.

Table 8: Poverty Measures of Total Household Income: P_1

	1991-1996	1996-1998	1998-2001	1991-2001
Actual P_1 begin of period	4.8652	8.5756	7.8453	4.8652
P. Effect	6.6263	13.805	13.015	6.7043
	(6.020, 7.244)	(13.07, 14.53)	(12.34, 13.71)	(6.082, 7.326)
P. and U. Effects	11.5451	11.843	15.851	12.5904
	(10.64, 12.44)	(11.12, 12.62)	(15.10, 16.58)	(11.76, 13.46)
P., U. and E. Effects	12.4667	13.084	16.832	12.6975
	(11.59, 13.37)	(12.35, 13.81)	(16.09, 17.63)	(11.76, 13.58)
P., U., E. and R. Effects	12.2650	13.105	17.231	12.8750
	(11.51, 13.09)	(12.37, 13.88)	(16.47, 18.01)	(11.95, 13.79)
Actual P_1 end of period	8.5756	7.8453	11.997	11.997

Note: Figures in parentheses are 95% Monte Carlo confidence intervals computed using 1000 simulations.

Table 9: Poverty Measures of Total Household Income: P_2

	1991-1996	1996-1998	1998-2001	1991-2001
Actual P_2 begin of period	2.3832	5.4230	4.6000	2.3832
P. Effect	4.6072	11.000	10.135	4.6095
	(4.008, 5.184)	(10.26, 11.73)	(9.45, 10.82)	(4.016, 5.188)
P. and U. Effects	8.9949	9.232	12.751	9.9808
	(8.137, 9.914)	(8.52, 10.02)	(11.99, 13.45)	(9.128, 10.89)
P., U. and E. Effects	9.9544	10.287	13.597	10.075
	(9.087, 10.86)	(9.57, 10.99)	(12.89, 14.39)	(9.164, 10.96)
P., U., E. and R. Effects	9.8449	10.309	13.867	10.204
	(9.060, 10.65)	(9.58, 11.06)	(13.12, 14.66)	(9.256, 11.15)
Actual P_2 end of period	5.4230	4.6000	7.8155	7.8155

Note: Figures in parentheses are 95% Monte Carlo confidence intervals computed using 1000 simulations.

Table 10: Inequality and Poverty Measures. 2001-2002

	Gini	P_0	P_1	P_2
Actual measure 2001	0.5245	26.304	11.997	7.815
P. Effect	0.5492	28.931	17.071	13.562
	(0.542, 0.557)	(27.93, 29.96)	(16.32, 17.89)	(12.79, 14.34)
P. and U. Effects	0.5558	30.409	18.272	14.656
	(0.547, 0.564)	(29.33, 31.45)	(17.48, 19.10)	(13.82, 15.47)
P., U. and E. Effects	0.5627	31.857	19.619	15.918
	(0.555, 0.571)	(30.82, 32.91)	(18.82, 20.49)	(15.12, 16.77)
P., U., E. and R. Effects	0.5647	32.198	19.830	16.069
	(0.557, 0.573)	(31.19, 33.21)	(19.04, 20.64)	(15.29, 16.91)
P., U., E., R., and I. Effects	0.5647	40.200	24.030	18.709
	(0.557, 0.573)	(39.12, 41.25)	(23.25, 24.76)	(17.96, 19.46)
P., U., E., R., I., and G. Effects	0.5647	39.18	23.433	18.318
	(0.557, 0.573)	(38.09, 40.22)	(22.64, 24.22)	(17.50, 19.09)
P., U., E., R., I., G., and S. Effects	0.5434	37.875	19.964	13.879
	(0.536, 0.551)	(36.83, 38.92)	(19.25, 20.69)	(13.19, 14.54)
Actual measure 2002	0.5468	38.845	20.376	14.097

Note: Figures in parentheses are 95% Monte Carlo confidence intervals computed using 1000 simulations.