Poverty and Inequality in Chile 1990-1998: Learning from Microeconomic Simulations*

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Abstract

This paper contributes to understand the microeconomic determinants of household income dynamics in poverty and inequality in Chile during the 90's . We use a micro-simulation based on the decomposition of distributional changes, developed by Bourguignon et.al. (2000). We estimate a participation model and an earnings equation for each economic agent. We examine how income distribution and poverty would change as a result of a different set of microsimulations. In particular, the distributional structure of 1998 is imposed in 1990.

The evidence suggest that while poverty responds strongly to the simulation exercises, the distribution of income appears less sensitive, and is therefore more stable. In particular, we can state that a reduction in poverty would have been observed in 1990 if the returns to education, the regional effects, the structure of non-observables, and the endowments of 1998 had been present. The opposite would have occurred in the case of considering the "returns on experience" and the structure of participation. With respect to the income distribution, in spite of its stability, the most interesting results come from a dynamic perspective. The observed inequality indicators remain at the same level between 1990 and 1998, but if 1998 prices had been observed in 1990, then an increase in inequality would have been registered. The changes in the return to education (and in its convexity) and the structure of participation also increase inequality. The effect of non-observables, in contrast, would have meant a better distributed income distribution in 1990.

Key Words: Income distribution, poverty, demographics, micro-simulations

JEL classification: C15, D31, J22, I21, I32

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1 Introduction

Chile was the best performing Latinamerican country since the middle of the 80s, showing an average rate of economic growth of 7.3% in the period 1990-1998[1]. As a consequence, the Chilean economy has practically doubled its per capita income, and additionally, its poverty indicators have been reduced significantly. The percentage of Chilean poor households reached 33.3% at the beginning of the nineties, this number dropping to only 17.8%[2] in 1998 [3]. This is more interesting when one observes that in the region the poverty rate during the 90s was well over those numbers shown by Chile, and that even though there was a regional decreasing trend of poverty, it was not as significant as in the Chilean case. Latin America presented an average poverty rate of 41% and 36% in 1990 and 1997[4], respectively [5].

Empirical evidence has shown that the economic growth has been the most important factor explaining poverty reduction. However, we still don't know through what channel this effect is produced [6]. Was the reduction in poverty the result of a change in the structure of labor participation or a change in prices (returns to education for example)? How important were changes in the demographic structure of Chile to the reduction of poverty? These questions still have no answers.

On the other hand, Chile has shown one of the largest income inequalities. Chile, Colombia, Brazil, Paraguay and South Africa are the countries with the largest income inequalities at a world level (See Figure I in Appendix). While in 1998 the richest 20% of the Chilean population received approximately 17 times more income than the poorest 20%, in the United State the richest 20% received 8.9 times more income than the poorest 20%. Furthermore, in Peru and South Korea the same statistic attained 10.5 times and 5.7 times respectively (UNPD (1995)).

The high level of Chilean income inequality was far from reverting. Between 1990-1998, in spite of the significant increase in social expenditures, the economic growth and the changes in the labor market legislation (the minimum wage increased around a 60.4% in real terms between 1990-1998), inequality remained stable at a significant high level. The increase in social expenditures and the sustained increases of the minimal wage are targeted to favor the lower deciles of income in the distribution, which suggests a reduction of inequality[7]. On the other hand, economic growth through its impact on labor demand, in particular in skilled labor demand, may induce increases in inequality. Therefore, the net impact of these factors is

[1] Source: Central Bank of Chile

[2] Source MIDEPLAN (1998)

[3] This good performance is a well documented fact in the literature. See for example Contreras et. al. (2001), Ferreira and Lithfield (1997) and Meller (2000)

[4] Source ECLAC (1999)

[5] Various studies have analyzed the sensitivity of the poverty data with respect to the methodological changes which might be present (see for example Székely et. al. (2000)). However, the fact that Chile has shown the most significant reduction in poverty in the 90's and that its general level of poverty is less than that of other countries of the region do not depend fundamentally on differences in the methodologies utilized for calculating the poverty rate (See ECLAC (2000))

[6] International evidence shows that although growth is necessary, it is not sufficient for reducing poverty. An example of this is Mexico in the period 1996-1998. Although the rate of per capita growth was near 10% the poverty rate fell only slightly. See Székely and Attanasio(2001)

[7] Contreras et. al. (2001)

ambiguous in determining its positive or negative effect on inequality[8].

This paper contributes to the understanding of the dynamic effects of income distribution and poverty in Chile during the 90's. This period is interesting because of the high economic growth, sustained inequality and poverty alleviation. We use a micro-simulation based decomposition of distributional changes, developed by Bourguignon et.al. (2000), which follows the line of John, Murphy and Pierce (1993). We estimate earning equations for 1990 and 1998. With this estimation we apply a simulation methodology on the overall income distribution. This decomposition technique has two advantages. First, it not only decomposes a particular inequality or poverty indicator, but also the changes in the overall distribution. Second, this decomposition allows us to examine the role of different factors on poverty and income inequality, such as: changes in return to schooling, differences in economic sector, regional effects, participation decisions, etc.

This paper is divided into nine sections, the first being this introduction. The second and third sections present the literature review and some stylized facts on Chilean inequality respectively. In the fourth section, the data is discussed while in the fifth section the complete model is presented. Section six shows the empirical strategy applied in the estimations, and section seven presents the results of the estimation process. In the eighth section the micro-simulation results are studied, and finally, the main conclusions of the research work are presented.

2 Literature on the Chilean case

In the last years a significant number of papers have analyzed the topics of poverty and distribution of income. Undoubtedly one of the principal reasons for this fact can be found in the important role that these concepts play in the context of developing social policies that allow the improvement of the standards of living (and therefore welfare) of a specific society.

However, the existing literature on Chile does not go beyond a descriptive analysis of the various indicators of poverty and distribution of income, and there are few studies that analyze the causes and factors that determined why Chile remained with one of the most unequal distributions of income during the nineties, while its poverty indicators showed a considerable reduction[9].

Among the descriptive studies, De Gregorio and Cowan (1996) and MIDEPLAN (1999) have emphasized the significant inequality in the distribution of income in Chile has been relatively stable over time, result of interested for this study. Robbins (1994) and Bravo and Marinovic (1997) study in more detail that result. They report a significant increase in wage inequality within wage earners between 1974 and 1987 in Santiago (see also Meller and Tokman (1996)) followed by a decrease in the 90s. Apparent stability could come from comparing data from 1970 (or before) with 1990 (or later) without considering the fluctuations in the middle. Contreras (2000) and Ruiz-Tagle (1999) present evidence supporting this point using a measure of total

[8]See Bravo, Contreras and Rau (1999)

[9]This is even more surprising if you consider that these topics have been the object of discussion during the last years

household income. Finally Bravo, Contreras and Rau (1999) show that stability in per-capita total household income between 1990 and 1996 is the result from opposite trends.

Likewise, Contreras and Ruiz-Tagle (1997) reveal significant disparities in the behavior of income distribution at a regional level, attributing them to the varying evolution of job-market demand for qualified and unqualified labor in distinct geographical zones. In addition, they present a series of methodological aspects that should be considered in the measurement of inequality, among them, the advantages and disadvantages of supposing that the income of the members of a family form a common fund, and the importance of incorporating into the estimations the economies of scale that could be produced within the families.

Ferreira and Litchfield (1997) present evidence on the stability in inequality in Chile between 1987-1994. They argue that the whole distribution have changed to the right reducing poverty and maintaining inequality relatively stable over time. They also present some preliminary evidence on the role of education in explaining the pattern in inequality. They conclude that education may be the most significant variable affecting not only the structure of inequality, but also the changes over time. This last effect is also found by Contreras (2000) using data of Greater Santiago from the Employment Survey of the Universidad de Chile. The main conclusion derived from this study is that, of all observable components, education is the most important in explaining wage inequality and its changes over time. Additionally, we also perceive that it is the return to years of schooling that contributes primarily to variations in inequality.

Contreras (2000) studies the changes in the distribution of income for Gran Santiago (Chile) for the period 1958-1996. The source of information utilized here is the University of Chile Employment Survey. The methodology applied by Contreras follows that utilized by Shorrocks (1984), and extended by Fields (2000). The methodology basically allows the decomposition of the hourly salary of each individual into different components starting from a Mincer equation. The principal result of the study is that the changes in education for the period account for at least 38% of the changes in the distribution of income (whether they are increases or decreases), and furthermore returns to education is the most important factor within this percentage explaining almost 80% of the power of education in account for inequality. A second result, slightly mentioned in the study, is the significant percentage of the changes in the distribution are attributed to non-observable elements (regression errors), a fact which is confirmed in this paper. Finally, that study does not study poverty.

Larrañaga (2001) follows an approach in the same line of Juhn, Murphy and Pierce (1993). This study decomposes the changes in the distribution of income into three components: endowments or observable variables, prices or returns, and non-observable components. Then through simulations is possible to identify and measure the effect of changes in each of those components over the overall salary distribution[10]. The data utilized comes from the 1990, 1992, 1994, 1996, and 1998 National Socio-Economic Characterization Surveys (CASEN) , which are aggregated for the construction of a panel of twenty economic sectors. Larrañaga concludes that the principal factors behind the changes in the distribution of average salaries are the

[10]The Juhn, Murphy, and Pierce decomposition, even though is similar to that of Bourguignon, does not consider a semi-structural economic model, so it could be considered less general, and more restricted with respect to its power.

structure of education, experience, and gender (all considered endowments), with changes in prices and non-observables being less important. Furthermore, changes in endowments have an equalizing effect, while prices and non-observables imply a worsening in the distribution of income. Finally, while Larrañaga does not directly mention changes in poverty, based on the results for the simulated means of salaries it can be inferred that it is the price effect that has the greatest explaining power. This, as will be seen, is also captured in the present paper.

3 Inequality in Chile: The Stylized Facts

Table I presents some illustrative indicators of inequality and poverty of Chile in the 90's. This table contains information on the following inequality measures: the coefficient of variation, Gini, the ratio between the richest 20% of the population and the poorest 20% (Q5/Q1), the log differences between the percentiles (90-10), (90-50) and (50-10), the log deviation or E(0), the Theil Entropy measure or E(1) and finally, the E(2). These last three indicators form part of a family of indices of Generalized Entropy. With respect to the poverty indicators three coefficients widely used in the literature are applied: the headcount or FGT(0), the poverty gap or FGT(1) and the FGT(2). All of these belong to the class of indicators FGT (Foster-Greer-Thorbecke). A detailed description of the characteristics of each of the indicators just mentioned is presented in Technical Appendix.

Table I

Inequality and Poverty Measures for per capita income of Household

	1990	1998
Inequality Indexes		
Coef. Var.	1.86	1.89
Gini	0.55	0.56
$\frac{Q5}{Q1}$	17.13	17.53
P90-P10	2.41	2.47
P90-P50	1.38	1.37
P50-P10	1.03	1.10
Log Deviation Measure - $E(0)$	0.549	0.566
Theil Entropy Measure - $E(1)$	0.654	0.670
$E(2)$	1.741	1.789
Poverty Indexes		
Head-Count - $P(0)$	0.373	0.234
Poverty Gap - $P(1)$	0.145	0.084
$P(2)$	0.079	0.044

Sources: Calculations based on 1990 and 1998 CASEN surveys

Based on the results in Table I, it is clear that the behavior of inequality and poverty differ significantly. On one hand, by using different indicators we can conclude that during the period 1990-1998 the income distribution in Chile remains stable. The indicator $P90 - P10$ shows a slight "improvement" from 1.38 to 1.37, while all the other indicators show higher values for 1998 compared to those in 1990. In particular, the GINI coefficient shows values of 0.55 and 0.56 for 1990 and 1998, respectively, which reflects that while the distribution of income did not worsen significantly for the period, it is far from improving[11]. Finally, the ratio between the average income of the fifth and the first quintile (Q5/ Q1), as well as the difference between the percentile 90 and the percentile 10 and the difference between percentile 50 and percentile 10, also show an increase in the inequality between 1990-1998. This effect is mainly explained by self-employment earnings (especially for the inequality increase in the lower half of the distribution) and wage income [12].

The poverty indicators in the same table shows a significant poverty alleviation in terms of incidence, depth, and relative size. In fact, Chile has been categorized as one of the most successful cases in the fight against poverty[13].

This particular mix of unambiguous reduction of poverty and stability in the distribution of income observed in the Chilean case can also be examined by a first order stochastic dominance analysis when the Lorenz curves and Generalized Lorenz curves for 1990 and 1998 are compared[14]. Figures I.1 and I.2 show just these curves for the years 1990 and 1998.

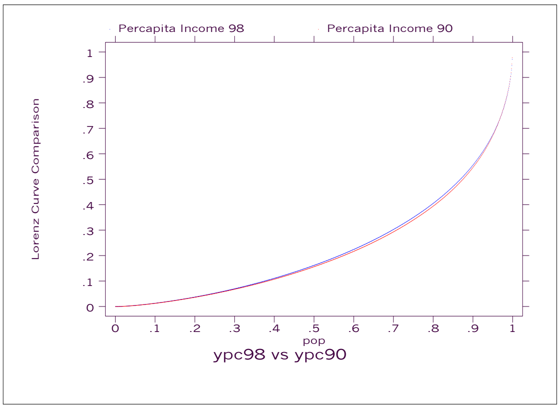


Figure I.1. Lorenz Curve

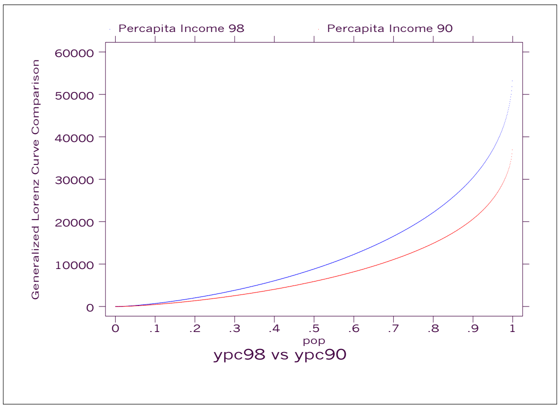


Figure I.2. Generalized Lorenz Curve

The result of first order stochastic dominance for the Lorenz curves (figure I.1) implies that

[11] In particular, the increase of unemployment in 1998 had an important effect in the income distribution. In fact, the rate of unemployment in the first quintile rose from 15.6% in 1996 to 27.7% in 1998, which undoubtedly had implications for the distribution of income

[12] See Bravo, Contreras and Rau (1999)

[13] In the Chilean case, Meller 1999 shows that for each percentage point of economic growth in the period 1987-1994 the poverty rate was reduced by 0.7%. For Indonesia (1970-1987) and Malaysia (1973-1987), the same statistic shows values of 0.6% y 0.8% , respectively

[14] The Lorenz curve shows the proportion of total income being perceived for a determined percentage of the population. The Generalized Lorenz curve, on the other hand, includes in its calculation the mean of the distribution, allowing in such a way the study of distributions of income with different means, which is exactly what we observe in Chile. In particular, the per capita household income mean for 1990 is 86,469 pesos (of 1998) and 125,145 pesos for 1998 (again in 1998 pesos). For more details on the concepts of Lorenz and Generalized Lorenz curves see Technical Appendix

neither the 1990 nor the 1998 income distribution could be considered as better distributed [15]. This finding should not surprise considering the evidence presented in Table I. What does appear as less expected is the result of non-dominance in the case of the Generalized Lorenz curve. If we consider that between 1990 and 1998 average salaries grew in real terms approximately 5.2% annually, it might be expected that from a social viewpoint the distribution of income in 1998 would be preferred over the distribution of 1990, which is precisely what indicates a first order stochastic dominance (FOSD) in Generalized Lorenz curves[16]. Two comments are important with respect to the preceding. First, if we consider the graphic analysis of Figure I.2 where the Generalized Lorenz curve of 1998 is over that of 1990 for almost the entire population, we can argue that the conditions existing in 1998 were at least equal or better than those of 1990. Second, the only intersection between both curves is produced when 0.4% of the population is considered, being the difference between the curves very close to zero for lower percentage. Therefore, although it is not possible to state that the Generalized Lorenz curve of 1998 first order dominates that of 1990, it is possible to state that, from a social point of view 1998 is actually preferable to 1990.

In conclusion, the evidence indicates that a minor increase in inequality is observed in the per capita income during the 90's in Chile, in conjunction with one of the most significant reductions of poverty[17].

4 Data and descriptive statistics

This study uses the National Socioeconomic Characterization Survey (CASEN). The survey is designed to describe and analyze the socioeconomic situation of Chilean households and it was conceived for the design of social policies. Relative to the number of observations, we use the information from 102,412 and 187,831 individuals in the case of CASEN 1990 and CASEN 1998, respectively. In terms of households, in 1990 we work with 25,793 households and in 1998 with 48,107. The surveys basically summarizes information on five topics: housing, education, health, employment, and income.

Table II shows the descriptive statistics for 1990 and 1998. Individual income is measured in constant Chilean (with base 1998). Schooling and experience are measured in years. Experience is defined as potential experience, ie. Age-schooling-6.

[15]At least by analyzing inequality coefficients that comply with the Dalton-Pigou principle of transference. The difficulty of finding stochastic dominance in the Chilean case has already been documented. See for example Ferreira and Litchfield (1998).

[16]More precisely, from a theoretical point of view, for any social welfare function that respects the equity (with a marginal social utility that is positive, decreasing, and concave) a particular distribution of income will be always preferred as long as the Generalized Lorenz curve associated with that distribution first order stochastically dominates any other Generalized Lorenz curve. See Deaton (1997).

[17]There are other elements, non considered above, such as subsidies and transfers from the government to poor households. While social expenditures increase by 88% in real terms between 1990-1998, the expenditure in health and education more than duplicates over the same period. Bravo, Contreras and Millán (2000) present evidence on the impact of total expenditures in social programs over inequality. They show for 1998, the ratio (Q5/Q1) is reduced from 19 times to 11 times when considering public expenditures. At the same time the minimum wage increased approximately 60.4% in real terms in the same period.

Table II
Descriptive statistics 1990-1998

Variable	1990		1998	
	Mean	Desv. Standar	Mean	Desv. Standar
Gender (Male=1)	0.524	0.499	0.519	0.499
Age	37.19	17.43	38.376	17.486
Monthly earnings (Principal occupation)	189,470	159,279	258,653	429,920.1
Other income	31,509	48,847	43,420	149,657
Years od Schooling	8.853	4.378	9.607	4.387
Average schooling years in the household	7.448	3.221	8.095	3.331
Technical education=1	0.0895	0.280	0.111	0.314
Secondary school	2.263	2.683	2.714	2.934
High school	.492	1.318	0.660	1.656
Children 0-2	0.266	0.517	0.202	0.451
Children 3-6	0.318	0.574	0.296	0.545
Children 7-13	0.528	0.804	0.543	0.776
Working age	3.681	1.639	3.490	1.492
Experience (age-6-exper)	22.387	19.244	22.807	19.329
Self-employed=1	0.226	0.418	0.202	0.401
Region1	0.0247	0.155	.0251	0.156
Region2	0.029	0.168	.028	0.167
Region3	0.0159	0.125	0.016	0.127
Region4	0.036	0.188	0.036	0.188
Region5	0.104	0.306	0.105	0.306
Region6	0.051	0.220	0.051	0.221
Region7	0.061	0.241	0.061	0.239
Region8	0.129	0.336	0.129	0.335
Region9	0.0567	0.231	0.056	0.230
Region10	0.070	0.255	0.068	0.252
Region11	0.005	0.072	0.005	0.074
Region12	0.010	0.100	0.010	0.101
Region13	0.402	0.490	0.404	0.490

By comparing 1990 and 1998 we observe a stable economic structure. An increase in real wages is observed, which is equivalent to a annual increase of 5.2% in real terms. Years of schooling is approximately 8.8 years in 1990 and is reported in 1998 at 9.6 years. These figures suggest the educational level in the nineties is greater than just primary education.

In each sample approximately a 50% of the population are males. On the other hand, more than 78% of workers are classified as salaried workers in 1990, therefore self-employed workers represent in the same year about 22% of the sample. In 1998 these percentages are 80% and 20% respectively, similar to the values for 1990. At a regional level, a 40% of the sample is concentrated in the Metropolitan Region. Regions V and VIII represent 10% and 13%, respectively. Among the regions with the lowest representation are regions XI and XII, which represent 0.5% and 1% in both years, respectively.

5 The Theoretical Model

The model used in this section follows Bourguignon, Fournier and Gurgang (2000). These authors based on a Bourguignon decomposition of income (which is also applied in this study), analyze the Taiwanese case for the period 1979-1994. The Taiwanese case is particularly interesting. From 1979 to 1994 Taiwan underwent structural changes that while diminishing poverty did not improve the distribution of income. The average rate of economic growth was close to 8% for the period, the years of education increased from 6.9 to 9.9 years, and there was an alteration of the productive structure such that the percentage of households related to agriculture diminished from 30,4% to 16.2%. At the same time, Taiwain reduced poverty significantly, but did not alter its distribution of income. In fact, the Gini coefficient calculated with individual salaries went from 0.33 in 1979 to approximately 0.31 in 1994, ranging from 0.30 and 0.34 for the 25 years considered in the study. Based on the Bourguignon decomposition, the authors show that far from observing a stable distribution of incomes (as shown by the descriptive analysis) various factors came together to produce this effect. Increases in the returns to education, in the structure of participation, and what are considered to be population changes between 1979 and 1994 had an unequal effect on the distribution of income, while on the other hand the changes in non-observable factors (read abilities or productivity) had an equalizing effect. Therefore, although the distribution of income seems stable, it was shown that there were compensating effects over the period, which meant that the inequality indices gave no evidence of significant change.

The same methodology was applied to the Brazilian case by Ferreira and Paes de Barros (1999) in informing the increase in extreme poverty during 1976-1996[18].

This is the Chilean version of the general semi-reduced model for household income. We estimate earning equations and a participation decision model for 1990 and 1998. The earning equation estimation was corrected for selection bias using the two-step Heckman procedure. The standard errors of the parameters were computed from the inverse Hessian of the full information matrix at the two-step solution for the parameter (See Heckman (1979)). The earnings equation was estimated separately for four groups including, salaried males, self-employed males, salaried females and self-employed females.

Additionally, a multinomial Logit was used in the estimation of labor supply (participation decision)[19], where the participation decision is modelled by three alternatives: participation in

[18]Ferreira and Paes de Barros (1999), shows that while reductions in the returns to education had an equalizing effect on the distribution of income, its effect on poverty went in opposite direction, and especially due to that is why these reductions were in some way related with increases in the informality of labor. The reduction on the returns to experience on the other hand, had effects as much on inequality as on poverty; the same held true for changes in participation. Finally, the effect of changes in the structure of demographic variables on years of schooling meant improvements both in poverty and distribution of income

[19]In the survey workers report the number of hours they work per week. In a preliminary stage an hour

labor market as a salaried worker, participation in the labor market as a self-employed worker and no participation. The model was estimated separately for heads of household, spouses and other family members. Both, the earnings equation and the multinomial Logit were estimated for people over 13 years old.

Therefore, our strategy may be summarized as follows. First, earnings equations in each year were estimated as was mentioned above using the two-step Heckman procedure with full information standard errors. From the estimation, a vector of parameters and error structure are obtained, which are later used in the microsimulations. Second, from the participation decision model a vector of parameters and probabilities for each agent are captured. This information is useful in modelling the changes in the participation structure when a variable or a parameter is modified. Thereafter, we create an error for each individual into the sample from a double-exponential distribution[20]. Finally, household income is calculated by adding up the individual incomes estimated earlier, conditioned for their occupational status. Other sources of income such as social transfers, are treated as exogenous variables.

5.1 The Model

The monthly household income of the family j with size t is:

$$Y_J = \sum_{t<T} y_{Jt}^{sa} D_t^{sa} + \sum_{t<T} y_{Jt}^{cp} D_t^{cp} + \sum_{t<T} \Psi_{Jt} \tag{1}$$

where y_{Jt}^{sa} and y_{Jt}^{cp} represents the earnings of the main occupation of salaried workers and self-employed persons, respectively. On the other hand, D_t^{sa} and D_t^{cp} are dummy variables which take a value equal to 1 when the agent participates in the labor market as salaried or self-employed worker, respectively . The last term shows other sources of income which are considered as exogenous.

The earnings equation for the agent of gender $l(l = male, female)$ classified as a worker type h(salaried or self-employed), is specified as:

$$E\{\ln(y_l^h)/y_l^h > 0\} = x_l^{h\prime}\beta_l^h + \rho_l^h\sigma_l^h\left(\frac{\phi(z_l^{h\prime}\xi)}{1-\Phi(z_l^{h\prime}\xi)}\right) \tag{2}$$

where $\ln(y_l^h)$ is the log of monthly income, x_l^h is a matrix of observable variables for individual characteristics. The last term $\left(\left(\frac{\phi(z_l^{h\prime}\xi)}{1-\Phi(z_l^{h\prime}\xi)}\right)\right)$ corresponds to the inverse Mills ratio. Finally, z_l^h is a set of individual characteristics for each agent, which is independent of x_l^h . Therefore, equation 2 can be write as:

$$\ln(y_l^h) = x_l^{h\prime}\beta_l^h + M_l^{h\prime}\varphi_l^h + v_l^h \tag{3}$$

equation was estimated. However, near 70% of the individuals report weekly hours at three identical levels: 40, 48 and 60 hours. Due to this fact, the estimation of an hour model is unsatisfactory, and therefore we decided to treat the participation decision as a multinomial logit with three alternatives

[20]See Bourguignon et. al.(2000)

As mentioned earlier, each individual in the sample can occupy only one occupational position, i.e. each individual can be occupied in a salaried position, or be self-employed, or simply be outside of the labor market (inactive) or unemployed[21]. The preceding would be of great importance for the purposes of the simulations. In order to see the importance, simply consider that the alteration of status or occupational position of the agent as a product of a determined microeconomic simulation would require the prediction of a new salary, which is not directly observable from the information given by the agent. More details on this can be found in Section 5.3.

The participation model for agent q (head of household, spouse, or other family member) can be written as $P(\Upsilon_q = j) = \frac{e^{m_q^{j\prime}\Omega_q}}{1+\sum_{k=1}^{3} e^{m_q^{k\prime}\Omega_q}}$ for $j = 2, 3$ and $P(\Upsilon_q = j) = \frac{1}{1+\sum_{k=1}^{3} e^{m_q^{k\prime}\Omega_q}}$ for $j = 1$,where the options $j = 1, 2, 3$ represents salaried, self-employed and inactive (or unemployed) respectively; and m_q is the observable information matrix for each individual. In this case, from a microsimulation perspective, the relevant vector of parameter is given by Ω_q . However, for each individual we need to compute utility: U_q^J ,such that obviously must satisfy $U_q^J > U_q^j$ for each $J \neq j$ and $j = 1, 2, 3$ .This procedure will allow us to create the dummy variables $D_t^s a$ and $D_t^c p$. Following Bourguignon, Ferreira y Lustig (1998), the final selected state is given by

$$J = Argmax\{U_q^j = m_q^{j\prime}\Omega_q + \mu_q^j, j = 1, 2, 3\} \tag{4}$$

where Ω_q is the vector to modify in the microsimulation, which could permit to generate a change in the individual decision. However, the problem is that the non-observable term (μ) is unknown. In order to solve this problem, we will use a double-exponential distribution conditioned for the observed decision (i.e. J such that $U_q^J > U_q^j$ for each $J \neq j$)[22]. This allow us to model the structure necessary for the error without having to modify the given participation decision.

Therefore, we can re-write (1) as follows:

$$Y_J|_{T_0} = [\sum_{t<T} y_{Jt}^{sa} D_t^{sa} + \sum_{t<T} y_{Jt}^{cp} D_t^{cp} + \sum_{t<T} \Psi_{Jt}]\big|_{T_0} = \Im_J(x_{T_0}, \beta_{T_0}, v_{T_0}, \mu_{T_0}, \Omega_{T_0}) \tag{7}$$

where Ψ_{T_0} represents the exogenous variables in the model. Hence, if we define Γ_T as a function which permits to characterize the distribution of per capita income of a sample of household

[21] For the purposes of the simulations the last two cases are equivalent

[22] Formally the error is obtained by inverting a double exponential. To be clear in this argument, lets consider for example that the error for selection is constructed starting from:

$$F(\mu_{z_1}/act = z_1) = exp(\frac{-\sum_{z=1,2,3} e^{m_q^{z\prime}\Omega_q}}{e^{m_q^{z_1\prime}\Omega_q}} e^{-\mu_{z_1}}) \tag{5}$$

where μ_{z_1} random variable uniformly distributed in the range $[0, 1]$. What happens with the error if the individual chooses an alternative different than z_1, say z_2 or z_3? In that case the error term is not well defined and we must impute an error term. Following Bourguignon, Fournier y Gurgang (2000) it can be demonstrated that:

$$F(\mu_z/act = z_1) = 1 - exp(\frac{-\sum_{i\neq z} e^{m_q^{i\prime}\Omega_q}}{e^{m_q^{z\prime}\Omega_q}} e^{-\mu_z}) \tag{6}$$

Therefore, the error to impute to the participation alternatives not chosen is obtained by inverting a double exponential constructed on the basis of a uniformly distributed variable, conditional on the decision that the individual made. See Bourguignon et. al. (2000) for extended explanation.

with size with N:

$$\Gamma_{T_0} = \Gamma_{T_0}(\Im_1(x_{T_0}, \beta_{T_0}, \upsilon_{T_0}, \mu_{T_0}, \Omega_{T_0}), ..., \Im_N(x_{T_0}, \beta_{T_0}, \upsilon_{T_0}, \mu_{T_0}, \Omega_{T_0})) \tag{8}$$

Therefore,

$$\Gamma_{T_0} = \Gamma_{T_0}(x_{T_0}, \beta_{T_0}, \upsilon_{T_0}, \mu_{T_0}, \Omega_{T_0}) \tag{9}$$

which is the basic structure for the microsimulations[23].

5.2 Microsimulations

As we mention before, the objective of this study is to analyze in detail the underground factors behind the characteristics of poverty and income distribution in Chile during the nineties. We micro-simulate the effects of imposing the structure of the model in 1998 over 1990, including both, observable and non-observable characteristics. In what follows we present in detail what elements are modified in each simulation exercise or "effect".

5.2.1 Participation Effect

The objective is to simulate what would be the impact on the income distribution if the 1998 participation structure were relevant in 1990. This exercise is done by changing the parameters obtained from the Multinomial Logit model. Given the specification (9) the participation effect is:

$$Ef_{Participation98-90} = \Gamma_{98}(x_{90}, \beta_{90}, \upsilon_{90}, \mu_{90}, \Omega_{98}) - \Gamma_{90}(x_{90}, \beta_{90}, \upsilon_{90}, \mu_{90}, \Omega_{90}) \tag{10}$$

5.2.2 Price Effect

This exercise considers how the income distribution varies when the parameters of the earning equation in 1998 are imposed on the 1990 model. In other words:

$$Ef_{Price98-90} = \Gamma_{98}(x_{90}, \beta_{98}, \upsilon_{90}, \mu_{90}, \Omega_{90}) - \Gamma_{90}(x_{90}, \beta_{90}, \upsilon_{90}, \mu_{90}, \Omega_{90}) \tag{11}$$

In addition, this simulation with the participation effect can be described as:

$$Ef_{Price98-90} + Ef_{Participation98-90} = \Gamma_{98}(x_{90}, \beta_{98}, \upsilon_{90}, \mu_{90}, \Omega_{98}) - \Gamma_{90}(x_{90}, \beta_{90}, \upsilon_{90}, \mu_{90}, \Omega_{90}) \tag{12}$$

[23] An alternative approach to apply the Bourguignon decomposition would be to use the estimated participation model (multinomial logit), in the correction of the self-selection bias of the earnings equations. This could be done by estimating a modified Mills ratio from the multinomial logit model, and then incorporating this value as an independent variable in the earnings equation. The studies that have applied the same methodology however, have not considered this alternative, and in several cases, neither have they included a correction for self-selection bias (See for example Ferreira and Paes de Barros (1999)).

Finally, the model structure permits replacing only a set of parameters from the vector β_T. In particular, if the vector is partitioned as ,$\beta_T = [\beta_T^1 : \beta_T^2]$, we obtain:

$$Ef^*_{Price98-90} = \Gamma_{98}(x_{90}, [\beta^1_{98} : \beta^2_{90}], v_{90}, \mu_{90}, \Omega_9) - \Gamma_{90}(x_{90}, \beta_{90}, v_{90}, \mu_{90}, \Omega_{90}) \tag{13}$$

Two simulation exercises were done under this strategy: the human capital effect (education and experience) and the regional effect.

5.2.3 Non-Observable Effect

The non-observable effect is simulated by using the error structure captured in the earnings equations. The goal is to modify the error structure from the base year, ie:

$$Ef_{Non-Observable98-90} = \Gamma_{98}(x_{90}, \beta_{90}, v_{90}(\frac{\sigma_{98}}{\sigma_{90}}), \mu_{90}, \Omega_{90}) - \Gamma_{90}(x_{90}, \beta_{90}, v_{90}, \mu_{90}, \Omega_{90}) \tag{14}$$

where σ_{98} and σ_{98} represents the standard deviation of the predicted error in equation (3) for the corresponding year. Combining this simulation with the price effect we get:

$$Ef_{Price98-90} + Ef_{Non-Observable98-90} = \Gamma_{98}(x_{90}, \beta_{98}, v_{90}(\frac{\sigma_{98}}{\sigma_{90}}), \mu_{90}, \Omega_{90}) - \Gamma_{90}(x_{90}, \beta_{90}, v_{90}, \mu_{90}, \Omega_{90}) \tag{15}$$

Finally, the last two simulations are combined with the participation effect.

5.2.4 Endowment Effect

The endowments and theirs changes over time also explain changes in income distribution and poverty.

If you define x_k as a vector belonging to matrix x, used in the equation of wages, and x_{-k} as the "complement" matrix of x_k, it is to say $x = [x_k : x_{-k}]$. Then it is possible to define, for the year T_0, the following linear projection, which defines the structure of x_{k,T_0} as:

$$x_{k,T_0} = x_{-k,T_0} u_{T_0} + n_{k,T_0} \tag{16}$$

and in the same manner for the year T_1

$$x_{k,T_1} = x_{-k,T_1} u_{T_1} + n_{k,T_1} \tag{17}$$

where $x_{-k} \perp n_k$ for all T. In such specification, the vector $n_{k,T}$ represents the non-observable characteristics of $x_{k,T}$ conditioned on $x_{-k,T}$. In this way, trough μ_T we can get the dependence of the variable of interest x_k, on $x_{-k,T}$. In this case, the non-observable effect means to obtain the standard error of the predicted residuals, $\varrho_{k,T}$.

Therefore, the values found for $\{u_{T_0}, u_{T_1}, \varrho_{T_0}, \varrho_{T_1}\}$, allow us to change the characteristics of x_{k,T_0} , transforming them to x^*_{k,T_0}, whose form can be obtained as:

$$x^*_{k,T_0} = x_{-k,T_0} u_{T_1} + n_{k,T_0} (\frac{\varrho_{T_1}}{\varrho_{T_0}}) \tag{18}$$

thus, we can then define $x^*_{T_0} = [x^*_{k,T_0}, x_{-k,T_0}]$ and the endowment effect as follows:

$$Ef_{Endowment 98-90} = \Gamma_{98}(x^*_{90}, \beta_{90}, v_{90}, \mu_{90}, \Omega_{90}) - \Gamma_{90}(x_{90}, \beta_{90}, v_{90}, \mu_{90}, \Omega_{90}) \tag{19}$$

Thus, the endowment effect attempts to capture the effect of educational structure and demographics on the distribution of household per capita income distribution.

In summary, replacing parameters, errors and variables from 1998 for 1990 allow us to identify movements inside the structure which define income distribution. Formally, the sumulations imply to evolve from $\Gamma_{T_0}(x_{T_0}, \beta_{T_0}, v_{T_0}, \mu_{T_0}, \Omega_{T_0})$ to $\Gamma_{T_1}(x_{T_1}, \beta_{T_1}, v_{T_1}, \mu_{T_1}, \Omega_{T_1})$.

5.3 The Interrelation between Salaries and the Participation Decision

In the context of the semi-structural model developed earlier it is necessary to analyze in detail the imputation and generation of the error terms. The easiest way of doing that it's by using an example.

Example 1 *Lets suppose that the estimation of the mincer equation for males who occupy a salaried position ($h = 1$) gives the following results for the year T_0:*

$$\ln(y^{h=1}_{l=m}) = x^{h=1\prime}_{l=m} \hat{\beta^{h=1}_{l=m,T_0}} + M^{h=1\prime}_{l=m} \hat{\varphi^{h=1}_{l=m,T_0}} + \hat{v^{h=1}_{l=m,T_0}} \tag{20}$$

where $\hat{\beta^{h=1}_{l=m,T_0}}, \hat{\varphi^{h=1}_{l=m,T_0}}$ y $\hat{v^{h=1}_{l=m,T_0}}$ represent the estimated parameters and sample error, respectively[24]*.*

On the other hand, lets suppose that estimations of the multinomial logit model for year T_0, for the case of individuals who are heads of household ($q = 1$) and whose occupational position is salaried ($j = 1$), is presented as follows:

$$J_{T_0} = Argmax\{U^j_{q=1} = m^{j\,\prime}_{q=1} \hat{\Omega_{q=1,T_0}} + \mu^j_{q=1}, j = 1, 2, 3\} = 1 \tag{21}$$

$$\Rightarrow \hat{P}(\Upsilon_{q=1} = j = 1) = \frac{1}{1 + \sum_{k=1}^{3} e^{m^{k\,\prime}_{q=1} \hat{\Omega_{q=1,T_0}}}} \quad (Salaried) \tag{22}$$

where $\hat{\Omega_{q=1,T_0}}$ represents the estimation of the parameters of the multinomial logit model.

[24] The sample error allows us to get an estimation of the variance of the population error, which is utilized for calculating the non-observable effect

Given the previous results, it is worth asking where the interrelation between the participation decisions and the income model can be found, within the context of our microeconomic simulations. To observe such an interrelation, lets assume that our objective is to analyze the impact of the participation effect. That is, lets suppose that, following the theoretical focus developed in Section 5.2, we complete the following exercise:

$$Ef_{ParticipationT_1-T_0} = \Gamma_{T_1}(x_{T_0}, \beta_{T_0}, v_{T_0}, \mu_{T_0}, \Omega_{T_1}) - \Gamma_{T_0}(x_{T_0}, \beta_{T_0}, v_{T_0}, \mu_{T_0}, \Omega_{T_0}) \tag{23}$$

with this expression we want to study the effect on the distribution of income of those changes present between years T_1 and T_0 on the parameters of the participation model[25]. *Given the characteristics of the semi-structural model, it is important to note that it is possible (and desirable) that some of the agents belonging to the salaried sector and who are heads of household ($q = 1$) in the period T_0, as a result of the microsimulation change their participation decision. By way of example, it is possible that with new values for the parameters of the participation model the following is met:*

$$J^*_{T_0} = Argmax\{U^j_{q=1} = m^j_{q=1}{}'\hat{\Omega}_{q=1,T_1} + \mu^j_{q=1}, j = 1,2,3\} = 2 \quad (Self-employed) \tag{24}$$

to agree with this expression the individual would modify his participation decision from salaried ($J_{T_0} = 1$) to self-employed ($J^*_{T_0} = 2$). What happens then with the salary of this individual considering that the salary reported in the survey is associated with a salaried occupation? The answer to this question is exactly what is found in the structure of the microsimulations. In agreement with what was set in Section 4.1, the income model is estimated both for the case of salaried worker ($h = 1$) as well as for the case of self-employed ($h = 2$), therefore it is possible to "predict" the salary for the "new occupational position" of the agent (self-employed) from the vector of observable variables [26] *and the vector of parameters estimated for self-employed workers. However, even though this implies to obtain a salary projection, it is also necessary to impute an error term, since otherwise it would not be possible to get a complete structure for the salary (more precisely the logarithm of salary) of the individual as presented in equation (3) of Section 5.1. Therefore, following Bourguignon, Ferreira and Lustig (1998), we assume that the error structure in our example is $\epsilon^{h=1}_{l=m}* = M^{h=1}_{l=m}{}'\varphi^{h=2}_{l=m} + \omega^{h=2}_{l=m}$, where $M^{h=1}_{l=m} = -\left(\frac{\phi(z^{h=1}_{l=m}{}'\xi)}{1-\Phi(z^{h=1}_{l=m}{}'\xi)}\right)$ is the probability of not being in the state h and $\omega^{h=2}_{l=m}$ is constructed as a normal random variable with mean 0 and standard deviation $\sigma^{h=2}_{l=m}$, estimated from the residual predicted in equation (3). Finally, the following expression is obtained for salary:*

$$\ln(y^{h*}_l) = x^{h=1}_{l=m}{}'\beta^{h=2}_{l=m} + M^{h=1}_{l=m}{}'\varphi^{h=2}_{l=m} + v^{h=2}_{l=m} \Rightarrow \ln(y^{h*}_l) = x^{h=1}_{l=m}{}'\beta^{h=2}_{l=m} + \epsilon^{h=1}_{l=m}* \tag{25}$$

Based on this example, we argue that while there is no apparent direct relation between the participation model and the salary model, the characteristics of the semi-reduced model are such that if a relation between the various stages is considered, it allows us to study changes in

[25] Although it has not been made explicit in the analysis, the validity of the microeconomic simulations is subject to the assumptions of exogeneity. In particular, there is a requirement that the assumptions necessary to assure super-exogeneity be met. See Engle, Hendry and Richard (1983)

[26] As in Section 5.1 we say that this vector is X^h_l, with $h = 1$ as a result of the individual initially deciding to participate as a salaried worker. Additionally, given that we are analyzing the case of heads of household, and considering that this is only for purposes of example, lets assume $l = m$, which is to say only the case of male heads of household are studied

the distribution of income and poverty more completely than a simple change of coefficients[27]. Furthermore, this is applicable for changes from inactivity or unemployment to either of the two occupation options[28].

6 Empirical Strategies

Following the structure of the theoretical model described before, the empirical strategy utilized in the study is separated in three parts: the empirical strategy for the earning equation, the empirical strategy for the participation decision, and the endowment effect empirical strategy.

6.1 Earnings Equation

The dependent variable is the natural log of monthly labor income in the activity h (with $h = sal., self-emp.$). The set of explanatory variables includes years of schooling (education), years of schooling in secondary education (education 8), years of schooling in superior education (education 12), a dummy variable for technical education, potential experience and its square, and regional dummies[29]. The specification used for the educational structure is based on the empirical difference that has been observed in the dynamic of educational returns in the case of Chile[30]. This evidence suggests that a convex return to schooling is appropriate as a specification in the earning equation.

The model is corrected for selectivity bias using the two-step Heckman procedure with full information standard errors. The Probit regression includes age and its square, number of children under 3 year old, number of children between 3 and 6 years, number of children between 7 and 13 years old and the number of people of working age (14 or older) within the household. This specification is used in both years and for salaried or self-employed males and females.

6.2 Participation Decision

As mentioned earlier a Multinomial Logit model is estimated using three alternatives: to participate as salaried worker, self-employed person or inactive/unemployed. The explanatory variables use in the model are a dummy variable for males (Gender), years of schooling(education) and its square (education2), the mean of years of schooling in the household, experience and its square, regional dummies, the number of children in the age categories described above

[27]The alteration of only the values of the coefficients estimated is basically what the Juhn-Murphy-Pierce decomposition takes into account

[28]With respect to the error in the multinomial logit model and to eventual imputations of these, in the case that the individuals alter their participation decision see footnote 26

[29]Region 12 is taken as a reference

[30]In particular, Bravo, Contreras and Medrano (1999) present evidence of convexity in the return to schooling for the Metropolitan region of Chile (Region 13 in Table II) when primary, secondary and high returns were analyzed.

(children 0-2, children 3-6 and children 7-13), and the number of people of working age within the household.

6.3 Endowment Effect

The following variables are considered in the analysis of the endowment effect: number of children of ages 0 to 2 years (children 0-2), number of children of ages 3 to 6 years (children 3-6), number of children ages of 7 to 13 years (children 7-13), number of people in working age, and years of schooling. The selected regressors for such estimations are: age, age squared, gender, and regional dummies.

7 Results

The theoretical model developed in section 5 imposes a structure that consists, first, in the estimation of four mincer equations for each of the two years of the analysis, 1990 and 1998. The following cases are considered:

1. Salaried Males
2. Self-employed Males
3. Salaried Females
4. Self-employed Females

In addition, the model considers that with respect to the participation decision of the agents, this should be estimated considering one of the following three positions of the agent in the household:

1. Head of Household
2. Spouses
3. Other Household Members

In each of them the individual has three distinct alternatives: salaried participant, self-employed participant, and non-participant.

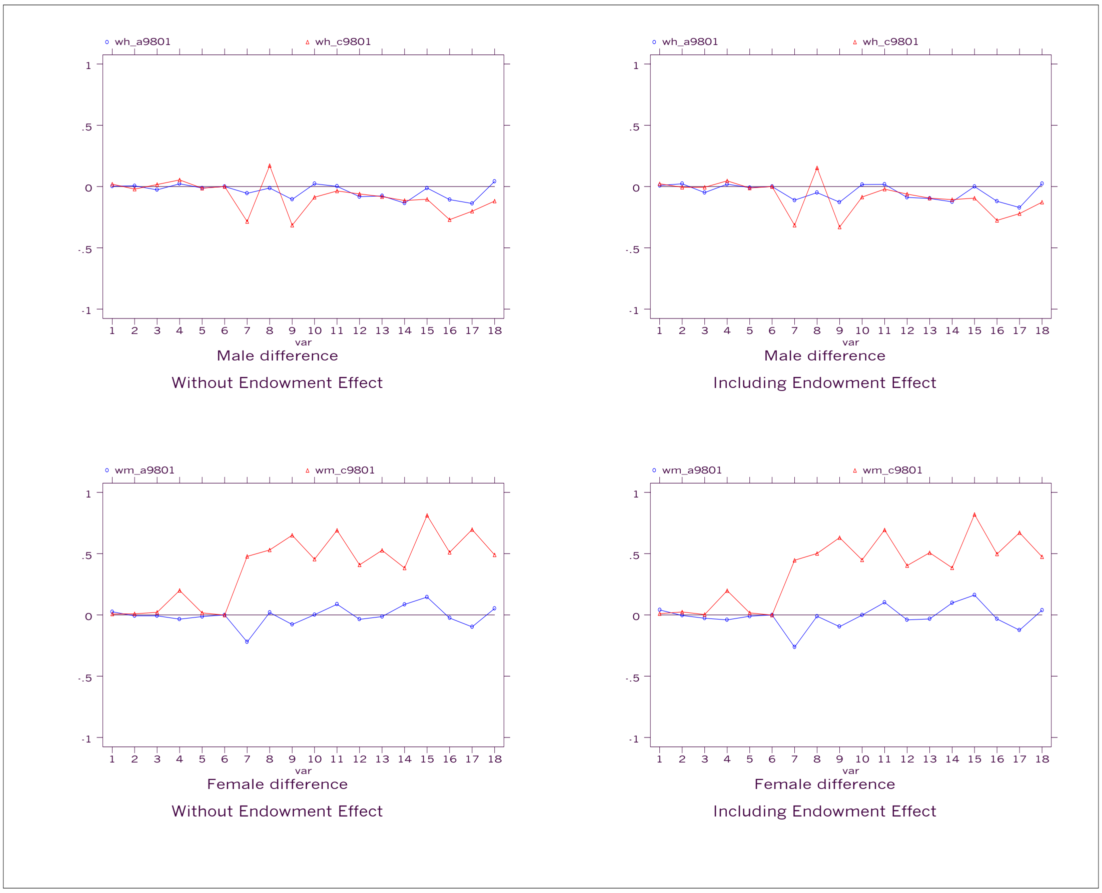
7.1 Earnings Equation (Mincer Equation)

As long as we estimate four different Mincer equations in each year, we must show the variation of the estimate coefficient for each case.

The Figure II presents the differences in the estimation for salaried men (wh_a9801) and self-employed men (wh_c9801) between 1998 and 1990, and likewise, the differences for salaried women (wm_a9801) and for self-employed women (wm_c9801) in the same period of time.

Figure II

Difference in estimation of men wage equation (1990-1998)



Notes: (1) Each number in the x-axis is related to the coefficient of the following regressors: 1=Schooling year, 2=Schooling year in secondary school ,3=Schooling year in university ,4=Technical education(dummy),5=Potencial experience,6=Potencial experience squared,7=Region I,8=Region II,9=Region III,10=Region IV,11=Region V,12=Region VI,13=Region VII,14=Region VIII,15=Region IX,16=Region X,17=Region XI,18=Region XIII.(2) wh_a9801 represents the case of salaried men and wh_c9801 represents the case of self-employed men. (3)wm_a9801 represents the case of salaried women and wm_c9801 represents the case of self-employed women.

When the changes in the coefficients of men are studied, clearly just the coefficient of regional dummies variables show some variation. In particular, only the return of Region II for self-employed and Region XIII for salaried men show a rise. In all the other regional coefficients, the estimations in 1990 have been higher. The other estimated parameters (age, gender, educational and experience variables) appear stable [31]. These results are robust for almost all estimations, including the wage equation for women and the different participation models. In addition,

[31] See Tables A and B in the Appendix for details

given the similarity between the cases of inclusion and non-inclusion of the endowment effect, these results are applicable to both cases and to female gender.

The most important results to consider in the case of women, are the presence of an increase in the return to schooling of technical education in the case of self-employed (a fact which is not evident for salaried women), a generalized increase in regional returns for self-employed women, and minor changes in the later for salaried women. As will be seen in the simulations, these changes are captured in the microeconomic model, and have important effects on the elements behind the distribution of income in Chile.

Lastly, just as in the case of men, the return to education remains almost constant (except the change in the return to technical education mentioned earlier), for both salaried and self-employed women.

Table K in the appendix presents the values for the variance of the estimated errors. These variances will become important in the microsimulations in the context of the non-observables effect.

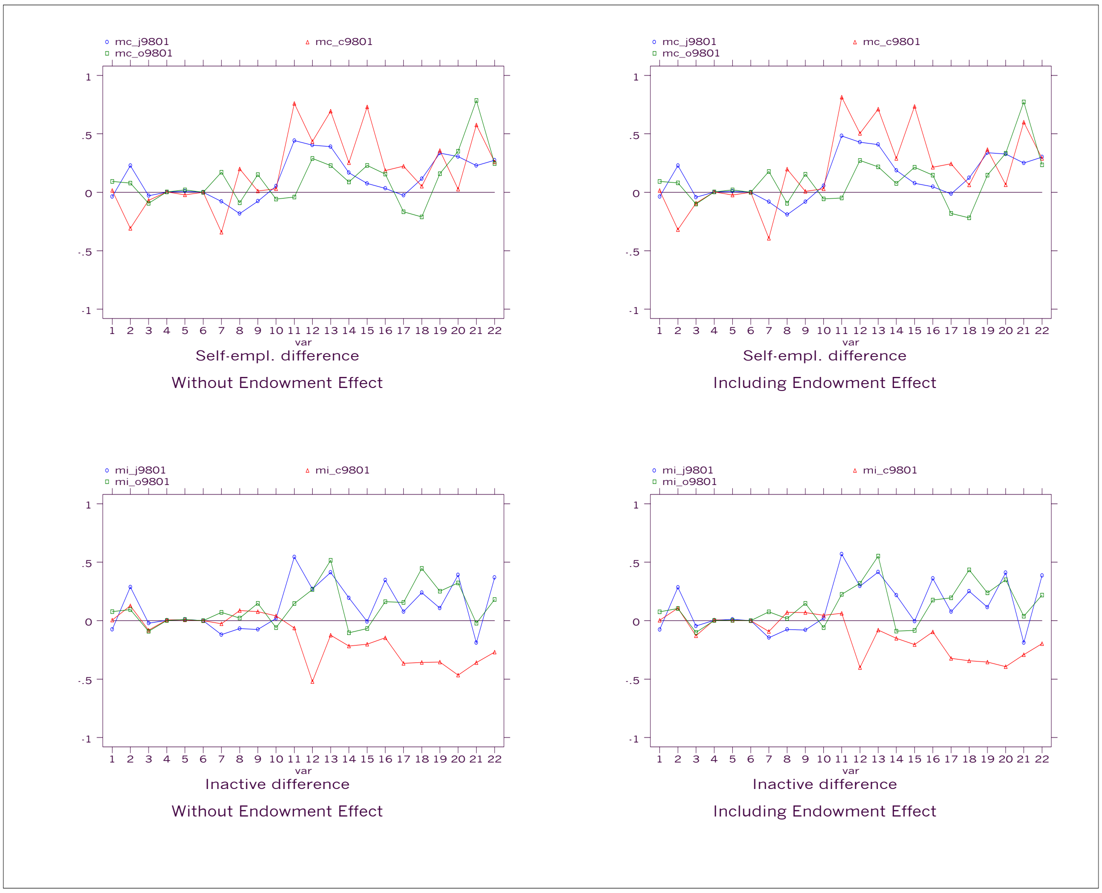
7.2 Labor Supply Decision (Multinomial Logit Model)

The estimation of the labor supply presents a relative instability in the comparison of the years 1990 and 1998. Figure III presents the differences in the parameters estimated between 1990 and 1998. In particular, if we analyze the estimates for the alternative of participating as a self-employed worker and as a non-participant in the labor market, we see that the largest changes occur (again) in the estimation of the regional parameters, the gender parameter and the demographic structure of the household. In addition, such instability shows particular differences in the comparison by position in the household [32], as for example in the case of self-employed spouses (serie mc_c9801) we find that the effect is in general an increase in the regional parameters, while in the case of inactivity (mi_c9801) we find for the same group that the variation goes in the opposite direction. Therefore,

[32]Remember that the model is estimated for head of household, spouse, and other family members

Figure III

Multinomial Logit Parameters: Difference 1998-1990



Notes: (1)Each number in the x-axis is related to the coefficient of the following regressors: 1=Average schooling years in household, 2=Gender (dummy) ,3=Schooling year,4=Square schooling year, 5=Potential experience,6=Square potential experience, 7=Children between 0 and 2 years old in household, 8=Children between 3 and 6 years old in household, 9=Children between 7 and 13 years old in household, 10=people within the household in working age, 11=Region I, 12=Region II, 13=Region III, 14=Region IV, 15=Region V, 16=Region VI, 17=Region VII, 18=Region VIII, 19=Region IX, 20=Region X, 21=Region XI, 22=Region XIII. (2) mc_j9801 and mi_j9801 represent the case of head of household, mc_c9801 and mi_c9801 represent the case of spouses, and mc_oj9801 and mi_oj9801 represent the case of other household members.

It is not possible to identify in advance any systematic change in the estimations that allow us to predict an unambiguous effect in participation or labor supply, and from there then, in the income distribution. What we can conclude, starting from the present results, is that whatever the changes have been in the structure of the labor supply in Chile during the period 1990-1998, the direction and relevance are not clear for the effect on the income distribution. In fact, in the next section we show that participation has not altered income distribution significantly.

The statistical significance of the estimations and other details are presented in the Appendix. The same is applicable to the detail of the parameters obtained in the application of the endowment effect[33].

[33]remember that, as presented in section 5, the endowment effect forces a complete re-estimation of the model for the alteration of the structure of the variables which are considered exogenous

8 Microsimulations

In this section we present the results obtained for the various simulations which were given in section 5 from a theoretical perspective.

In what follows, the principal objective is to answer the question: What would have happened to the income distribution in Chile in 1990 if the microeconomic structure of 1998 had been imposed on the economy? In other words, what is sought is to try to characterize in what way the various elements behind the distribution of income changed during the period 1990 to 1998. Thus, the result of each simulation (or effect) allows us to observe what the observed income distribution would have been in the year 1998, in terms of income distribution, if said change (effect) had not been produced.

The results of the simulations are presented from two perspectives. The first utilizes the poverty and distribution of income indicators listed and explained in the technical appendix, showing what the values of these indicators would have been under the various scenarios simulated. Briefly, the poverty indexes are $P(0)$ (called the headcount index, $P(1)$ or the poverty gap, and $P(2)$ (all members of the Foster-Greer-Thorbecke family), while the inequality indicators are the Gini coefficient, $E(1)$ (or the mean log deviation), $E(1)$ (or the T-Theil index), and $E(2)$.

The second perspective studies the first order stochastic dominance on the Lorenz curve and Generalized Lorenz curves of the distribution of income resulting from each one of the simulation exercises with respect to the distribution of income observed in 1990. In this way, we present a detailed analysis of the dynamic factors behind the stable and unequal distribution of income and the reduction of poverty; both events observed in Chile during the decade of the nineties.

8.1 Poverty and Income Distribution Analysis

Table III presents the results of the microeconomic simulations with respect to poverty and inequality indicators.

It is important to note that the structure of Table III agrees with the order used in carrying out the simulations. Rows numbered from (1) to (7) only present those indicators resulting from the simulation exercises therein mentioned, while rows numbered (10) to (16) and from (18) to (25) incorporate the participation and endowment effects, respectively, together with price effects (education, experience, education-experience, region and prices) and non-observables. Likewise, the effects associated with rows numbered from (26) to (31) include the effects of endowment and participation as well as those that appear next to the respective number. Rows (9), (17) and (25) on the other hand, present the results for the participation, endowment, and participation-endowment, excluding all the price and non-observable effects. Finally, row (32) presents the results when all the effects are applied.

Table III

Microsimulations 1990-1998 : Poverty and Inequality Indexes

Microsimulation	Inequality Indexes					Poverty Indexes		
	Gini	$Q(5)/Q(1)$	$E(0)$	$E(1)$	$E(2)$	$P(0)$	$P(1)$	$P(2)$
Observed 1990	0.558	17.137	0.549	0.654	1.741	0.373	0.145	0.079
Observed 1998	0.565	17.538	0.566	0.670	1.789	0.234	0.084	0.044
(1)Education	0.561	17.752	0.557	0.652	1.667	0.339	0.131	0.071
(2)Experience	0.560	17.734	0.553	0.656	1.752	0.401	0.160	0.087
(3)Education and Experience	0.564	18.066	0.564	0.659	1.701	0.371	0.147	0.081
(4)Region	0.564	18.401	0.569	0.665	1.732	0.371	0.143	0.079
(5)Price Effect	0.567	19.173	0.579	0.668	1.697	0.374	0.151	0.083
(6)Non-Observable Effect	0.542	15.837	0.514	0.599	1.465	0.359	0.137	0.073
(7)Prices and Non-observable	0.553	18.032	0.547	0.614	1.396	0.363	0.145	0.079
(8)Participation Effect	0.560	17.512	0.552	0.659	1.773	0.384	0.152	0.084
(9)Education	0.556	17.551	0.548	0.637	1.613	0.332	0.128	0.070
(10)Experience	0.556	17.201	0.544	0.642	1.693	0.391	0.156	0.085
(11)Education and Experience	0.559	17.892	0.554	0.643	1.636	0.362	0.144	0.079
(12)Region	0.560	18.412	0.562	0.655	1.697	0.363	0.143	0.078
(13)Price Effect	0.563	18.957	0.570	0.655	1.652	0.365	0.148	0.081
(14)Non-Observable Effect	0.539	15.876	0.511	0.591	1.437	0.352	0.135	0.073
(15)Prices and Non-observable	0.556	17.980	0.544	0.608	1.379	0.358	0.143	0.078
(16)Endowment Effect	0.557	16.996	0.546	0.649	1.718	0.369	0.143	0.077
(17)Education	0.566	18.574	0.572	0.664	1.680	0.309	0.119	0.064
(18)Experience	0.560	17.285	0.552	0.657	1.759	0.388	0.153	0.083
(19)Education and Experience	0.569	18.854	0.578	0.672	1.720	0.327	0.128	0.070
(20)Region	0.564	18.434	0.569	0.667	1.752	0.374	0.147	0.080
(21)Price Effect	0.573	20.063	0.595	0.683	1.740	0.335	0.132	0.072
(22)Non-Observable Effect	0.542	15.531	0.514	0.600	1.470	0.360	0.137	0.073
(23)Prices and Non-observable	0.559	18.849	0.563	0.628	1.428	0.329	0.127	0.069
(24)Endowment and Participation	0.554	17.043	0.544	0.640	1.679	0.360	0.139	0.075
(25)Education	0.564	18.554	0.570	0.654	1.638	0.301	0.116	0.0634
(26)Experience	0.557	17.332	0.550	0.648	1.715	0.378	0.150	0.081
(27)Education and Experience	0.567	18.843	0.576	0.663	1.677	0.318	0.125	0.068
(28)Region	0.562	18.458	0.568	0.661	1.725	0.364	0.143	0.078
(29)Price Effect	0.571	20.073	0.594	0.676	1.710	0.325	0.129	0.071
(30)Non-Observable Effect	0.541	15.970	0.513	0.595	1.446	0.353	0.135	0.072
(32)All Effects	0.558	18.943	0.562	0.625	1.412	0.320	0.125	0.068

8.1.1 Simulating Income Distribution

By imposing the 1998's coefficients or returns to education, experience, and region, we can argue that the 1990's conditions of inequality would have been worse. This can be seen based on the results of the various inequality indicators (rows (1), (2), (3), (4) and (5) in table III). Then, we can state the these factors had a negative effect on the distribution of income during the past decade. In particular, the price effect (Row (5)), that is shown by imputing all the coefficients of the salary equations of 1998 on 1990, produce the result of an increase in both the Gini coefficient and in the ratio of quintiles, $E(0)$ and $E(1)$, with $E(2)$ appearing as the only exception, showing a significant increase in the ratio of quintiles from 17.137 (the effective value for 1990) to 19.173 (which is even greater that the 17.538 observed in 1998). By altering the non-observable factors (Row (6)) in education of salaried employees for 1990, a better distribution of income is observed. In this case the ratio of the quintiles drops to 15.837, and the Gini coefficient reaches a value of 0.542. When the simulation exercise corresponds to altering in 1990 both prices and non-observables, a general improvement in the distribution of income is observed.

The participation effect (Row (8)) shows as a result a slight increase in the inequality indicators (except $E(2)$). However, this result is not the most interesting of changing the structure of participation in 1990. Just as is mentioned at the beginning of this section, Rows (9), (10), (11), (12), (13), and (14) show the results for the price effects and non-observables, incorporating the participation effect as well, and it is here that interesting results emerge. For although the price effect, it alone accounts for a worsening of the distribution in the nineties, and its interrelation with the price and non-observable effects produces different results. In particular, upon comparing the various inequality indices associated with price effects and non-observables in this case, in contrast to the case where the participation effect is not incorporated, it can be observed that, although a similar trend exists, now the increases in the inequality indicators are smaller, and the reduction are more significant. This is reflected with greater strength in the case of the experience effect (Row (10)), since while initially this effect was associated with an unambiguous increase in the inequality indicators (Row (2)), upon incorporating the endowment effect the result is completely different, with a reduction in all the inequality indicators being observed relative to the year 1990. Likewise, the result of an improvement in the distribution of income remains unchanged when the non-observable effect (together with participation) is included (Row (14)).

The simulation exercise associated to the endowment effect, i.e. to the change in the structure of the regressors in the salary regressions, shows a slight decrease in the inequality indicators (Row(16)). The value of the Gini coefficient is 0.557, slightly less than the 0.558 observed in 1990. Nevertheless, when the price ,non-observable, and endowment effect are jointly modelled some surprises are found. In this case, while the endowment effect alone implies a reduction in the inequality indicators, when this is incorporated into the price effects (Rows (17), (18), (19), (20), (21) y (23)), the results show a tendency to worsen the distribution more important than that of the "pure" price effects (Rows (1), (2), (3), (4), (5) y (6)). For example, when the results for simultaneous price and non-observable effects (Row (7)), are compared with doing the same exercise but incorporating the endowment effect (Row (23)), it can be observed that while in the former case the equalizing effect of the non-observables dominates the unequalizing effect of prices, in the later it is these last that dominate, causing an increase in the Gini coefficient, $Q(5)/Q(1)$ and $E(0)$ with respect to that observed in 1990. This is very different from what occurs in the case of non-including the endowment effect[34].

When the participation and endowment effects are considered in the simulation exercise (Row (24)), it can be concluded that the endowment effect dominates, since the final result implies a reduction in all the indicators of inequality with respect to 1990. Finally, when these effects are carried out jointly with the price and non-observable effects, similar results are obtained to those found in the case of only considering these two effects. Therefore, increases are observed in the inequality indicators when prices are the elements altered in 1990 (Rows (25), (26), (27), (28) and (29)), and an improvement in the distribution of income when the non-observable factors are those utilized in the simulation (Row (30)).

Finally, upon incorporating all the elements within a single simulation exercise, the changes observed in the inequality indicators are not in one direction. Although the ratio of the quintiles ($Q(5)/Q(1)$ and the coefficient $E(0)$ show values greater than those of 1990, the coefficients $E(1)$ and $E(3)$ show decreases, while the Gini coefficient appears unaltered (Row (31)).

8.1.2 Simulating Poverty

The analysis on the poverty indicators is simpler than that of the inequality indicators. We show that the significant decrease in the poverty indicators that Chile showed during the past decade (Rows "1990 observed" and "1998 observed"), is well captured in the microeconomic simulations. Additionally, given that the results obtained in carrying out the exercises relative to the price and non-observable effects are consistent throughout Table V, the cases in which these are aggregated to the endowment and participation effects are not analyzed in detail.

The most important result in the analysis of the poverty indicators is undoubtedly the one associated with the returns to education (Row(1)). If, for example, the headcount ($P(0)$) in 1990 is compared with the result of imputing the returns to education of 1998 on 1990, this indicator goes from 0.373 to 0.332, which means a drop close to 15%. Thus, it can be concluded that the change in the returns to education had great importance for effects of the reduction of poverty. The indicators $P(1)$ and $P(0)$, for their part, also show decreases. The changes in the regional parameters[35]

Changes in the returns to experience, in contrast to what is observed in the cases of returns to education and regional parameters, had a negative effect on the poverty indicators. In fact,

[34]In fact, upon comparing the incorporation of the endowment effect (Row(23)) as opposed to not including it (Row (7)) all the inequality indicators increase.

[35]It is very important to clarify that in analyzing the changes in the regional coefficients we could replace the constant of the salary equations, these are associated with dummy variables, and therefore, the constant contains the effect of region omitted. In the case of the poverty analysis, this was not carried out, since upon replacing the constant, we would also be imputing the increases in productivity present in the period 1990-1998. In any case, when the constant is replaced, the values observed in the poverty indicators drop significantly (headcount close to 0.24, values of $E(1)$ around 0.09, and $E(2)$ never greater than 0.06). This is interesting since it allows us to relate the commonly accepted explanation for the reduction of poverty (economic growth) with a change in the median productivity of workers (the constant in the salary regression).

headcount shows an increase close to 3 points with respect to that observed in 1990, reaching a value of 0.401 (Row (2)). However, when returns to experience and returns to education are both utilized in a simulation exercise, it is education that dominates, as can be appreciated in Table III (Rows (3), (11), (19) and (27)), the result is a decrease in the various poverty indicators.

When all the coefficients of the salary equations of 1998 are imputed on the structure of 1990 (price effect), the result is a slight worsening of poverty in Chile (Row (5)). This seems to say that even when the returns to education would have had a positive and significant effect on the various poverty indicators during the last decade in Chile, when these are "aggregated" to the rest of the changes, their effect disappears. It can be stated then that compensating effects exist between the various returns. Is the same result obtained when participation and/or endowment effect are also included?. The answer is no. Simply by inspecting Table V (Rows (13), (21) and (29)) it can be concluded that when the participation and/or endowment effects are incorporated, the result of the price effect is now a decrease in the poverty indicators. To further point out this fact, when the endowment, participation and price effects are considered simultaneously, the estimated headcount is 0.320, a value much lower than the 0.373 observed in 1990.

Finally, the exercises having the smallest impact on poverty are those including the non-observable, endowment, and participation effects. While the first two of these have positive effects on the poverty indicators (Rows (6) and (16)), the participation effect gives an increase in all poverty indicators as a result (Row (9)).

8.2 First-Order Stochastic Dominance Analysis

After having analyzed the indicators of inequality and poverty, now we analyze the first order stochastic dominance in Lorenz curves and Generalized Lorenz curves. Table IV presents the results from the study of stochastic dominance[36].

[36] Each row of the Table IV studies the first-order stochastic dominance relation between a simulated Lorenz or Generalized Lorenz curve and the observed (1990) Lorenz or Generalized Lorenz curve.

Table IV

Microsimulations 1990-1998 : First-Order Stochastic Dominance

Lorenz Curve and Generalized Lorenz Curve

Microsimulation	Lorenz	Generalized Lorenz
	FOSD	FOSD
(1)Education	–	Dominates
(2)Experience	–	–
(3)Education and Experience	–	–
(4)Region	–	Dominates
(5)Price Effect	–	–
(6)Non-Observable Effect	–	–
(7)Prices and Non-observable	Dominates	Dominates
(8)Participation Effect	–	–
(9)Education	Dominates	Dominates
(10)Experience	–	–
(11)Education and Experience	–	Dominates
(12)Region	–	Dominates
(13)Price Effect	–	–
(14)Non-Observable Effect	Dominates	–
(15)Prices and Non-observable	Dominates	Dominates
(16)Endowment Effect	Dominates	Dominates
(17)Education	–	Dominates
(18)Experience	–	–
(19)Education and Experience	–	Dominates
(20)Region	–	–
(21)Price Effect	–	Dominates
(22)Non-Observable Effect	–	–
(23)Prices and Non-observable	–	Dominates
(24)Endowment and Participation	Dominates	Dominates
(25)Education	–	Dominates
(26)Experience	–	–
(27)Education and Experience	–	Dominates
(28)Region	–	Dominates
(29)Price Effect	–	Dominates
(30)Non-Observable Effect	Dominates	Dominates
(32) All Effects	–	Dominates

The results in Table IV correspond to what would be expected. Given the results obtained in the analysis of disaggregated inequality indicators, where in many cases we found that while some rose, others fell, it could have been inferred that there would be few cases in which the Lorenz curve of a specific effect would first order stochastically dominate those of 1990, which in practical terms would mean that there are few cases in which all the aggregated inequality indicators, that belong to the class of generalized entropy, would have values less than those observed in 1990. Nevertheless, in the context of dominance for Lorenz curves, in the majority of cases where this is presented an exercise associated with non-observables has been carried out. In fact, in more than 50% of the cases where first order stochastic dominance is presented in the Lorenz curve a simulation exercise of the non-observable components was carried out. This finding does not allow a priori to identify specific improvements in the distribution associated with non-observables. However it does provide relevant information about the development of future research. Additionally, the endowment effect also shows that, from the point of view of equality, this has implied unambiguous improvements in the distribution of income.

As far as the results for the Generalized Lorenz curves, it is important to mention that given that these control for differences in the means of the distributions[37], they take into consideration the social benefits produced by reduction in the poverty indicators (in particular the Poverty Gap or $P(1)$[38]. Therefore, it is not strange that numerous cases are found where, from a social welfare point of view, the distribution of income resulting from the simulation exercises was preferable to that observed in 1990, or in other words, that first order stochastic dominance was present in the Lorenz curves. The most robust results are those associated with the returns to education. In those cases, without being concerned if the changes in returns were accompanied by changes in the structure of participation and/or endowment, the Generalized Lorenz curve simulated are always found to be above that observed in 1990. This is in agreement with what is presented in the previous section, where changes in the returns to education had a significant impact on the reduction of poverty during the decade of the nineties. Additionally, it is interesting to observe that when the price and non-observable effects are aggregated to those of endowment and participation (simultaneously) the result is first order stochastic dominance, except in the case of experience (Row (26)). Next, considering Row (31) in Table IV, we argue that the simulated distribution of income based on all the effects first order stochastically dominates the observed in 1990, which implies that from a social point of view, this would be preferable. This finding is expected, due to that in general the simulated distribution presents lower poverty indicators (See Table IV, Row (31)) than those observed. The reason for this is simply that these exercises emulate the best poverty conditions existing in 1998, thus giving the expected result.

In Appendix the Lorenz curves and Generalized Lorenz curves utilized in the analysis of stochastic dominance are presented graphically.

[37]See Technical Appendix for more detail
[38]See Deaton (1993)

9 Conclusions

This paper examines the dynamics of income distribution in Chile during 1990-98. This period is interesting due to the sustained level of high inequality and the drastic reduction in poverty.

By using a microsimulation model the paper contributes to the literature with a detailed analysis on the factors that play a role in the determination of income distribution and their changes over time.

The evidence shows that behind an apparent stable income distribution there are significant movements of its determinants. Variables such as returns to education, experience, and regional components have a negative effect on inequality over time.

On the other hand, the endowment effects, which are related to the stock of education, and demographical characteristics of the population, have a positive effect on reducing income inequality. Similarly, the non-observables are also reducing inequality.

Indeed, this effect is more significant than the former. However, we still do not know what are the factors behind such effect. Therefore, it is clear that, beyond a stable distribution of income, Chile has been subject to several changes in the components that determine its income distribution, which were not identified by previous research.

The robustness of the previous results was examined by using First Order Stochastic Dominance in Lorenz Curve.

In relation to poverty, the most important result is that the change in the returns to education explains a significant reduction in poverty. However, such effect implies a worsening in inequality.

In addition, the endowment and non-observable effects have also a positive impact in reducing poverty. The participation effect on the other hand, implies an increase in poverty indicators.

Finally, by using a parametric analysis and the first order stochastic dominance (in Generalized Lorenz Curve), the paper demonstrates that a society may improve welfare despite a high and sustained level of inequality. This type of analysis is of increasing importance for policy makers because it stresses how crucial it is to decompose the dynamics of income distribution.

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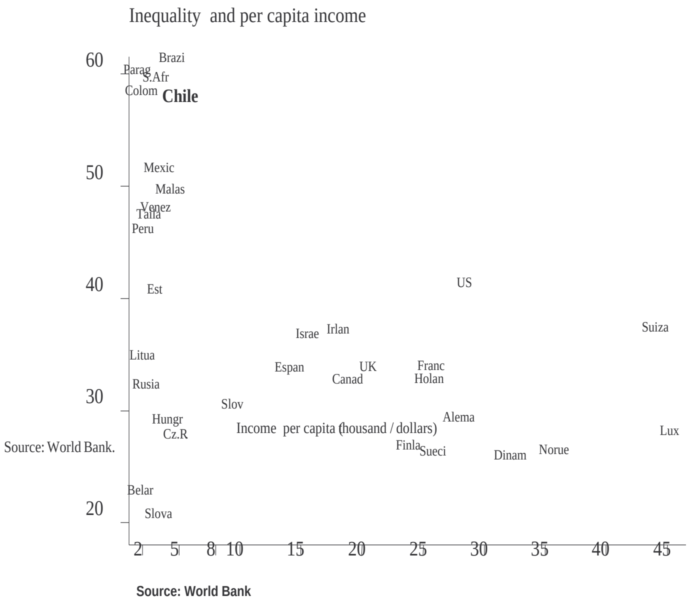
APPENDIX

Figure I Inequality in the World - Gini Coefficient



A. Without Endowment Effect: Earning Equation - 1990

Variable	Salaried males	Salaried females	Self-employed males	Self-employed females
Education	0.0445	0.0379	0.0151	0.0343
Education8	0.0927	0.0758	0.1262	0.0857
Education12	0.0661	0.0337	0.0138	0.0272
Technical Edu	-0.0154	-0.0077	0.0700	-0.2126
Experience	0.0503	0.0146	0.0355	0.0028
Experience2	-0.0006	-0.0002	-0.0006	0.0000
Region I	-0.0392	0.2557	0.0492	0.1516
Region II	0.0850	0.0459	0.0265	0.0700
Region III	-0.0344	0.1834	-0.0771	-0.2238
Region IV	-0.2925	-0.1433	-0.2341	-0.2197
Region V	-0.2531	-0.0559	-0.2165	-0.4589
Region VI	-0.1869	-0.0232	-0.1331	-0.1433
Region VII	-0.3382	-0.1285	-0.2051	-0.2889
Region VIII	-0.2171	-0.1221	-0.2936	-0.1703
Region IX	-0.3745	-0.4138	-0.3190	-0.3476
Region X	-0.2441	-0.0500	-0.1512	-0.1729
Region XI	0.0444	0.2986	0.1119	0.0245*
Region XIII	-0.1065	0.1567	0.0468	-0.0497
Cons	9.6365	11.1688	9.5460	11.0498
Probit				
Age	0.1825	0.1005	0.1353	0.1001
Age2	-0.0023	-0.0010	-0.0019	-0.0011
Children0-2	0.1684	0.0406	-0.1757	0.0071
Children3-6	0.0270	0.0843	-0.1226	-0.0228
Children7-13	-0.0484	0.0161	-0.1241	-0.0369
Working Age	-0.0457	-0.0148	0.0219	-0.0445
cons	-2.9297	-3.0770	-2.7483	-3.4894
Lambda	0.1117	-0.5840	0.1207	-0.4458

* *:p-value>0.05*

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B. Without Endowment Effect: Earning Equation - 1998

Variable	Salaried males	Salaried females	Self-employed males	Self-employed females
Education	0.0473	0.0578	0.0417	0.0422
Education8	0.0988	0.0546	0.1197	0.0952
Education12	0.0396	0.0500	0.0069	0.0490
Technical Edu	0.0079	0.0470	0.0360	-0.0126
Experience	0.0385	0.0013	0.0222	0.0190
Experience2	-0.0004	0.0000*	-0.0002	-0.0002
Region I	-0.0945	-0.0300	-0.1708	0.6299
Region II	0.0729	0.2175	0.0471	0.6005
Region III	-0.1388	-0.1313	-0.1551	0.4264
Region IV	-0.2692	-0.2295	-0.2325	0.2354
Region V	-0.2516	-0.0922	-0.1289	0.2318
Region VI	-0.2689	-0.0828	-0.1678	0.2653
Region VII	-0.4152	-0.2101	-0.2186	0.2394
Region VIII	-0.3511	-0.2356	-0.2084	0.2124
Region IX	-0.3865	-0.5166	-0.1733	0.4656
Region X	-0.3505	-0.3203	-0.1764	0.3380
Region XI	-0.0927	0.0972	0.0152*	0.7216
Region XIII	-0.0636	0.0382	0.0995	0.4409
Cons	10.8226	12.8455	10.6407	10.8257
Probit				
Age	0.1764	0.1077	0.1488	0.1115
Age2	-0.0021	-0.0010	-0.0020	-0.0012
Children0-2	0.1954	0.0417	-0.1301	-0.0324
Children3-6	0.1065	0.0077	-0.1017	0.0216
Children7-13	-0.0239	-0.0052	-0.1622	-0.0073
Working Age	-0.0623	-0.0074	-0.0142	-0.0536
cons	-2.9137	-3.4478	-2.8277	-3.7890
Lambda	-0.0527	-0.7072	-0.1334	-0.1487

** :p-value>0.05*

C. Without Endowment Effect: Multinomial Logit - 1990

	Heads of households		Spouses		Other relatives	
Variable	Self-emp	Non-part	Self-emp	Non-part	Self-empl	Non-part
Average Education	0.0198	0.0696	-0.0309	0.0041	-0.0886	0.0392
DGender	-0.0323	-1.7446	0.0976	-2.6577	0.8347	-0.8881
Education	0.0854	0.1801	0.1886	0.2818	0.1114	-0.1048
Education2	-0.0070	-0.0102	-0.0114	-0.0235	-0.0056	-0.0044
Experience	0.0207	-0.0508	0.0582	-0.0570	0.0084	-0.2675
Experience2	0.0003	0.0021	-0.0003	0.0016	0.0007	0.0051
Children0-2	0.0254	0.1954	0.3744	0.4796	-0.0465	-0.0349
Children3-6	0.1427	0.1005	0.0100*	0.2404	0.0630	0.0579
Children7-13	0.0578	0.0419	0.0660	0.1170	-0.0725	0.0302
Working Age	-0.0419	-0.0409	-0.0009*	-0.0589	-0.0198	-0.0014*
Region I	0.2144	-0.1099	-0.2885	-0.0644	0.1792	0.3870
Region II	-0.1327	-0.1024	-0.3407	0.6643	-0.1237	0.2987
Region III	-0.0998	-0.1060	-0.4892	0.1483	0.0896	0.4040
Region IV	0.1901	0.0118*	-0.2295	0.1602	0.2630	0.4625
Region V	0.0756	0.2275	-0.6583	0.0404	-0.0699	0.4418
Region VI	-0.1546	-0.2233	-0.4948	0.0615	-0.4715	0.1242
Region VII	0.3454	0.1140	-0.3923	0.2958	0.2309	0.1085
Region VIII	0.0158*	0.4328	-0.1618	0.5206	0.1038	0.2792
Region IX	0.5544	0.2435	-0.2795	0.4123	0.3442	0.4442
Region X	0.0983	-0.1228	-0.2490	0.3918	0.0550	0.1016
Region XI	0.1064	-0.1369	-0.7544	0.0492*	-0.2558	0.0057*
Region XIII	-0.0061*	-0.1966	-0.3620	-0.1483	-0.2005	0.0696
cons	-2.0443	-1.5400	-2.3785	1.1930	-2.2190	3.3105

** :p-value>0.05*

D. Without Endowment Effect: Multinomial Logit - 1998

	Heads of households		Spouses		Other relatives	
Variable	Self-emp	Non-part	Self-emp	Non-part	Self-empl	Non-part
Average Education	-0.0183	-0.0055	-0.0158	0.0083	0.0036	0.1169
DGender	0.1952	-1.4573	-0.2113	-2.5305	0.9129	-0.7939
Education	0.0550	0.1582	0.1189	0.1997	0.0162	-0.1957
Education2	-0.0049	-0.0077	-0.0079	-0.0168	-0.0030	-0.0025
Experience	0.0289	-0.0406	0.0367	-0.0504	0.0291	-0.2580
Experience2	0.0001	0.0018	0.0000*	0.0015	0.0004	0.0050
Children0-2	-0.0540	0.0759	0.0330	0.4529	0.1243	0.0364
Children3-6	-0.0406	0.0330	0.2098	0.3276	-0.0268	0.0794
Children7-13	-0.0198	-0.0344	0.0766	0.1940	0.0782	0.1787
Working Age	0.0103	-0.0224	0.0288	-0.0182	-0.0786	-0.0613
Region I	0.6569	0.4339	0.4711	-0.1274	0.1380	0.5339
Region II	0.2708	0.1690	0.0939	0.1427	0.1652	0.5644
Region III	0.2908	0.3070	0.2059	0.0233*	0.3172	0.9201
Region IV	0.3565	0.2070	0.0235*	-0.0579	0.3509	0.3589
Region V	0.1510	0.2197	0.0721	-0.1617	0.1593	0.3744
Region VI	-0.1215	0.1232	-0.3091	-0.0851	-0.3163	0.2865
Region VII	0.3184	0.1912	-0.1685	-0.0694	0.0646	0.2646
Region VIII	0.1312	0.6727	-0.1096	0.1638	-0.1068	0.7255
Region IX	0.8902	0.3510	0.0784	0.0578	0.5030	0.6965
Region X	0.4032	0.2671	-0.2226	-0.0736	0.4054	0.4237
Region XI	0.3337	-0.3278	-0.1780	-0.3101	0.5303	-0.0167*
Region XIII	0.2671	0.1715	-0.1021	-0.4178	0.0453	0.2512
cons	-2.3659	-1.7278	-2.4412	0.8595	-2.6623	3.4071

** :p-value>0.05*

E. With Endowment Effect: Earning Equation - 1990

Variable	Salaried males	Salaried females	Self-employed males	Self-employed females
Education	0.0379	0.0343	0.0006*	0.0310
Education8	0.0758	0.0607	0.1235	0.0708
Education12	0.0886	0.0555	0.0368	0.0457
Technical Edu	-0.0126	0.0002*	0.0761	-0.2111
Experience	0.0470	0.0131	0.0324	0.0021
Experience2	-0.0006	-0.0002	-0.0005	0.0001
Region I	0.0154	0.2847	0.0918	0.1835
Region II	0.1219	0.0645	0.0565	0.0980
Region III	-0.0113	0.1993	-0.0601	-0.2053
Region IV	-0.2858	-0.1439	-0.2319	-0.2136
Region V	-0.2696	-0.0709	-0.2316	-0.4629
Region VI	-0.1806	-0.0221	-0.1273	-0.1374
Region VII	-0.3183	-0.1156	-0.1868	-0.2690
Region VIII	-0.2272	-0.1300	-0.3063	-0.1728
Region IX	-0.3863	-0.4223	-0.3357	-0.3553
Region X	-0.2315	-0.0450	-0.1437	-0.1587
Region XI	0.0776	0.3166	0.1397	0.0495*
Region XIII	-0.0871	0.1654	0.0601	-0.0344
Cons	9.6581	11.1421	9.6231	10.9535
Probit				
Age	0.1816	0.1004	0.1348	0.0998
Age2	-0.0022	-0.0010	-0.0018	-0.0010
Children0-2	0.1945	0.0466	-0.2049	0.0071
Children3-6	0.0321	0.0840	-0.1238	-0.0230
Children7-13	-0.0489	0.0161	-0.1250	-0.0369
Working Age	-0.0520	-0.0155	0.0204	-0.0508
cons	-2.8941	-3.0737	-2.7312	-3.4687
Lambda	0.1230	-0.5667	0.1289	-0.4084

** :p-value>0.05*

F. With Endowment Effect: Earning Equation - 1998

Variable	Salaried males	Salaried females	Self-employed males	Self-employed females
Education	0.0473	0.0578	0.0417	0.0422
Education8	0.0988	0.0546	0.1197	0.0952
Education12	0.0396	0.0500	0.0069	0.0490
Technical Edu	0.0079	0.0470	0.0360	-0.0126
Experience	0.0385	0.0013	0.0222	0.0190
Experience2	-0.0004	0.0000*	-0.0002	-0.0002
Region I	-0.0945	-0.0300	-0.1708	0.6299
Region II	0.0729	0.2175	0.0471	0.6005
Region III	-0.1388	-0.1313	-0.1551	0.4264
Region IV	-0.2692	-0.2295	-0.2325	0.2354
Region V	-0.2516	-0.0922	-0.1289	0.2318
Region VI	-0.2689	-0.0828	-0.1678	0.2653
Region VII	-0.4152	-0.2101	-0.2186	0.2394
Region VIII	-0.3511	-0.2356	-0.2084	0.2124
Region IX	-0.3865	-0.5166	-0.1733	0.4656
Region X	-0.3505	-0.3203	-0.1764	0.3380
Region XI	-0.0927	0.0972	0.0152*	0.7216
Region XIII	-0.0636	0.0382	0.0995	0.4409
Cons	10.8226	12.8455	10.6407	10.8257
Probit				
Age	0.1764	0.1077	0.1488	0.1115
Age2	-0.0021	-0.0010	-0.0020	-0.0012
Children0-2	0.1954	0.0417	-0.1301	-0.0324
Children3-6	0.1065	0.0077	-0.1017	0.0216
Children7-13	-0.0239	-0.0052	-0.1622	-0.0073
Working Age	-0.0623	-0.0074	-0.0142	-0.0536
cons	-2.9137	-3.4478	-2.8277	-3.7890
Lambda	-0.0527	-0.7072	-0.1334	-0.1487

** :p-value>0.05*

G. With Endowment Effect: Multinomial Logit - 1990

	Heads of households		Spouses		Other relatives	
Variable	Self-emp	Non-part	Self-emp	Non-part	Self-empl	Non-part
Average Education	0.0197	0.0711	-0.0315	0.0043	-0.0887	0.0406
DGender	-0.0332	-1.7424	0.1075	-2.6369	0.8328	-0.8971
Education	0.0972	0.2036	0.2116	0.3292	0.1161	-0.0954
Education2	-0.0069	-0.0106	-0.0115	-0.0239	-0.0054	-0.0045
Experience	0.0218	-0.0519	0.0608	-0.0514	0.0085	-0.2610
Experience2	0.0002	0.0020	-0.0003	0.0014	0.0007	0.0050
Children0-2	0.0282	0.2220	0.4272	0.5464	-0.0529	-0.0395
Children3-6	0.1511	0.1079	0.0110*	0.2559	0.0670	0.0617
Children7-13	0.0610	0.0452	0.0696	0.1245	-0.0760	0.0314
Working Age	-0.0455	-0.0447	-0.0014*	-0.0645	-0.0213	-0.0012*
Region I	0.1755	-0.1340	-0.3423	-0.1905	0.1876	0.3081
Region II	-0.1559	-0.1258	-0.4090	0.5434	-0.1067	0.2456
Region III	-0.1175	-0.1089	-0.5059	0.1041	0.1006	0.3671
Region IV	0.1696	-0.0111*	-0.2663	0.0925	0.2762	0.4482
Region V	0.0735	0.2239	-0.6637	0.0422	-0.0553	0.4581
Region VI	-0.1681	-0.2374	-0.5233	0.0104*	-0.4630	0.1100
Region VII	0.3331	0.1158	-0.4127	0.2527	0.2453	0.0686
Region VIII	0.0090*	0.4212	-0.1720	0.5073	0.1114	0.2913
Region IX	0.5520	0.2361	-0.2866	0.4122	0.3573	0.4592
Region X	0.0756	-0.1425	-0.2864	0.3195	0.0721	0.0747
Region XI	0.0837	-0.1388	-0.7783	-0.0185*	-0.2420	-0.0553
Region XIII	-0.0341	-0.2149	-0.3913	-0.2216	-0.1892	0.0326
cons	-2.1171	-1.6913	-2.5659	0.8948	-2.2958	3.3147

** :p-value>0.05*

H. With Endowment Effect: Multinomial Logit - 1998

	Heads of households		Spouses		Other relatives	
Variable	Self-emp	Non-part	Self-emp	Non-part	Self-empl	Non-part
Average Education	-0.0183	-0.0055	-0.0158	0.0083	0.0036	0.1169
DGender	0.1952	-1.4572	-0.2112	-2.5305	0.9129	-0.7939
Education	0.0550	0.1582	0.1189	0.1997	0.0162	-0.1957
Education2	-0.0049	-0.0077	-0.0079	-0.0168	-0.0030	-0.0025
Experience	0.0289	-0.0406	0.0367	-0.0504	0.0291	-0.2580
Experience2	0.0001	0.0018	0.0000*	0.0015	0.0004	0.0050
Children0-2	-0.0540	0.0759	0.0330	0.4529	0.1243	0.0364
Children3-6	-0.0406	0.0330	0.2098	0.3276	-0.0268	0.0794
Children7-13	-0.0198	-0.0344	0.0766	0.1940	0.0782	0.1787
Working Age	0.0103	-0.0224	0.0288	-0.0182	-0.0786	-0.0613
Region I	0.6569	0.4339	0.4711	-0.1274	0.1380	0.5339
Region II	0.2708	0.1690	0.0939	0.1427	0.1652	0.5644
Region III	0.2908	0.3070	0.2059	0.0233*	0.3172	0.9201
Region IV	0.3565	0.2070	0.0235*	-0.0579	0.3509	0.3589
Region V	0.1510	0.2197	0.0721	-0.1617	0.1593	0.3744
Region VI	-0.1215	0.1232	-0.3091	-0.0851	-0.3163	0.2865
Region VII	0.3184	0.1912	-0.1685	-0.0694	0.0646	0.2646
Region VIII	0.1312	0.6727	-0.1096	0.1638	-0.1068	0.7255
Region IX	0.8902	0.3510	0.0784	0.0578	0.5030	0.6965
Region X	0.4032	0.2671	-0.2226	-0.0736	0.4054	0.4237
Region XI	0.3337	-0.3278	-0.1780	-0.3101	0.5303	-0.0167*
Region XIII	0.2671	0.1715	-0.1021	-0.4178	0.0453	0.2512
cons	-2.3659	-1.7278	-2.4412	0.8595	-2.6623	3.4071

** :p-value>0.05*

I. Endowment Effect Equation - 1990

Variable	Children 0-2	Children 3-6	Children 7-13	Working age	Education
Age	-0.0155	-0.0153	-0.0099	0.0292	0.4741
Age2	0.0001	0.0001	0.0000	-0.0004	-0.0058
DGender	-0.0161	-0.0206	-0.0102	0.0714	0.1181
Region I	0.0570	0.0237	0.0068	0.5292	0.7696
Region II	0.0536	0.0864	0.0707	0.3798	0.5075
Region III	0.0932	0.1031	0.1453	0.4199	-0.0517
Region IV	0.0349	0.0458	0.0629	0.5170	-0.2576
Region V	0.0401	-0.0153	-0.0020*	0.2746	0.2822
Region VI	0.0386	-0.0130	0.0553	0.4046	-0.6719
Region VII	0.0129	-0.0007*	0.0641	0.4010	-0.9100
Region VIII	0.0224	-0.0046	0.0686	0.5279	-0.3530
Region IX	0.0749	0.0546	0.0610	0.4153	-0.6240
Region X	0.0183	0.0240	0.0551	0.4211	-0.7714
Region XI	0.0287	0.0063	0.0484	-0.0258	-0.8271
Region XIII	0.0355	-0.0089	-0.0695	0.4722	0.7475
Cons	0.5990	0.7416	0.9827	2.6699	0.3820

:p-value>0.05

J. Endowment Effect Equation - 1998

Variable	Children 0-2	Children 3-6	Children 7-13	Working age	Education
Age	-0.0127	-0.0140	-0.0102	0.0230	0.5233
Age2	0.0001	0.0001	0.0000	-0.0003	-0.0063
DGender	-0.0189	-0.0204	-0.0198	0.0530	0.0774
Region I	0.0755	0.0159	0.1972	.2440	0.3893
Region II	0.1224	0.0719	0.2330	0.3023	0.2391
Region III	0.0642	0.0778	0.3025	0.2784	-0.2197
Region IV	0.0821	0.0856	0.2338	0.4817	-0.2984
Region V	0.0419	0.0247	0.1574	0.4553	0.3987
Region VI	0.0744	0.0339	0.1577	0.4605	-0.7132
Region VII	0.0158	-0.0048	0.1959	0.3785	-1.0950
Region VIII	0.0378	0.0138	0.1762	0.5365	-0.2623
Region IX	0.0785	0.0321	0.2141	0.4447	-0.5131
Region X	0.0566	0.0472	0.2587	0.3572	-0.8681
Region XI	0.0295	0.0665	0.2033	0.0531	-1.1037
Region XIII	0.0437	0.0318	0.1335	0.3626	0.5961
Cons	0.4633	0.6639	0.8613	2.6499	0.2275

:p-value>0.05

K. Earning Equations: Residual Variance 1990 -1998

Case	1990	1998
Salaried Men	0.47	0.41
Self-employed Men	0 75	0.51
Salaried Women	0.38	0.40
Self-employed Women	0.94	0.71
Including Endowments		
Salaried Men	0.47	0.41
Self-employed Men	0.78	0.58
Salaried Women	0.39	0.41
Self-employed Women	0.95	0.72

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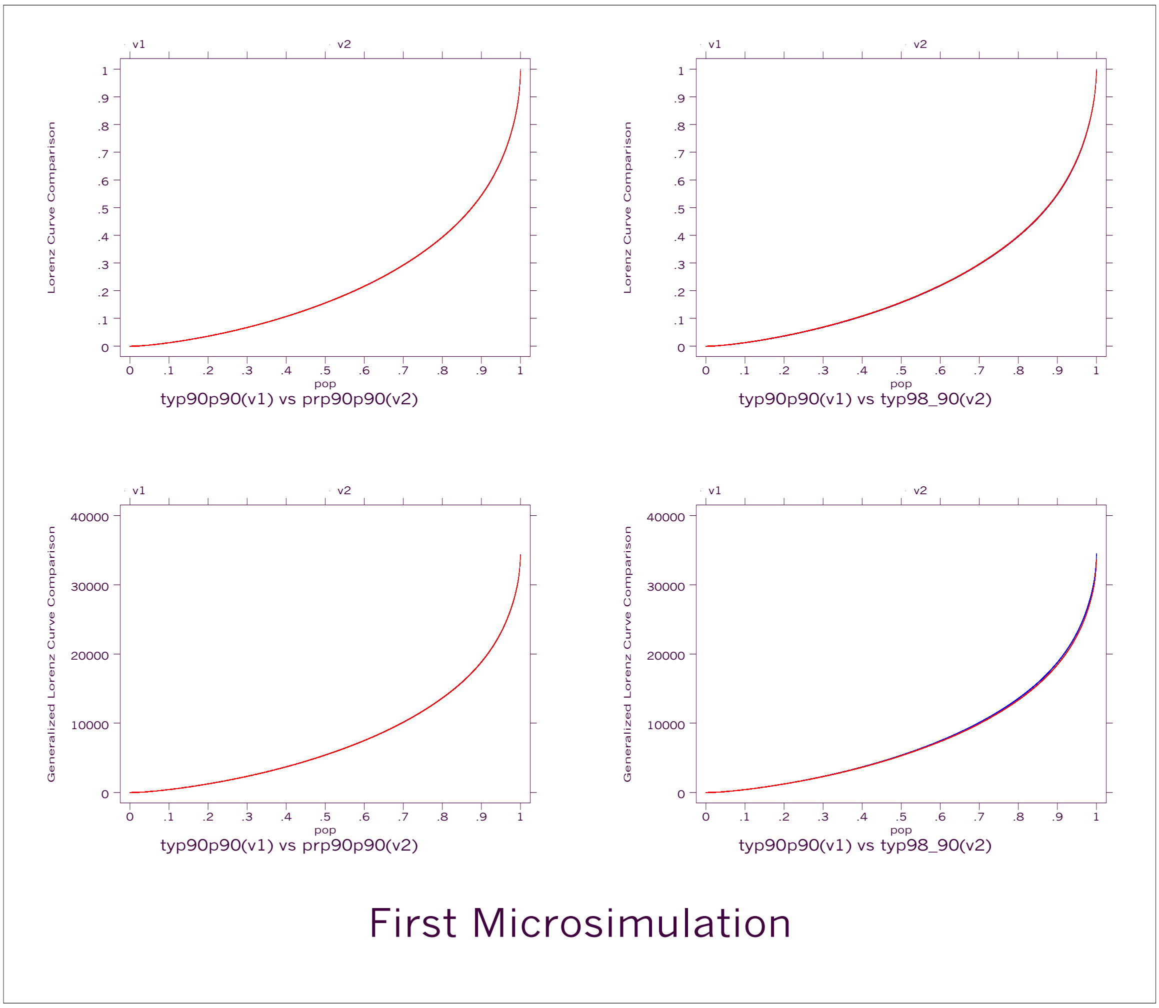
I.- Without Endowment Effect

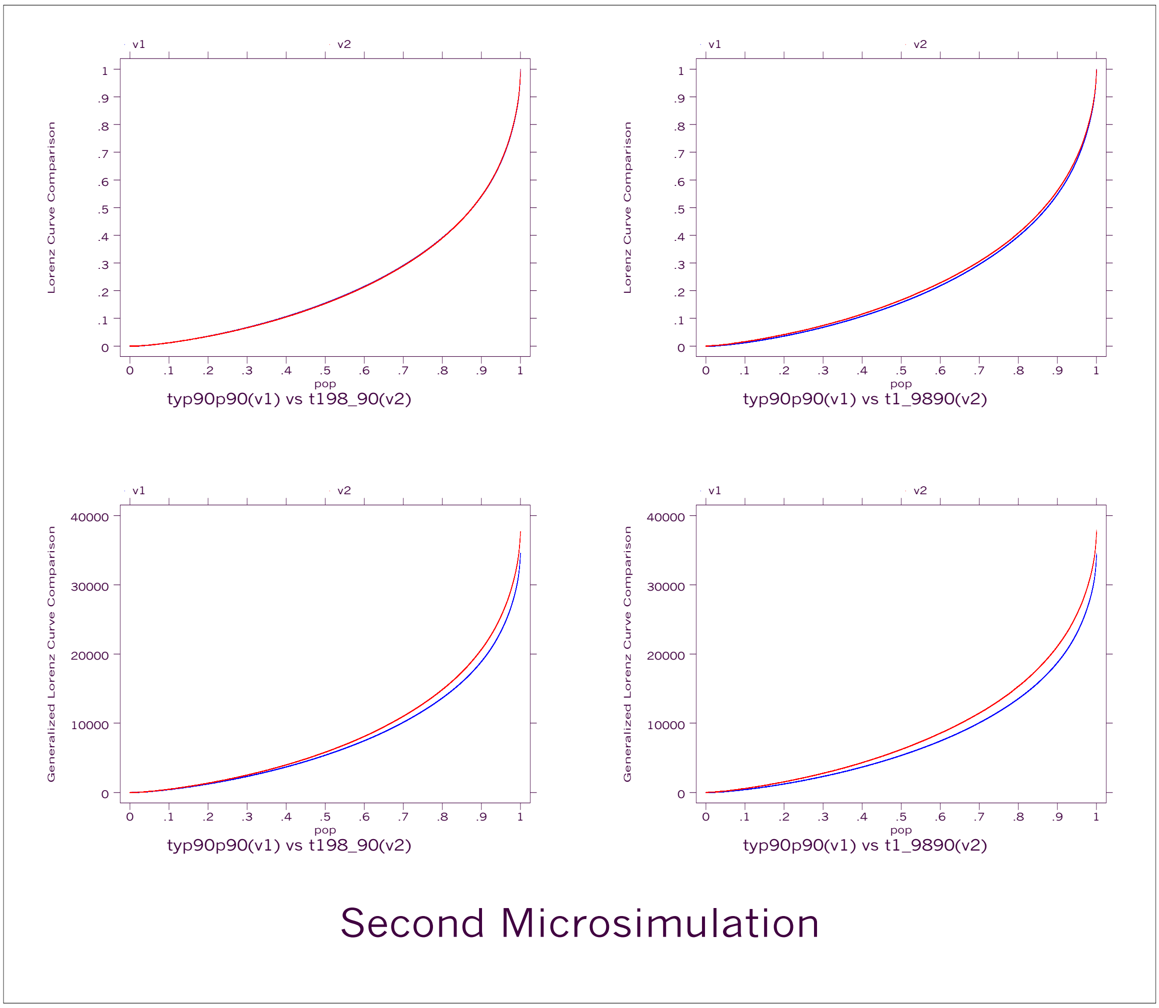
Figure 1
First Order Stochastic Dominance: Estimated 1990 vs Observed 1990



Note: The first graph (upper left) compares the Lorenz curve observed in 1990 with that estimated by the model. The second (upper right) compares the Lorenz curve observed in 1990 with that predicted by the model, but now including the participation effect. The lower two graphs the same logic is applied but in the context of Generalized Lorenz curve

Figure 2

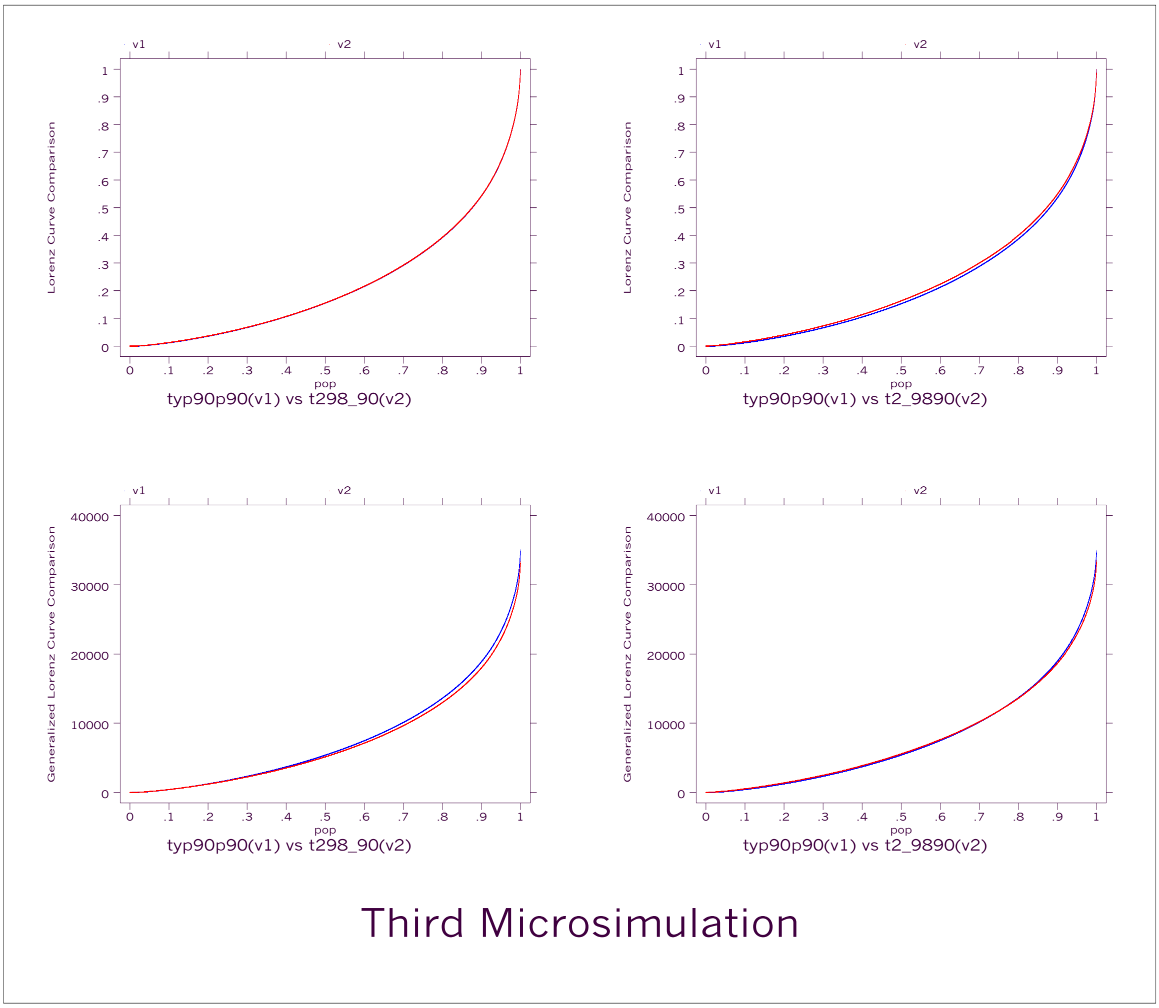
First Order Stochastic Dominance: Education (price) effect vs Observed 1990



Note: The first graph (upper left) compares the Lorenz curve observed in 1990 with that estimated by the model when the education (price) effect is applied. The second (upper right) compares the Lorenz curve observed in 1990 with that predicted by the model when the education effect is applied, but now including the participation effect. The lower two graphs the same logic is applied but in the context of Generalized Lorenz curve

Figure 3

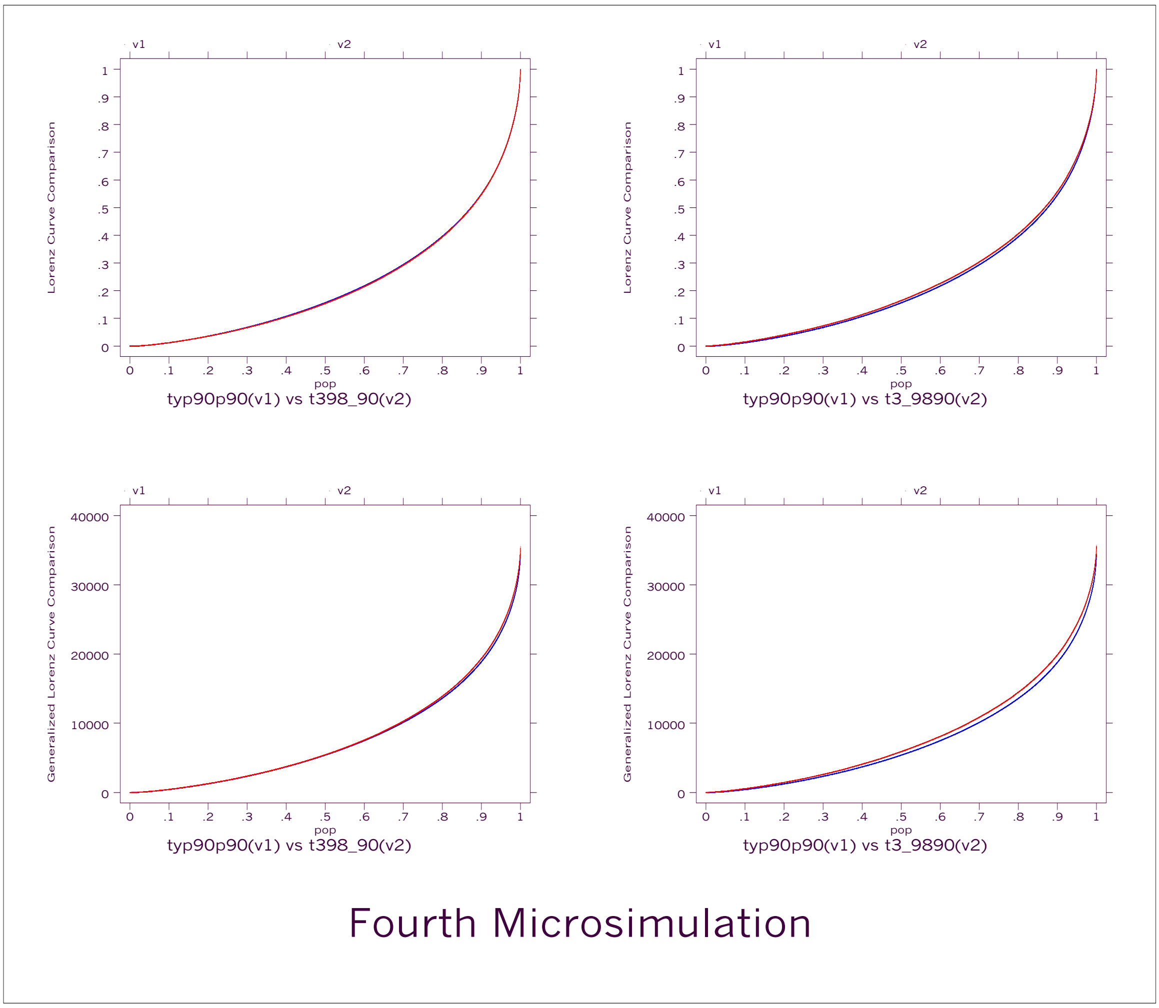
First Order Stochastic Dominance: Experience (price) effect vs Observed 1990



Note: The first graph (upper left) compares the Lorenz curve observed in 1990 with that estimated by the model when the experience (price) effect is applied. The second (upper right) compares the Lorenz curve observed in 1990 with that predicted by the model when the experience effect is applied, but now including the participation effect. The lower two graphs the same logic is applied but in the context of Generalized Lorenz curve

Figure 4

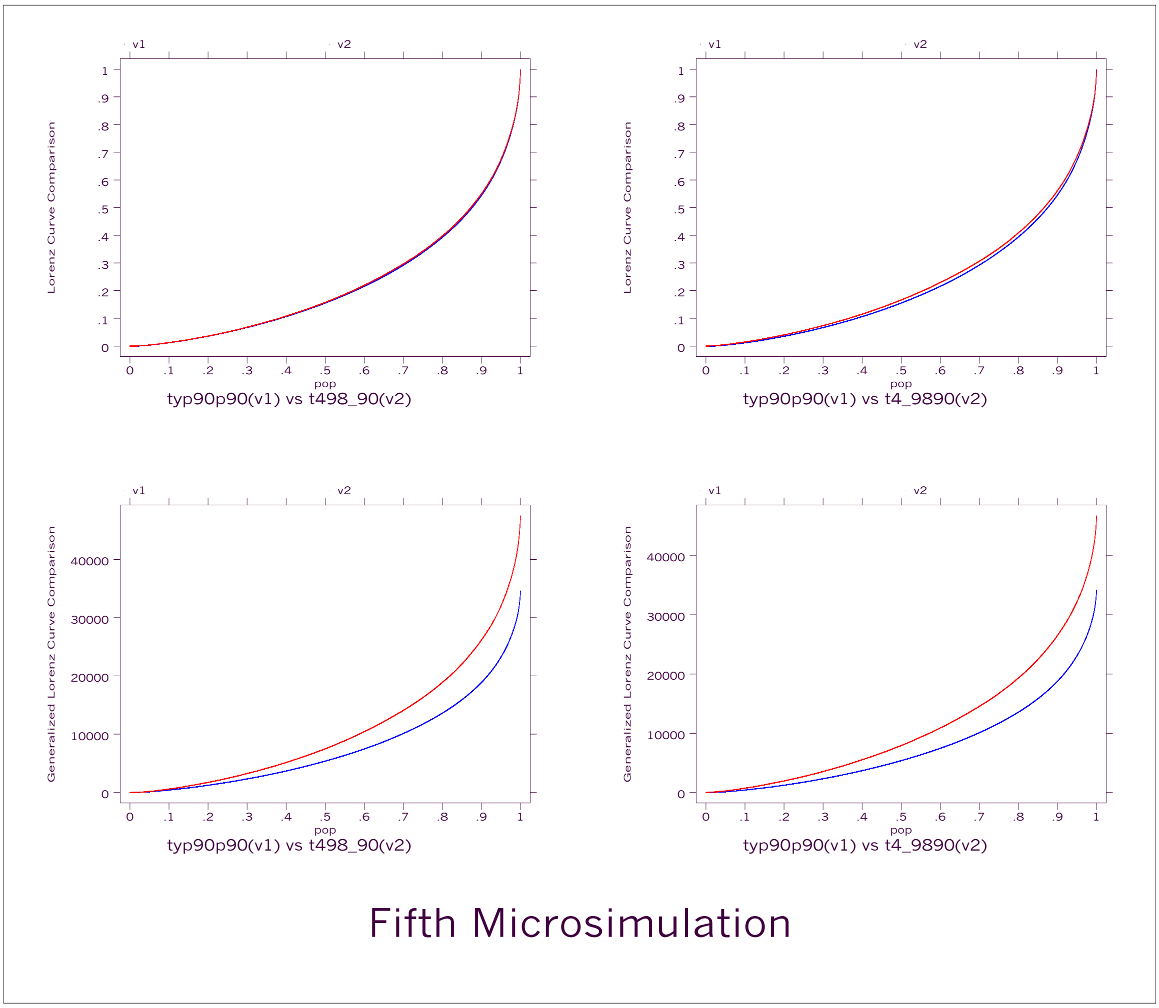
First Order Stochastic Dominance: Education and Experience (price) effects vs Observed 1990



Note: The first graph (upper left) compares the Lorenz curve observed in 1990 with that estimated by the model when the experience and education (price) effects are applied. The second (upper right) compares the Lorenz curve observed in 1990 with that predicted by the model when the experience and education effects are applied, but now including the participation effect. The lower two graphs the same logic is applied but in the context of Generalized Lorenz curve

Figure 5

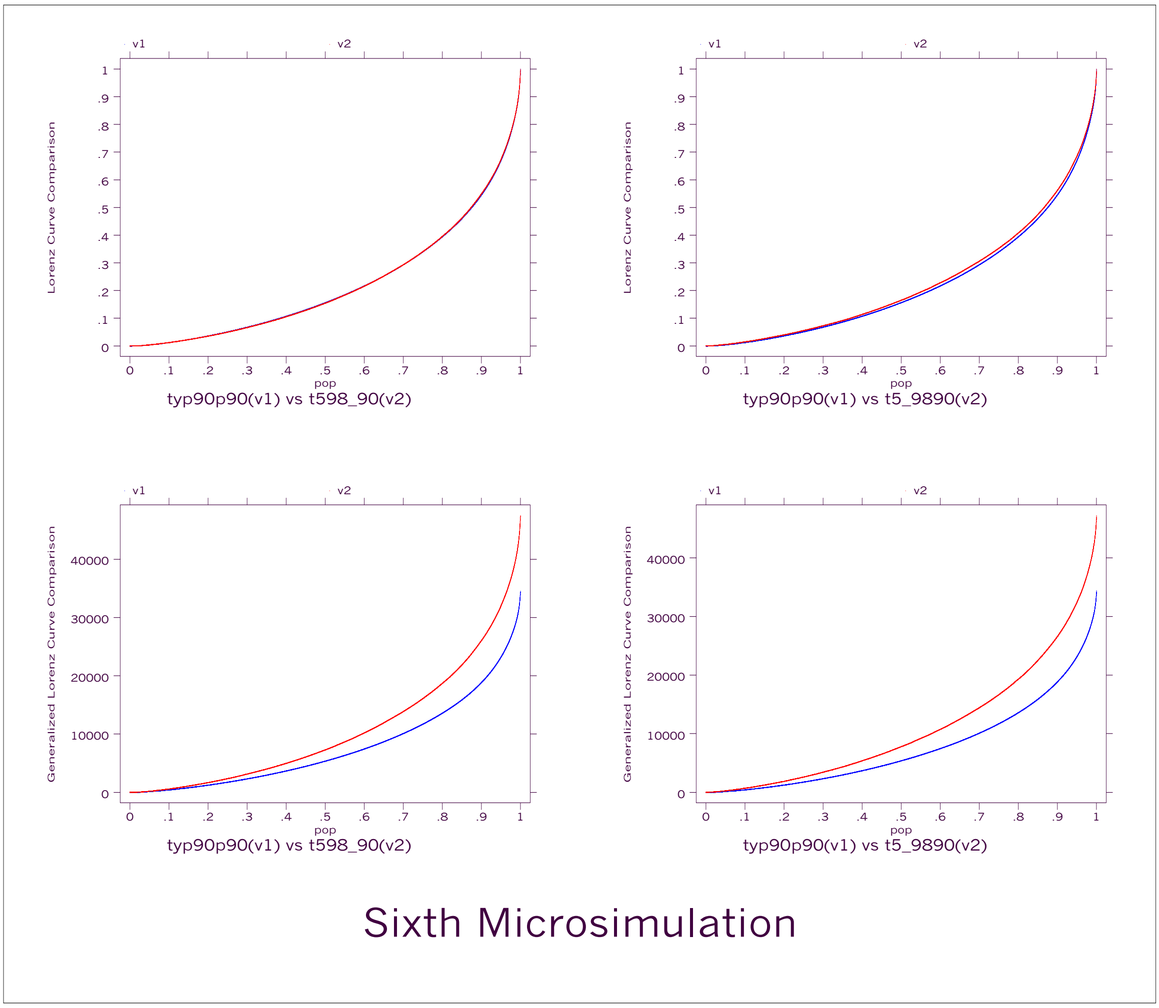
First Order Stochastic Dominance: Region (price) effect vs Observed 1990



Note: The first graph (upper left) compares the Lorenz curve observed in 1990 with that estimated by the model when the region (price) effect is applied. The second (upper right) compares the Lorenz curve observed in 1990 with that predicted by the model when the region effect is applied, but now including the participation effect. The lower two graphs the same logic is applied but in the context of Generalized Lorenz curve

Figure 6

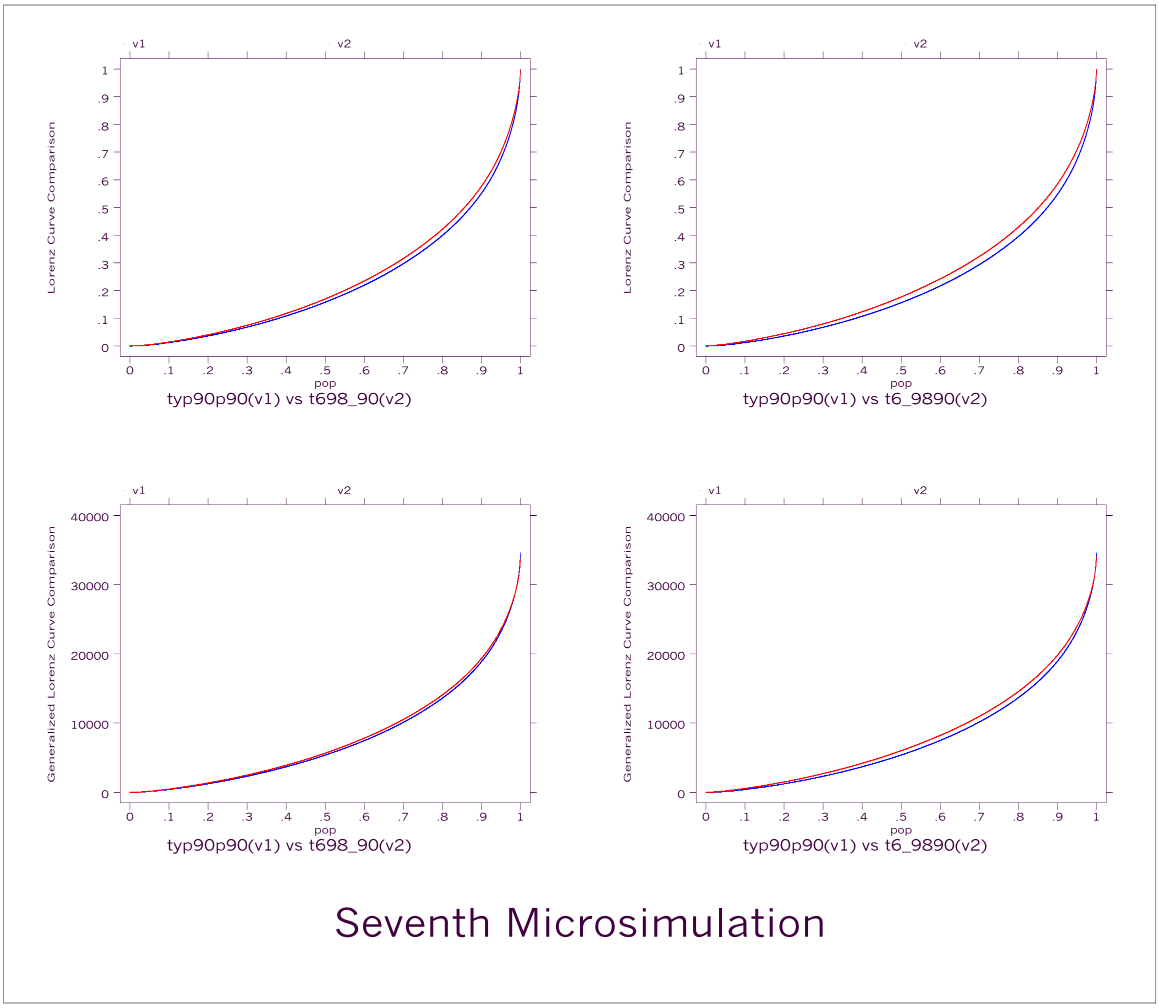
First Order Stochastic Dominance: Price effect vs Observed 1990



Note: The first graph (upper left) compares the Lorenz curve observed in 1990 with that estimated by the model when the price effect is applied. The second (upper right) compares the Lorenz curve observed in 1990 with that predicted by the model when the price effect is applied, but now including the participation effect. The lower two graphs the same logic is applied but in the context of Generalized Lorenz curve

Figure 7

First Order Stochastic Dominance: Non-observables effect vs Observed 1990



Note: The first graph (upper left) compares the Lorenz curve observed in 1990 with that estimated by the model when the non-observables effect is applied. The second (upper right) compares the Lorenz curve observed in 1990 with that predicted by the model when the non-observables effect is applied, but now including the participation effect. The lower two graphs the same logic is applied but in the context of Generalized Lorenz curve