# The Effect of Unemployment on Labor Earnings Inequality: Argentina in the Nineties*

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**Abstract**

In this paper we develop a methodology that allows us to quantify the effect of changes in unemployment rates on labor income inequality. We estimate individual earnings functions for employed people conditional on a working status polychotomous model and we establish a formal procedure to assign wages to unemployed workers. We simulate the probability distribution of unemployed persons of particular year on a base year. By computing inequality measures using the actual and simulated populations we are able to assess the impact of unemployment on earnings inequality. Additionally, we simulate changes in participation and in the returns to human capital. An application using microdata from Argentina is presented. The results suggest that unemployment accounts for a large part of the increase in earnings inequality that this country experienced between 1991 and 1998.

Key words: Income inequality, Selectivity bias, Unemployment, Wages.
JEL Classification: C25, D31, E24.

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# 1 Introduction

Recently, there has been a renewed and growing concern about increasing income inequality and its 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. The performance regarding labor markets has been disappointing too. Although the rate of growth has been positive during the period, the rate of job creation decelerated and unemployment rates increased. The distribution of labor earnings has became more unequal too, thus understanding the microeconomic processes by which individual incomes change over time becomes very relevant in order to design economic policies to reduce the observed inequality.

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) 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 labor earnings inequality.

The main objective of this paper is to develop a methodology that, by taking into account explicitly the disequilibrium in labor markets can be used to address the question of how changes in unemployment affect the observed inequality. As a by-product of this analysis we establish a formal procedure to assign wages to unemployed people. We incorporate our methodology into the micro-simulation approach developed by Bourguignon et al., such that we can measure the impact of changes in the distribution of workers' socio-demographic characteristics and in the rates of return to human capital on earnings inequality.

We apply our methodology to assess the impact of changes in the rate of returns to individual characteristics, changes in labor force participation, and changes in the rate of unemployment on labor earnings inequality observed in Argentina during the nineties. The raise in unemployment explains 43% of the total increase in inequality between 1991 and 1998, when measured by the Gini coefficient. Changes in the returns to individual characteristics –particularly increasing returns to education – explain 32% of the total change. These effects are quite different when computed for men and women separately. In the case of women, 60% of the observed increase in labor income inequality is due to changes in the unemployment rate while only 22% is due to changes in the rate of returns to human capital. For the group of men, only 23% of the total increase in inequality is due to increasing unemployment and 36% is due to changes in the rate of returns to individual characteristics. Although the effect of changes in the labor force participation rate on labor income inequality is not statistically significant, it has a positive sign for men and a negative sign for women. This means that changes in the labor force participation have had an equalizing effect on the distribution of earnings for women and an unequalizing effect on the distribution of men's.

The rest of the paper is organized as follows. In Section 2 we describe the methodology used to trace the impact of unemployment on the distribution of labor income. We propose a procedure for inputting wages to unemployed persons based on the estimation of individual labor earnings equations conditional on a working status polychotomous model. Once this is done, we simulate changes in the working status of individuals in different years with respect to their working status in a base year and compute two measures of income inequality –Gini coefficient and coefficient of variation- on the actual and simulated income distribution. Unemployment effect is computed by comparing the inequality measures in both distributions. In Section 3, we describe the characteristics of the argentine labor market using household survey data. During the nineties, the argentine labor market was characterized by high rates of unemployment and therefore constitutes a good example to apply our methodology. Section 4 presents an application of the procedure to Argentina. We show that unemployment accounts for a large part of the observed increase in earnings inequality during the 1990s. The conclusions are found in Section 5.

## 2 Model and Estimation Methodology

The model we consider in this section is a working status one. In this model, individuals can be among three mutually exclusive alternatives. These alternatives are (1) employed, (2) unemployed and, (3) out of the labor force. We assume there are $N_1$ individuals employed, $N_2$ individuals unemployed and $N_3$ individuals inactive, such that the total number of economic agents is $N = N_1 + N_2 + N_3$. Given their socio-economic characteristics and the structural features of the labor market, individuals select the alternative that maximizes their utility.

Let $V_{ij}$ be the maximum utility attainable for individual $i$ if she is in state $j$. If we assume $V_{ij}$ to be linear,

$$(1) \qquad V_{ij} = d_j' x_i + u_{ij}, \qquad i = 1,2,\ldots,N$$

where $x_i$ is a vector of explanatory variables that captures all relevant information for the individual to selects the alternative for which $V_{ij}$ is a maximum, and $u_{ij}$ is a disturbance assumed to be independently and identically Gumbel distributed.

If the individual is employed, the market labor wage (in logs) is given by:

$$(2) \qquad W_{1i} = b_1' Z_{1i} + e_{1i}, \qquad i = 1,2,\ldots, N_1$$

where the subscript $i$ refers to the $i^{th}$ individual, $Z_{1i}$ is a vector of exogenous variables, $e_{1i}$ is a disturbance term. Selectivity bias occurs in equation (2) if the disturbances $\varepsilon_i$ and the disturbances $u_{ij}$ in (1) are correlated. We correct for this problem by using a two-stage method proposed by Lee (1983). This method is an extension of the well known Heckman's two-stage procedure (Heckman 1976). Basically, it transforms the working status polychotomous model into a binary decision problem in which the individual is in the state that provides her the highest utility (see Appendix 1).

Using this specification it is possible to show that, conditional on the individual being in state *s*,

$$W_s = b_s^{'} Z_s - r_s \left( f(J(d_s^{'} X_s)) \big/ F(d_s^{'} X_s) \right) + x_s = b_s^{'} Z_s + w_s, \qquad (3)$$

where $E(x_s|$ *individual is in s*$) = 0$, $f$ is the standard normal density function, $F$ is the logistic function, $J = F^{-1}F$, $F$ denotes the standard normal distribution function and $X_s$ is a partition of $X$ (see Appendix 1). The term in parentheses on the right hand side of equation (3) is the selectivity correction term. Notice that with only two alternatives in the working status model, and using the standard normal distribution instead of the logistic function $F$, the selectivity correction term is just the Heckman's sample bias correction term.

Therefore, equation (3) can be consistently estimated, for $s=1$, in two stages. In the first stage we estimate a working status polychotomous model by the logit maximum likelihood method and we get estimators of δ. In the second stage, we estimate equation (3) after replacing the parameters δ by the estimators obtained in the first stage. The disturbances of this last equation are heteroskedastic and correlated across different sample observations. We construct the correct asymptotic variance-covariance matrix following Lee, Maddala and Trost (1980) (see Appendix 1).

After we estimate individual wage equations for the employed people, next step is to assign wages to the unemployed. In order to do this, we need to generate a residual term for the unemployed individuals as if they were employed in order to compute for them a labor wage. Since the residual term of the wage equation, $w_1$, is not observed for individuals not employed, it is necessary to draw it conditionally on the observation that is available. This is done by drawing $y_1$ from a standard normal distribution and then computing,

$$\hat{w}_2 = -\hat{r}_1 \left( f(J(\hat{d}_1^{'} X_2)) \big/ F(\hat{d}_1^{'} X_2) \right) + \hat{s}_{x_1} \Psi_1, \qquad (4)$$

for the unemployed. The first term of equation (4) is the expected value of $w_2$ conditional on the person being employed. The estimation of the standard deviation of $\xi_1$, $\sigma_{\xi 1}$, is obtained in the least squares estimation of (3) for the employed individuals. Therefore, wages for unemployed persons are computed as

(5) $$\widehat{W}_2 = \hat{b}_1^{'} Z_2 + \hat{w}_2.$$

Once each person in the economically active population has a wage, the third step consists on simulating the probability distribution of the unemployed in a particular year into the base year.

Suppose we want to simulate the distribution of unemployed persons in year $t+k$ $(k>0)$ on the economically active population of year $t$. First, we compute the proportion of unemployed people in the economically active population in year $t+k$ with respect to twelve age, gender and education cells. These cells were computed using sex, two education levels (less than high school, and completed high school or more) and three age groups (14 to 24 years old, 25 to 44 years old, and more than 45 years old). Next, we simulate this probability distribution on the economically active population of year $t$ by drawing random numbers appropriately. For those individuals whose working status change from being unemployed to be employed in the simulated population, we compute wages using equation (5). For those individuals who remain employed in the simulated population we use their actual wage.

We take into account the imprecision generated by the whole simulation technique by doing a double Monte-Carlo. We repeat the simulation for several draws of the unobserved residual term $w_2$ and within each draw we repeat several times the simulation of the probability distribution of the unemployed in year $t+k$ on year $t$.

Finally, we measure the impact of unemployment on labor income inequality by computing and comparing inequality measures calculated for both actual and simulated populations.

We incorporate this approach into the micro-simulation methodology developed by Bourguignon et al. (1998). This approach is based on the estimated coefficients of the labor income equations and it allows for an assessment of the partial impacts of changes in the rates of return to individual characteristics and/or changes in the distribution of human capital on the observed inequality. These effects are isolated by simulating the "changes in prices" or "changes in the endowments" and trace their impact on the observed income inequality. In particular, we trace the impact of changes in the rates of return to personal characteristics, in participation and unemployment to determine the relative importance of these factors in explaining the changing earnings inequality.

# 3 Labor Market in Argentina

In this section we characterize unemployment and labor income in Greater Buenos Aires (GBA) using microdata. We use the Permanent Household Survey (EPH) from the National Statistical Institute (INDEC) for 1991 through 1998. The data cover the city of Buenos Aires and the Greater Buenos Aires region. The area is exclusively urban, and comprises fifty 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.

The unemployment rate increased dramatically during the 1990s[1]. 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%[2]. By October 1998 the unemployment rate was over 13%.

Figure 1 about here

Figure 1 shows this evolution in detail. During this period, participation rates increased 4 percentage points while the employment ratio in 1998 was lower than in 1991 (see Table 1).

Table 1 about here

[1] To be consistent with the rest of the analysis, all our figures for unemployment refer to Greater Buenos Aires.
[2] Average unemployment rate in Greater Buenos Aires between 1974 and 1990 was 4.3%.

Unemployment rates vary substantially across groups of workers. Table 2 presents unemployment rates by sex, age and schooling. Women tend to have larger unemployment rates than men. This is true even when we control by schooling attainment. During the second half of the 1990s, when unemployment went up, female unemployment rates were around 30% higher than men's.

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[3]. Workers under 20 have an unemployment rate that more than double those 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. With regard to sex differences this is not true. In fact, the difference in unemployment rates between men and women in the US has disappeared in the last 15 years.

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 labor earnings by percentile. The evolution between 1991 and 1998 was not homogeneous across groups. While the bottom 10% of the distribution suffered a reduction, the rest increased their real labor earnings. From 1991 to 1994, real 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 tenth of the distribution, the reduction was larger than 15%. The final years of our sample show additional reductions in labor income for most income groups, but particularly for the very bottom of the distribution. In sum, over the 1991-98 period, the bottom tail of the distribution experienced a serious decrease of real wages; the middle group increased theirs between 10% and 17%, while those in a more privileged position enjoyed important increments.

Table 3 about here

In this context of high unemployment and increasing differences in wages between those workers in the bottom and those in the top of the distribution, capturing the impact of changes in unemployment, returns to personal characteristics and participation on earnings inequality becomes more than relevant.

In order to outline the effect of increasing unemployment on income inequality we take 1991 (October) as our base year. We simulate the probability distribution of unemployed persons in 1994, 1996 and 1998 on our base year. For each of those years we estimate, by head counting, the probability distribution of being unemployed. This is done for twelve categories of the active population, defined by age, sex and education as described in the methodology section. Then, we simulate this unemployment distribution on 1991 by drawing appropriate random numbers. 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.

[3] This is true even that participation rate 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

Therefore, the probability distribution of unemployed people in 1991 corresponds to the beginning of the convertibility period.

# 4 Impact of Unemployment on Income Inequality

## 4.1 Estimation of Wage Equations

Our first step is to estimate a working status polychotomous 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 (vector X in equation (4)), we have included: age and its square, sex, education, a dummy to reflect if the individual is currently attending school, a dummy to indicate if married, interaction between sex 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 presented them in Table 4. 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

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41%; by 1998 that figure went down to 35%.

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.

Using the working status polychotomous estimated coefficients, we construct the sample selection bias correction, $-f\left(J\left(\hat{d}_1 X_1\right)\right)/F\left(\hat{d}_1 X_1\right)$, as described in the methodology section. This sample bias correction term captures 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.

Next, we proceed to estimate the wage function for the employed workers (employees, self-employed and proprietors) as described by equation (3). The explanatory variables (vector $Z_1$ in equation (3)) 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, $-\phi/F$, 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 8% 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

The selectivity correction term, $-\phi/F$, presents a larger statistical effect at the beginning and at the end of the period, when unemployment is lower. Among the years we are considering, 1996 presents the highest unemployment rate. The correction for working status is not significant in that year. This means that the correction term enters the earnings function in the way we would expect. Its coefficient is larger, in absolute value, and more significant for those years when unemployment is lower. The explanation for this result is that when the unemployment rate reaches very high levels, in the argentine case due to a severe macroeconomic adverse shock, it is likely to affect many workers that do not have a large probability of being unemployed during normal times. Therefore, the probabilities of being unemployed and employed become more alike for different types of workers and the selectivity correction term looses significance.

## 4.2 Simulation Procedure

We use the estimates in Tables 4 and 5 to compute wages for the unemployed following the procedure presented in Section 2. First, we calculate the standard deviation of the wage equation residuals in each year, $\sigma_{\xi 1}$. Second, we generate random numbers ($\Psi$) from a normal distribution with zero mean and $\sigma_{\xi 1}$ standard deviation. Third, using equation (4) we compute estimated residuals, $\omega_2$, for the unemployed people. Finally, using (5) we assign wages for those individuals unemployed in each year. We repeat this procedure two hundred times. A summary of these estimated wages along with the actual wages is presented in Table 6. As expected, estimated average wages are lower than actual wages of employed workers in almost every category we divided the data. On average, the difference between the estimated and actual wages is approximate 18%. This result is not surprising and is consistent with the fact that, to some extent, the unemployed could be out of job because they are less productive than those employed. Therefore, if they were employed they would receive a lower salary.

Table 6 about here

Once the wages for unemployed persons have been estimated for each one of the two hundred generations of $\omega_2$, we simulate the distribution of workers of year $t+k$ on the active population of year $t$ one hundred times. This procedure gives us a double Monte-Carlo of 20,000 simulations. We then compute inequality measures for the simulated distributions of workers in year $t$.

Consider for example the years 1991 and 1998 and the Gini coefficient as our measure of inequality. We first compute the Gini coefficient for the actual distribution of labor earnings for all active workers in both years ($Gini_{91}$ and $Gini_{98}$). Then, we simulate the distribution of unemployment of 1998 in 1991 and compute what would have been the Gini coefficient in that case ($Gini_{91}(U_{98})$). This procedure is repeated 20,000 times. Then we computed the average $Gini_{91}(U_{98})$ coefficient over the 20,000 simulations. The difference between $Gini_{91}$ and the average $Gini_{91}(U_{98})$ measures the unemployment impact on the Gini coefficient between 1991 and 1998. We call this difference unemployment effect. Similarly we simulate changes in participation and in the returns to human capital to compute participation and price effects respectively. Also, we are able to compute 95% Monte-Carlo confidence intervals for each of the inequality measures computed over the simulations.

## 4.3 Effects on Earnings Inequality

Table 7 shows actual and estimated inequality measures using the methodology described above. We use two measures of inequality: Gini coefficient and coefficient of variation. Each panel in the table begins showing the actual inequality in 1991. The following rows show how inequality in 1991 would have been under different assumptions based on the distribution of workers in the end year. We first estimate the 1991 inequality measures assuming a different distribution of unemployment. Next row shows them assuming that participation has changed too. The third estimation is based on changes in unemployment and changes in returns to personal characteristics of workers. Finally, the last row in each panel shows the actual inequality measures for the end year. The numbers in parentheses below each inequality measure show the 95% confidence interval for that measure.

Table 7 about here

We note first the very severe change in inequality during these years. Both measures increased substantially between 1991 and 1998, reaching a peak in 1996 after the Mexican Crisis.

It is clear from the tables that unemployment has increased inequality and its effect has been large. It has raised both measures of inequality in every interval under consideration and the effect is statistically significant at 95% confidence level. This means inequality in 1991 would have been larger than the actual figure if the distribution of unemployment had been that of 1994, 1996 or 1998. Therefore, measured by any of the two statistics, unemployment had an unequalizing effect over the whole period[4].

The effect of changes in participation is less clear. It always increases the Gini coefficient but it reduces the coefficient of variation. Moreover, as shown by the 95% confidence intervals, these inequality measures that take into account the change in unemployment and participation are not statistically different from those that only simulate changes in the unemployment. This means that the increase in earnings inequality shown by these figures is due to unemployment and not to participation. Finally, the price effect is always positive indicating prices increased inequality during the period under study. This effect is particularly large and statistically significant at the end of the period analyzed.

Table 8 presents unemployment, participation and price effects as percentage of the 1991 inequality measures. The first panel shows the effects as a percentage of the Gini coefficient. The next panel shows the same effects but as a percentage of the coefficient of variation. In this table it can be seen more clearly that the unemployment effect has a large impact on earnings inequality. Unemployment appears to be the most important cause of increasing earnings inequality during the whole period when we use the Gini coefficient. The price effect also increases labor earnings inequality. When measured by the coefficient of variation, this effect is the largest after 1996.

Table 8 about here

Figures 2 and 3 show these effects as measured by the Gini coefficient. In Figure 2 the first curve from the top represents the actual value of the Gini coefficient at each year.

[4] This conclusion is consistent with the findings of Frenkel and González (1999). This is an interesting contrast with what seems to have happened in Mexico during the same period, where inequality increased substantially due to an increasing wage gap between high and low skill workers while unemployment remained low (see Ros and Lustig, 1999).

The second curve is the simulated 1991 Gini coefficient that holds unemployment distribution and "prices" constant as they were in 1994, 1996 and 1998 ($Gini_{91}$(U,Pr)); the third curve shows the Gini coefficient holding constant unemployment distribution and participation rates as they were in 1994, 1996 and 1998 ($Gini_{91}$(U,Pt)). The fourth line is the Gini coefficient holding constant the unemployment rate as it was in 1994, 1996 and 1998 ($Gini_{91}$(U)). Finally, the last line shows the value of the Gini coefficient in 1991. The area between the first two lines from the top is the unexplained change while the vertical difference between the second and third line is the price effect and the vertical distance between the fourth line and the fifth line shows the unemployment effect. The area between the first and fifth line is the total change on the observed inequality as measured by the Gini coefficient.

Since, as was mentioned in Section 3, women tend to have larger unemployment rates than men and their labor market dynamics can be quite different, we performed a deeper analysis by looking at unemployment, participation and price effects by sex. This analysis will allows us to see if the unemployment effect have been different for these two groups.

We repeat the micro-simulation approach for men and women separately. The results are found in tables 9 and 10 for women and tables 11 and 12 for men. As we can observe, the increase in earnings inequality is larger among women than among men in all intervals under analysis. For both groups the effect of unemployment is large and significant. The unemployment effect seems to be relatively more important and constant among women than among men. In fact, it is the only effect that is statistically significant for women during the whole period. If we consider the Gini coefficient, for example, we see that at any time the unemployment effect accounts for more than 60% of the total increase in inequality among women. Meanwhile, in the case of men, this effect explains most of the change between 1991 and 1994 but reduces its importance by the end of the period. When the unemployment grew most, between 1991 and 1996, its effect contributed similarly –around 60% of the total change- to both groups.

Tables 9 and 10 about here

The participation effect is not statistically significant for any group. However the tendency is to have an equalizing effect on the income inequality for women and an unequalizing effect on the income inequality for men.

The price effect has contributed to increase labor earnings inequality mostly at the end of the period under study. In the case of women, the effect is positive and gains importance in the last years but it does not appear to be significant. Among men, it is only statistically significant when comparing 1991 and 1998, but then is the dominant effect. Until 1996 the unemployment effect seemed to be the main explanation for the increase in inequality among men. In the last years, its relative importance diminished and the price effect became the largest contributor to the increase in inequality.

Tables 11 and 12 about here

## 5 Conclusions

In this paper we proposed a methodology to trace the impact of unemployment on the observed earnings inequality. Based on estimations of a labor wage equation conditional on a working status polychotomous model we assigned wages to those people that are unemployed. Then, by simulating the unemployment distribution of a particular year on a base year, and computing measures of income inequality, –on the actual and simulated populations– we were able to identify the change in the observed inequality due to the increase in unemployment. We can also calculate the effects of changes in labor market participation and in the returns to personal characteristics of workers.

We applied our procedure to the Argentine labor market finding that unemployment accounts for a large part of the increasing inequality during the nineties. This fact is much more pronounced for women than for men.

## Appendix 1

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

$$(A1) \qquad p_s = \max_{j \neq s} V_j - u_s$$

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

$$(A2) \qquad F(p_s) = \exp(p_s) \bigg/ \left[ \exp(p_s) + \sum_{j \neq s} \exp(d_j' X) \right],$$

and the probability that the individual is in state *s* is

$$P_s = \frac{\exp(d_j' X)}{\sum_{j=1}^{3} \exp(d_j' X)},$$

which is the conditional logit model (see McFadden, 1974). Let $F$ denote the standard normal distribution function. The transformation $J = F^{-1}F$ is strictly increasing, and the transformed random variable $p_s^*$ where $p_s^* = J(p_s)$ will be a standard normal variate.

Therefore, the individual will be in alternative *s* if and only if $J(d_s'X) > p_s^*$. This specification implies that, conditional on the individual being in state *s*,

$$(A3) \qquad W_s = b_s' Z_s - r_s \left( f(J(d_s' X_s)) \big/ F(d_s' X_s) \right) + x_s = b_s' Z_s + w_s,$$

where $E(x_s|\ individual\ is\ in\ s) = 0$, *f* 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 (A3) 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 δ are obtained. Replacing these estimators into (A3), in the second stage we estimate the following equation,

$$(A4) \qquad W_1 = b_1' Z_1 - r_1 \left( f(J(\hat{d}_1' X_1)) \big/ F(\hat{d}_1' X_1) \right) + \tilde{x}_1.$$

The disturbances of equation (A4) 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×N matrix given by,

$$\Lambda = diag\left[ \frac{f^2(J(\hat{d}' X))}{F(\hat{d}' X)(1 - F(\hat{d}' X))} \right],$$

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

$$A = diag\left[ J(\hat{d}' X_1) \frac{f(J(\hat{d}' X_1))}{F(\hat{d}' X_1)} + \left[ \frac{f(J(\hat{d}' X_1))}{F(\hat{d}' X_1)} \right]^2 \right].$$

Next, define the vector,

$$Y_1 = \left[Z_1, -f(J(d_s^{'} X_s))/F(d_s^{'} X_s)\right].$$

Then, the asymptotic covariance matrix of estimators in model (A4) is

$$(A5) \qquad \operatorname{var}\begin{pmatrix} \hat{b}_1 \\ \hat{r}_1 \end{pmatrix} = s_1^2\left(Y_1^{'}Y_1\right)^{-1} - \hat{r}_1\left(Y_1^{'}Y_1\right)^{-1}Y_1^{'}\left(A - A\,X_1\left(X^{'}\Lambda X\right)^{-1}X_1^{'}A\right)Y_1\left(Y_1^{'}Y_1\right)^{-1}.$$

**Table 1. Employment, Unemployment and Participation Rates**

| | 1991 | 1994 | 1996 | 1998 |
|---|---|---|---|---|
| Unemployment Rate: | | | | |
| % Labor Force | 5.3% | 13.2% | 18.9% | 13.5% |
| % Total Population | 2.9% | 7.4% | 11.1% | 7.9% |
| Participation Rate | 54.7% | 56.4% | 58.4% | 58.6% |
| Employment Ratio | 51.8% | 49.0% | 47.3% | 50.7% |

Note: computations using population 14 years old and older.

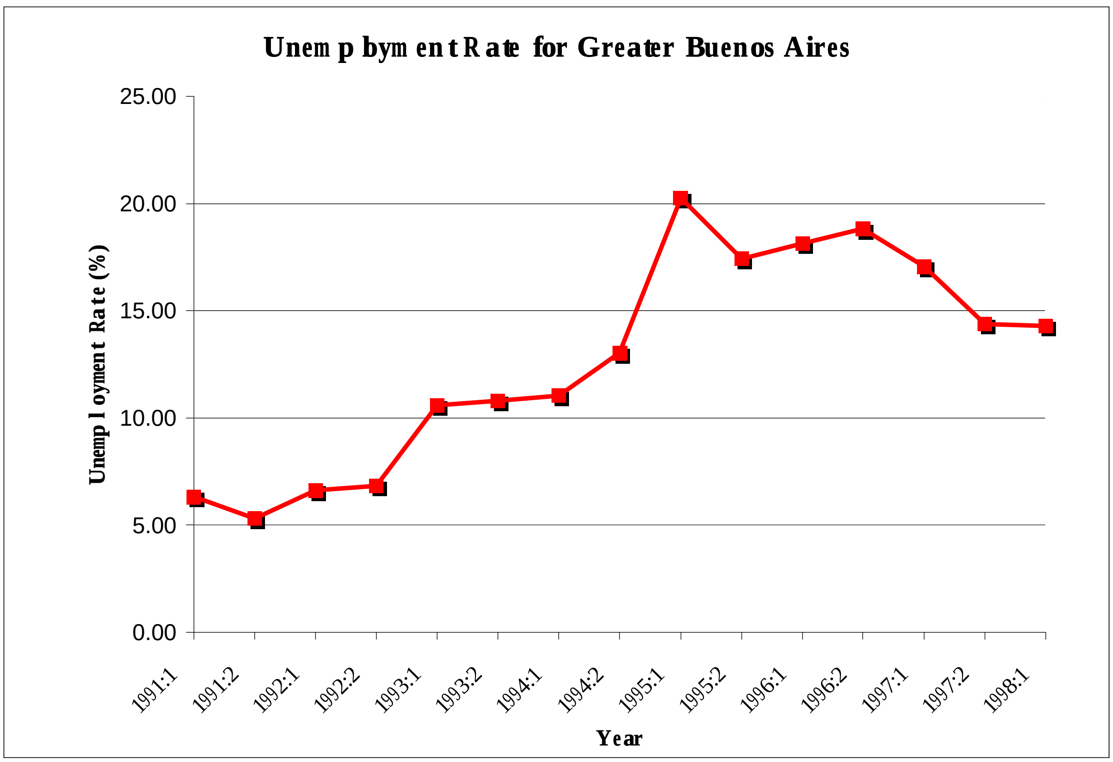


**Figure 1**

**Table 2. Unemployment Rates**

| | 1991 | 1994 | 1996 | 1998 |
|---|---|---|---|---|
| Unemployment Rate by Sex | | | | |
| Female | 5.90% | 15.83% | 22.07% | 15.89% |
| Male | 4.99% | 11.60% | 16.93% | 11.93% |
| | | | | |
| Unemployment Rate by Age | | | | |
| < 20 | 16.62% | 34.79% | 46.79% | 34.94% |
| 20-34 | 5.54% | 12.33% | 19.13% | 13.53% |
| 35-49 | 3.67% | 9.23% | 14.45% | 10.37% |
| > 50 | 3.15% | 12.28% | 15.47% | 11.80% |
| | | | | |
| Unemployment Rate by Education | | | | |
| Primary Incomplete | 5.01% | 14.58% | 21.84% | 19.00% |
| Primary Complete | 5.44% | 14.16% | 21.15% | 16.41% |
| Secondary Incomplete | 6.41% | 17.25% | 23.02% | 16.58% |
| Secondary Complete | 6.04% | 12.74% | 16.33% | 10.78% |
| University Incomplete | 3.64% | 12.34% | 20.18% | 11.04% |
| University Complete | 3.55% | 3.59% | 8.23% | 5.03% |

**Table 3. Evolution of Monthly Labor Earnings**

| Real Labor Income | 1991 | 1994 | 1996 | 1998 |
|---|---|---|---|---|
| Centile | | | | |
| 5 | 164 | 207 | 121 | 104 |
| 10 | 218 | 258 | 202 | 200 |
| 20 | 273 | 357 | 302 | 300 |
| 30 | 341 | 414 | 403 | 400 |
| 40 | 409 | 517 | 454 | 450 |
| 50 | 477 | 569 | 504 | 530 |
| 60 | 545 | 620 | 605 | 600 |
| 70 | 682 | 827 | 756 | 800 |
| 80 | 818 | 1034 | 1008 | 1000 |
| 90 | 1091 | 1447 | 1512 | 1500 |
| 95 | 1636 | 2068 | 2016 | 2120 |
| Percentage Change | 1991-94 | 1994-96 | 1996-98 | 1998-91 |
| Centile | | | | |
| 5 | 26% | -42% | -14% | -36.42% |
| 10 | 19% | -22% | -1% | -8.30% |
| 20 | 31% | -15% | -1% | 10.04% |
| 30 | 21% | -3% | -1% | 17.38% |
| 40 | 26% | -12% | -1% | 10.04% |
| 50 | 19% | -11% | 5% | 11.09% |
| 60 | 14% | -3% | -1% | 10.04% |
| 70 | 21% | -9% | 6% | 17.38% |
| 80 | 26% | -3% | -1% | 22.27% |
| 90 | 33% | 4% | -1% | 37.55% |
| 95 | 26% | -3% | 5% | 29.60% |

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

**Table 4. Working Status Polychotomous Model**

Panel 1: Employed compared to Out of the Labor Force:

| | 1991 | 1994 | 1996 | 1998 |
|---|---|---|---|---|
| Constant | -3.953 | -5.538 | -5.676 | -5.770 |
| | (12.40) | (18.95) | (19.29) | (20.21) |
| Age | 0.248 | 0.351 | 0.364 | 0.337 |
| | (13.21) | (21.65) | (22.24) | (22.40) |
| $Age^2$ | -0.003 | -0.005 | -0.005 | -0.004 |
| | (15.17) | (24.58) | (24.79) | (25.23) |
| Education | 0.144 | 0.150 | 0.129 | 0.165 |
| | (14.32) | (14.82) | (12.92) | (16.34) |
| Attending School | -2.506 | -2.585 | -2.367 | -2.158 |
| | (22.05) | (23.52) | (21.30) | (20.06) |
| Male | 0.515 | 0.629 | 0.396 | 0.495 |
| | (4.88) | (6.12) | (3.92) | (5.15) |
| Married | -1.498 | -1.841 | -1.866 | -1.595 |
| | (13.70) | (14.56) | (15.04) | (13.03) |
| Married * Male | 2.146 | 2.474 | 2.532 | 1.976 |
| | (11.83) | (13.10) | (14.25) | (11.64) |
| Head | 0.517 | -0.022 | 0.274 | 0.605 |
| | (4.11) | (0.160) | (2.23) | (4.68) |
| Child | -0.663 | -0.803 | -0.729 | -0.860 |
| | (7.44) | (8.65) | (7.78) | (9.13) |
| Spouse Unemployed | 0.591 | 0.451 | 0.794 | 0.603 |
| | (1.73) | (2.50) | (4.68) | (3.20) |
| Male * Child | 1.095 | 1.106 | 0.953 | 1.122 |
| | (8.23) | (8.03) | (6.80) | (8.42) |

**Table 4 (Cont.). Working Status Polychotomous Model (cont.)**

Panel 2: Unemployed compared to Out of the Labor Force

| | 1991 | 1994 | 1996 | 1998 |
|---|---|---|---|---|
| Constant | -4.565 | -3.561 | -4.009 | -3.877 |
| | (7.37) | (9.00) | (10.81) | (9.78) |
| Age | 0.179 | 0.210 | 0.261 | 0.234 |
| | (5.57) | (9.69) | (12.51) | (11.53) |
| Age$^2$ | -0.003 | -0.003 | -0.004 | -0.003 |
| | (7.30) | (12.57) | (14.87) | (14.28) |
| Education | 0.112 | 0.066 | 0.047 | 0.048 |
| | (5.17) | (4.65) | (3.69) | (3.29) |
| Attending School | -2.956 | -2.700 | -2.181 | -2.477 |
| | (10.26) | (14.95) | (14.77) | (13.91) |
| Male | 0.609 | 0.513 | 0.407 | 0.167 |
| | (2.77) | (3.60) | (3.69) | (1.24) |
| Married | -2.331 | -1.962 | -2.082 | -2.052 |
| | (8.56) | (10.75) | (14.77) | (11.64) |
| Married * Male | 2.606 | 2.259 | 2.251 | 2.209 |
| | (6.60) | (8.50) | (9.96) | (8.68) |
| Head | -0.187 | -0.140 | -0.033 | 0.131 |
| | (0.67) | (0.775) | (0.22) | (0.79) |
| Child | -0.330 | -0.687 | -0.474 | -0.788 |
| | (1.35) | (4.44) | (3.58) | (5.10) |
| Spouse Unemployed | N/A. | 0.852 | 1.035 | 1.429 |
| | N/A. | (3.46) | (3.95) | (5.10) |
| Male * Child | 0.707 | 0.614 | 0.534 | 1.045 |
| | (2.24) | (2.94) | (2.86) | (5.11) |
| | | | | |
| Sample size | 7988 | 8472 | 8623 | 8755 |
| $\chi^2(22)$ | 4573.93 | 5225.58 | 5128.93 | 5075.89 |
| p-value | 0.000 | 0.000 | 0.000 | 0.000 |

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

**Table 5. Wage Estimation**

Dependent Variable: Log Hourly Wages

| | 1991 | 1994 | 1996 | 1998 |
|---|---|---|---|---|
| Age | 0.0635 | 0.0591 | 0.0709 | 0.0717 |
| | (11.075) | (9.508) | (9.149) | (10.380) |
| Age$^2$ | -0.0007 | -0.0006 | -0.0007 | -0.0007 |
| | (8.894) | (7.449) | (7.259) | (7.971) |
| Education | 0.0826 | 0.0802 | 0.0887 | 0.1050 |
| | (26.473) | (25.410) | (26.685) | (31.808) |
| Male | 0.1065 | 0.0719 | 0.0755 | 0.1963 |
| | (3.555) | (2.530) | (2.402) | (6.513) |
| $-\phi/F$ | -0.1018 | -0.0652 | -0.0420 | -0.1459 |
| | (2.520) | (1.518) | (0.812) | (3.066) |
| Constant | -1.4945 | -0.9415 | -1.3708 | -1.7147 |
| | (11.599) | (6.661) | (7.736) | (10.251) |
| Adjusted $R^2$ | 0.27 | 0.24 | 0.27 | 0.31 |
| Sample size | 2902 | 3332 | 3298 | 3681 |

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

**Table 6. Estimated Hourly Wages for Unemployed Workers**

| | 1991 | | | 1994 | | | 1996 | | | 1 |
|---|---|---|---|---|---|---|---|---|---|---|
| | E | U | U/E | E | U | U/E | E | U | U/E | E |
| Average | 2.63 | 2.28 | 0.87 | 4.25 | 3.55 | 0.83 | 4.35 | 3.47 | 0.80 | 4.55 |
| By Sex: | | | | | | | | | | |
| Male | 2.62 | 2.18 | 0.83 | 4.19 | 3.50 | 0.83 | 4.33 | 3.39 | 0.78 | 4.67 |
| Female | 2.65 | 2.45 | 0.92 | 4.35 | 3.61 | 0.83 | 4.38 | 3.56 | 0.81 | 4.35 |
| By Schooling: | | | | | | | | | | |
| Primary Incomplete | 1.85 | 1.39 | 0.75 | 3.10 | 2.60 | 0.84 | 2.92 | 2.40 | 0.82 | 2.82 |
| Primary Complete | 1.94 | 1.83 | 0.95 | 3.15 | 2.95 | 0.94 | 3.08 | 2.78 | 0.90 | 3.02 |
| Secondary Incomplete | 2.15 | 2.13 | 0.99 | 3.55 | 3.43 | 0.97 | 3.28 | 3.20 | 0.98 | 3.22 |
| Secondary Complete | 3.07 | 2.45 | 0.81 | 4.28 | 4.24 | 0.99 | 4.13 | 4.05 | 0.98 | 4.45 |
| University Incomplete | 3.21 | 3.75 | 1.16 | 5.55 | 4.61 | 0.83 | 4.45 | 4.35 | 0.98 | 5.18 |
| University Complete | 5.55 | 4.38 | 0.79 | 8.26 | 6.91 | 0.84 | 9.48 | 7.08 | 0.75 | 9.49 |

Note: Based on averages on 200 simulations. E: employed; U: unemployed.

**Table 7. Estimated Inequality Measures of Labor Earnings**

| | Gini Coefficient | Coefficient of Variation |
|---|---|---|
| **1991 – 1994** | | |
| Actual 1991 | 0.422 | 0.998 |
| 1991 Simulating 1994 Unemployment | 0.460 | 1.045 |
| | (0.451 0.469) | (1.018 1.068) |
| 1991 Simulating 1994 Unemployment and Participation | 0.462 | 1.034 |
| | (0.452 0.471) | (0.997 1.066) |
| 1991 Simulating 1994 Unemployment and Prices | 0.461 | 1.058 |
| | (0.453 0.470) | (1.032 1.081) |
| Actual 1994 | 0.479 | 1.091 |
| | | |
| **1991 – 1996** | | |
| Actual 1991 | 0.422 | 0.998 |
| 1991 Simulating 1996 Unemployment | 0.497 | 1.116 |
| | (0.487 0.507) | (1.083 1.145) |
| 1991 Simulating 1996 Unemployment and Participation | 0.500 | 1.109 |
| | (0.489 0.510) | (1.067 1.147) |
| 1991 Simulating 1996 Unemployment and Prices | 0.512 | 1.179 |
| | (0.502 0.521) | (1.145 1.209) |
| Actual 1996 | 0.549 | 1.500 |
| | | |
| **1991 – 1998** | | |
| Actual 1991 | 0.422 | 0.998 |
| 1991 Simulating 1998 Unemployment | 0.465 | 1.054 |
| | (0.456 0.473) | (1.025 1.077) |
| 1991 Simulating 1998 Unemployment and Participation | 0.466 | 1.040 |
| | (0.456 0.475) | (1.005 1.073) |
| 1991 Simulating 1998 Unemployment and Prices | 0.497 | 1.197 |
| | (0.489 0.505) | (1.164 1.222) |
| Actual 1998 | 0.521 | 1.353 |

Note: Inequality measures refer to labor earnings only and include employees, proprietors,self-employed and unemployed workers. 95% confidence intervals in parenthesis.

**Table 8. Unemployment, Participation and Price Effects**

| | 1991-94 | 1991-96 | 1991-98 |
|---|---|---|---|
| **Gini Coefficient** | | | |
| Total Change | 13.5% | 30.1% | 23.5% |
| Unemployment Effect | 9.0% | 17.8% | 10.2% |
| Participation Effect | 0.5% | 0.6% | 0.2% |
| Price Effect | 0.3% | 3.4% | 7.6% |
| Explained Change | 9.7% | 21.8% | 17.9% |
| **Coefficient of Variation** | | | |
| Total Change | 9.3% | 50.3% | 35.6% |
| Unemployment Effect | 4.7% | 11.8% | 5.6% |
| Participation Effect | -1.1% | -0.7% | -1.3% |
| Price Effect | 1.3% | 6.3% | 14.3% |
| Explained Change | 4.9% | 17.4% | 18.6% |

Note: figures shown as percentage of 1991 inequality measures.

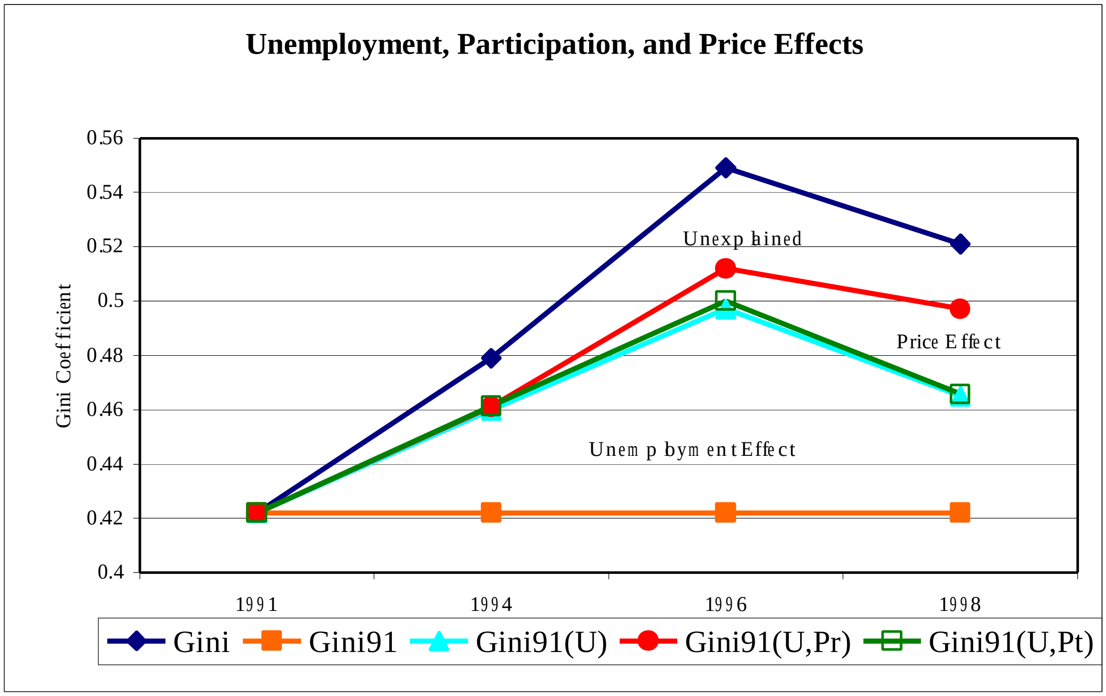
Unemployment, Participation, and Price Effects
Gini Coefficient
0.56
0.54
0.52
0.5
0.48
0.46
0.44
0.42
0.4
1991
1994
1996
1998
Unexplained
Price Effect
Unemployment Effect
Gini
Gini91
Gini91(U)
Gini91(U,Pr)
Gini91(U,Pt)

**Figure 2**

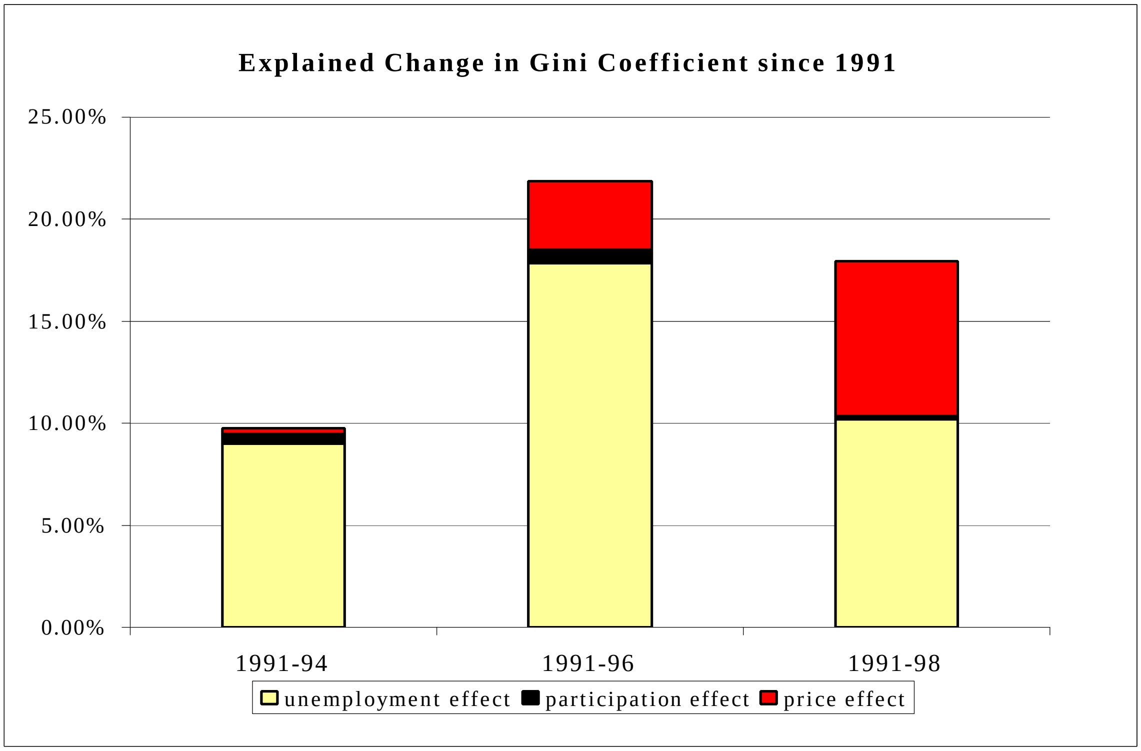
Explained Change in Gini Coefficient since 1991
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
1991-94
1991-96
1991-98
unemployment effect
participation effect
price effect

**Figure 3**

**Table 9. Women: Estimated Inequality Measures of Labor Earnings**

| | Gini Coefficient | Coefficient of Variation |
|---|---|---|
| **1991 – 1994** | | |
| Actual 1991 | 0.410 | 0.933 |
| 1991 Simulating 1994 Unemployment | 0.477 | 1.047 |
| | (0.450, 0.509) | (0.943 1.116) |
| 1991 Simulating 1994 Unemployment and Participation | 0.470 | 0.993 |
| | (0.438 0.501) | (0.891 1.091) |
| 1991 Simulating 1994 Unemployment and Prices | 0.481 | 1.053 |
| | (0.452 0.511) | (0.947 1.118) |
| Actual 1994 | 0.502 | 1.120 |
| **1991 – 1996** | | |
| Actual 1991 | 0.410 | 0.933 |
| 1991 Simulating 1996 Unemployment | 0.513 | 1.110 |
| | (0.481 0.558) | (0.994 1.228) |
| 1991 Simulating 1996 Unemployment and Participation | 0.507 | 1.063 |
| | (0.476 0.541) | (0.936 1.196) |
| 1991 Simulating 1996 Unemployment and Prices | 0.526 | 1.150 |
| | (0.495 0.569) | (1.033 1.260) |
| Actual 1996 | 0.574 | 1.380 |
| **1991 – 1998** | | |
| Actual 1991 | 0.410 | 0.933 |
| 1991 Simulating 1998 Unemployment | 0.484 | 1.055 |
| | (0.456 0.519) | (0.942 1.136) |
| 1991 Simulating 1998 Unemployment and Participation | 0.471 | 0.990 |
| | (0.437 0.499) | (0.878 1.091) |
| 1991 Simulating 1998 Unemployment and Prices | 0.511 | 1.142 |
| | (0.485 0.543) | (0.999 1.221) |
| Actual 1998 | 0.534 | 1.233 |

Note: Inequality measures refer to labor earnings only and include employees, proprietors,self-employed and unemployed workers. 95% confidence intervals in parenthesis.

**Table 10. WOMEN: Unemployment, Participation and Price Effects**

| | 1991-94 | 1991-96 | 1991-98 |
|---|---|---|---|
| **Gini Coefficient** | | | |
| Total Change | 22.4% | 40.0% | 30.2% |
| Unemployment Effect | 16.3% | 25.1% | 18.0% |
| Participation Effect | -1.7% | -1.5% | -3.2% |
| Price Effect | 1.0% | 3.2% | 6.6% |
| Explained Change | 15.6% | 26.8% | 21.5% |
| **Coefficient of Variation** | | | |
| Total Change | 20.0% | 47.9% | 32.2% |
| Unemployment Effect | 12.2% | 19.0% | 13.1% |
| Participation Effect | -5.8% | -5.0% | -6.9% |
| Price Effect | 0.6% | 4.3% | 9.3% |
| Explained Change | 7.1% | 18.2% | 15.5% |

Note: figures shown as percentage of 1991 inequality measures.

**Table 11. Estimated Inequality Measures of Labor Earnings, Men only**

| | Gini Coefficient | Coefficient of Variation |
|---|---|---|
| **1991 – 1994** | | |
| Actual 1991 | 0.429 | 1.035 |
| 1991 Simulating 1994 Unemployment | 0.455 | 1.056 |
| | (0.435 0.476) | (0.981 1.129) |
| 1991 Simulating 1994 Unemployment and Participation | 0.468 | 1.099 |
| | (0.448 0.489) | (1.021 1.155) |
| 1991 Simulating 1994 Unemployment and Prices | 0.456 | 1.076 |
| | (0.436 0.478) | (1.011 1.134) |
| Actual 1994 | 0.459 | 1.041 |
| **1991 – 1996** | | |
| Actual 1991 | 0.429 | 1.035 |
| 1991 Simulating 1996 Unemployment | 0.492 | 1.127 |
| | (0.473 0.514) | (1.025 1.178) |
| 1991 Simulating 1996 Unemployment and Participation | 0.503 | 1.153 |
| | (0.478 0.525) | (1.058 1.223) |
| 1991 Simulating 1996 Unemployment and Prices | 0.506 | 1.193 |
| | (0.487 0.526) | (1.096 1.244) |
| Actual 1996 | 0.532 | 1.283 |
| **1991 – 1998** | | |
| Actual 1991 | 0.429 | 1.035 |
| 1991 Simulating 1998 Unemployment | 0.450 | 1.041 |
| | (0.430 0.467) | (0.964 1.092) |
| 1991 Simulating 1998 Unemployment and Participation | 0.462 | 1.077 |
| | (0.440 0.483) | (0.981 1.144) |
| 1991 Simulating 1998 Unemployment and Prices | 0.483 | 1.180 |
| | (0.463 0.501) | (1.093 1.244) |
| Actual 1998 | 0.521 | 1.277 |

Note: Inequality measures refer to labor earnings only and include employees, proprietors,self-employed and unemployed workers. 95% confidence intervals in parenthesis.

**Table 12. MEN: Unemployment, Participation and Price Effects**

| | 1991-94 | 1991-96 | 1991-98 |
|---|---|---|---|
| **Gini Coefficient** | | | |
| Total Difference | 7.1% | 24.0% | 21.4% |
| Unemployment Effect | 6.1% | 14.7% | 4.9% |
| Participation Effect | 3.0% | 2.6% | 2.8% |
| Price Effect | 0.2% | 3.3% | 7.7% |
| Explained Change | 9.3% | 20.5% | 15.4% |
| **Coefficient of Variation** | | | |
| Total Difference | 0.6% | 24.0% | 23.4% |
| Unemployment Effect | 2.0% | 8.9% | 0.6% |
| Participation Effect | 4.2% | 2.5% | 3.5% |
| Price Effect | 1.9% | 6.4% | 13.4% |
| Explained Change | 8.1% | 17.8% | 17.5% |

Note: figures shown as percentage of 1991 inequality measures

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