FERTILITY, INEQUALITY AND GROWTH: THE CASE OF URUGUAY

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Fertility may have direct effects on income growth and inequality. If fertility rates increase for the poor but decrease for the rich, this may affect income growth downwards and, most of all, it may have a considerable impact on income inequality. If income growth and inequality are potentially affected, poverty incidence may also change.

We estimate the magnitude of the effects of fertility changes on mean income and specially, on the distribution of income and on poverty for a middle income Latin American country, Uruguay. The specific question that we are trying to address is how much of the change in income inequality and in poverty, that took place over the past twenty years (1986-2006) in Uruguay is caused by differential changes in reproductive behaviour. The paper is organized as follows: first we present some basic information about fertility, income distribution and economic growth in Uruguay (section 1). Then we outline the methodology of microsimulation (or microeconometric decompositions) (section 2). Afterwards, we present the main results of our microsimulations (section 3) and finally we present some final comments (section 4).

1. Fertility, inequality and growth in Uruguay

1.1 Demographic factors

Uruguay is the country with lower incidence of poverty and income inequality in Latin America (CEPAL, 2007). It also has one of the lowest total fertility rates (TFR) in the region: only Chile and Cuba present lower rates. During the last 25 years, all countries in the region have experienced a decrease in TFR.

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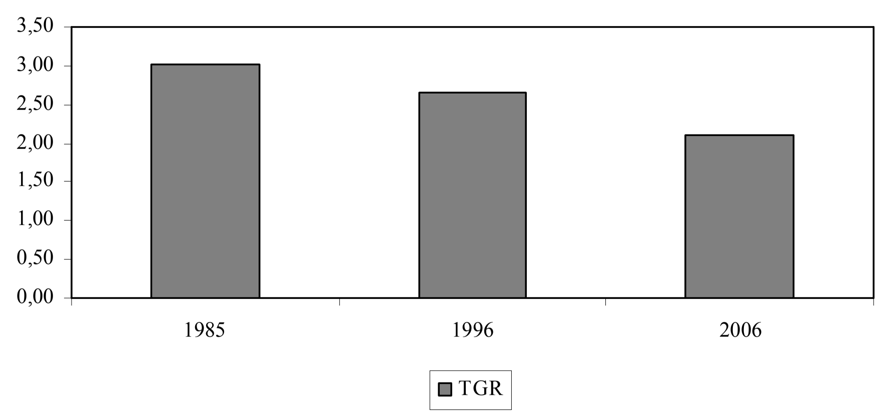
Uruguay has also gone through that process: its TFR has decreased from 3,02 in 1985 to 2,66 in 1996, and finally lowered to 2,11 in 2006 (Graph 1)[2]. In this way, the current TFR of Uruguay is very close to the replacement level. It must be noted that changes related to the first demographic transition took place in Uruguay by the end of the XIX century and the beginning of the XXth, an early date compared to the rest of the region.[3] This led to fertility and mortality showing low rates by the seventies. From then on, these indicators continued to present a decreasing trend, but at a slower pace (Pellegrino, 2003).

Graph 1. Evolution of Total Fertility Rate. Uruguay. 1985, 1996 and 2006



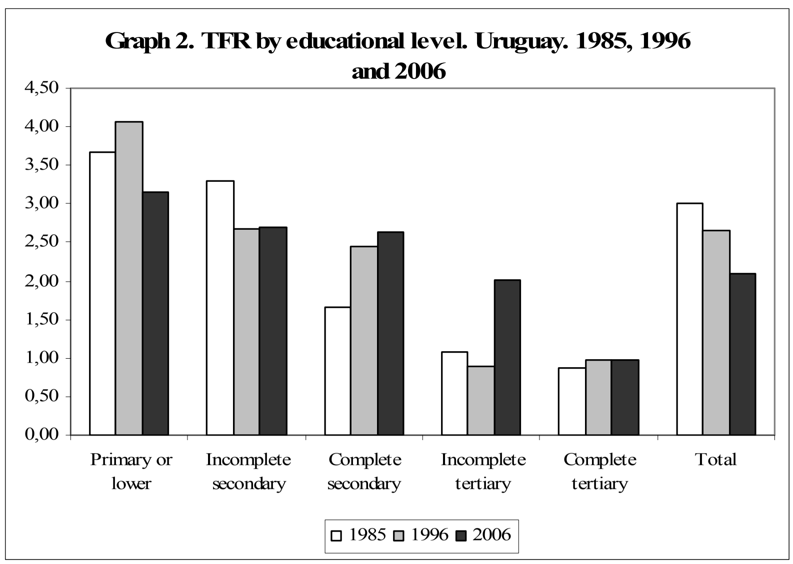
Source: own estimations based on CPV85, CPV96 and ENHA06.

The stylized fact of decreasing TFR with level of education is also found in Uruguay. In 2006, TFR among more educated women (with complete tertiary education) was lower than one (0.96), whereas among less educated women (primary education or less) it reached

[2] Figures of TFR for Uruguay are calculated using census data for 1985 and 1996, and data from the household survey in 2006. In that year the household survey included, for the first time, questions about the number of born children, so this data is used to calculate TFR for 2006, as the next census will only be available in 2010. TFR calculations are corrected following Brass (1974) procedure. The evolution of the Uruguayan TFR based on administrative records and population projections is presented in Figure A.1. It is only available for the period 1996-2006.

[3] Demographic transition refers to a sequence of three periods: in the first period, fertility and mortality rates are high and mortality tends to be highly variable, with population growth fluctuating widely. In the second period, age specific mortality decreases, raising life expectancy and accelerating population growth. In the third period, the secular decline in fertility begins and population growth levels off.

3.15. The overall decreasing trend in fertility during the past twenty years is the result of different behaviours at different socio economic strata (Graph 2). Although the pattern is not completely clear, the decrease in TFR between 1986 and 1996 was mainly due to the decrease in the fertility of women with medium and higher education (incomplete secondary and tertiary). In that period women with primary education or lower increased their fertility rate. An important change took place in the following decade, as the decrease in TFR between 1996 and 2006 is mainly driven by the change in reproductive behaviour of women with lower education: TFR of women with primary education or lower decreases from 4.1 to 3.1. A similar decrease in fertility among less educated women in recent years is reported for all Latin American countries by Chackiel and Schkolnik (2004).



Source: own estimations based on CPV85, CPV96 and ENHA06.

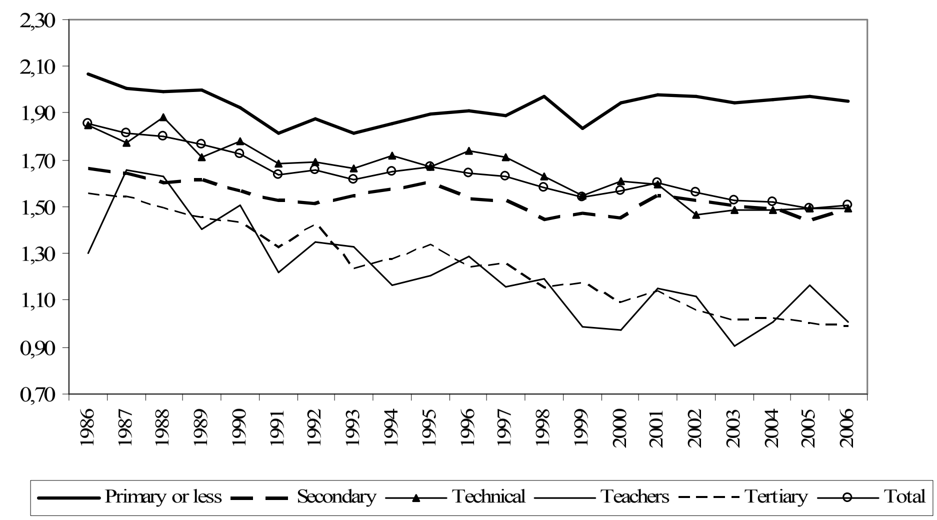
The simulations carried out in this paper are based on the Uruguayan household surveys for 1986, 1996 and 2006, as they are the only available source of detailed information on income.[4] Only the 2006 survey includes the questions that allow computing TFRs. For that reason, our exercise has to be based on a proxy of fertility: the number of children in the household. This variable is often used as a proxy for fertility in the economic literature

[4] Ideally, we would like to consider the household survey for 1985, the same year of the census. But this data base is not available.

(Paes de Barro *et al* 2000; Klasen and Woltermann 2005, Gasparini and Marchionni 2007, among others).

For the analysis of the number of children in the household, we can construct the whole time series for the period 1986-2006. The number of children decreased during the last twenty years in all households, no matter the educational level. Nevertheless, the rates were differential according to the household head's education (Graph 3).

Graph 3. Number of children per household and educational level. Household head lower than 50



Source: based on household survey

The pattern is clearer when we consider the number of children instead of the fertility rate. During the period, the number of children decreased almost 19%, changing from 1,86 to 1,51 (estimations based on households whose head is younger than 50). The rate of change has been higher the higher the level of education of the household head. Whereas the number of children decreased 5,4% for those households where the head had primary education or less, it decreased 36,5% when we consider households headed by persons with tertiary education (Table 1). [5]

[5] Although the number of children per household is usually considered as a proxy of fertility, both variables do not exactly reflect the same. In our case, we are considering the level of education of household head, and not mother's level of education.

Table 1. Change in the number of children per household. Household head younger than 50.

	Primary or less	Secondary	Technical	Teachers	Tertiary	Total
1986-1996	-7,6%	-7,8%	-5,9%	-1,2%	-20,5%	-11,7%
1996-2006	2,4%	-2,7%	-14,2%	-21,5%	-20,1%	-8,1%
1986-2006	-5,4%	-10,3%	-19,3%	-22,4%	-36,5%	-18,9%

Source: based on household surveys

As expected, the analysis by income decile shows a similar pattern.[6] The rates of decrease of the number of children were differential by income decile (Table 2). The mean average change in the number of children for households belonging to deciles 1 to 5 was 15,5% for the period 1986-2006, whereas the figure for deciles 6 to 10 was 29,4%.

Table 2. Average number of children by income decile. Households with head younger than 50. 1986-2006.

	Average number of children			Percentage change		
	1986	1996	2006	1986-1996	1996-2006	1986-2006
Decile 1	3,51	3,25	2,96	-7,2%	-9,1%	-15,6%
Decile 2	2,76	2,42	2,49	-12,4%	3,1%	-9,6%
Decile 3	2,29	1,98	2,02	-13,5%	2,4%	-11,5%
Decile 4	2,10	1,79	1,69	-14,8%	-5,2%	-19,3%
Decile 5	1,81	1,59	1,42	-12,2%	-10,7%	-21,5%
Decile 6	1,62	1,37	1,23	-15,4%	-10,3%	-24,1%
Decile 7	1,51	1,30	1,04	-13,8%	-20,6%	-31,5%
Decile 8	1,36	1,07	0,90	-21,4%	-15,6%	-33,6%
Decile 9	1,10	0,96	0,78	-13,4%	-18,6%	-29,5%

[6] The concept of income refers to per capita household income, and includes social benefits and imputed rents for housing.

Decile 10	0,92	0,75	0,66	-18,5%	-12,2%	-28,4%
Total	1,86	1,64	1,51	-11,7%	-8,1%	-18,9%
Dec.10/Dec. 1	0,262	0,231	0,223			
Source: based on household surveys						

These data show that fertility behaviour is not homogenous along income strata. Lower education women show higher fertility, a pattern found in all countries. Whereas from 1986 to 1996 the decrease in total fertility seems to be driven by educated women, the decreasing trend found between 1996 and 2006 is mainly explained by the behaviour of less educated women.

If we consider the number of children in the household, the decreasing trend of the last twenty years is mainly explained by households whose head is highly educated.

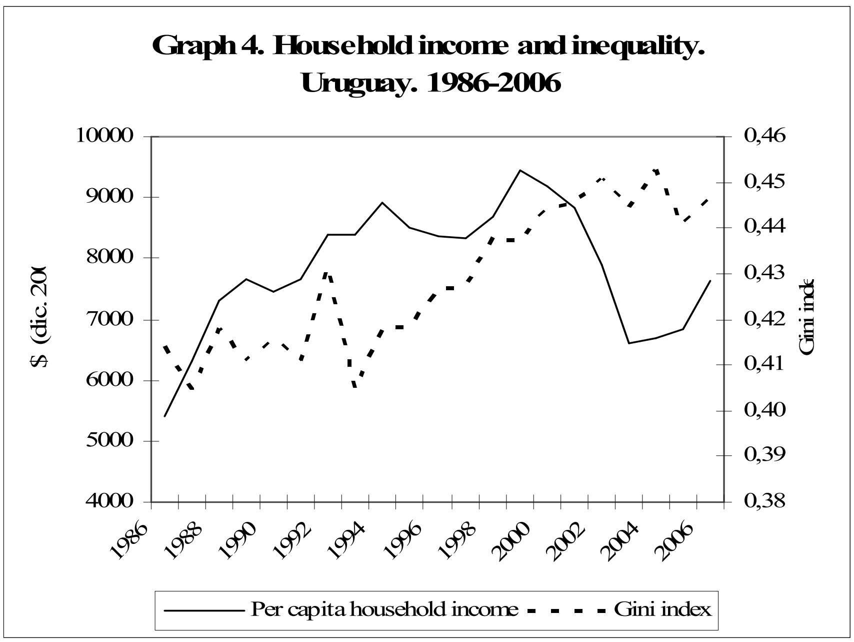
1.2 Income growth, inequality and poverty

In our micro-simulation, the growth component is reflected by household income and not by GDP changes as in the macroeconomic strand. Although both variables differ in their contents, they show a very high correlation and similar evolution.[7] During the last twenty years, average per capita household income showed important fluctuations in Uruguay. From 1986 to 1994 it increased steadily in real terms. Between 1995 and 1997 there was a small decline in household real income, followed by two years of considerable increase (4% in 1998, 9% in 1999). After that, a period of recession began, and finished in the severe economic crises of 2002 and 2003. This recessive episode was due to a series of domestic and external shocks and implied an acute crisis of the financial system. In 2002 GDP fell 11 % and the exchange rate slumped 90%. The recession also had a severe impact on unemployment, which reached its highest level in the last twenty years: 17% of the active population. Household income, on the other hand, suffered a severe drop starting in 1998. Between 1998 and the end of 2002, it was cut by more than a fifth, leaving it at a level 7% lower than in 1991. Most of the fall occurred after 1999 and particularly during 2002 (World Bank, 2004).

[7] The correlation between GDP per capita and per capita household income is 93% for Uruguay for the period 1991-2006.

Although GDP began to recover in 2003, household income again decreased significantly that year (16%), and it only began to recover in the last two years of the period. Nevertheless, household income has still not reached the pre-crises level.

In regard with income inequality, it did not show important changes in the first ten years of the period under analysis[8]. For that reason, income distribution was described as stable until the mid nineties (Vigorito, 1999). From then on, all the inequality indexes show an increasing trend. The Gini index, for example, was 0.41 in 1986, 0.42 in 1995, and rose to 0.45 in 2006 (Graph 4). Other inequality indexes show a similar pattern (see Figure A.2).



Source: based on household surveys

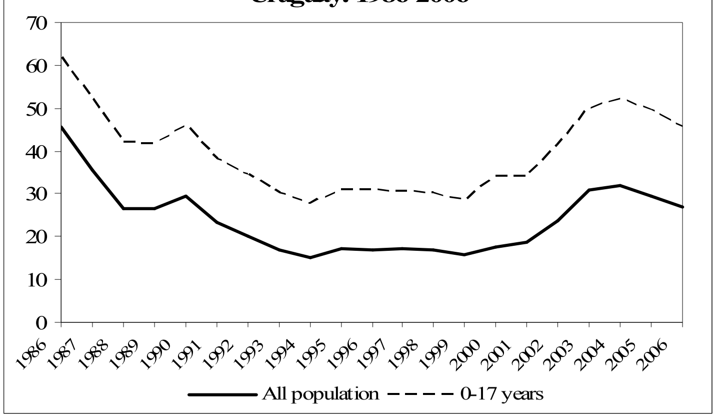
This increase in income inequality at the household level comes from the labour market, as it is mainly explained by the increase in wage inequality. This is related to the fact that returns to skills increased significantly during the nineties. Different factors may have influenced the evolution of returns: openness, skill biased technological change, changes in wage bargaining, different evolution of real public transfers, among others (Bucheli and

[8] Uruguay is the country with lower income inequality in Latin America

Furtado, 2005; PNUD, 2005).The relative importance of each factor as an explanation of the increase in inequality remains a matter of discussion.

Poverty decreased significantly between 1985 and 1995, and remained stable between 1996 and 1999 (Graph 5 and Table A.19). During 1999-2002 it increased by more than 8 percentage points (almost 60%). Most of this increase occurred during 2001-2002, poverty incidence almost doubled during that year. As mentioned, GDP began its recovery in 2003 (in that year it rose 2,2%), but household income and poverty did not. Only in 2004 a slight decrease in poverty is found. This trend went on the two following years. Nevertheless, poverty incidence has still not recovered its pre-crises level.

Graph 5. Poverty incidence. Uruguay. 1986-2006



Source: based on household surveys

Poverty profiles about Uruguay always emphasize the differences of poverty incidence among age groups (World Bank 2003; Amarante *et al* 2005; PNUD 2005). Child poverty was 45.6% in 2006, whereas poverty incidence among the whole population was 26.8%. This difference between child and adult poverty incidence is found for most Latin American countries, although the pattern is more acute in the case of Uruguay.

As an illustration, the levels of the variables of interest for our micro-simulation in three points in time, 1986, 1996 and 2006 are depicted in Table 3. Based on their evolution, discussed above, we selected these cutting points for the micro-simulations. Between 1986 and 1996 poverty and TFR (or its proxy, the number of children in the household) fell significantly whereas inequality slightly increased. In the following decade, the increasing trend in inequality went on, as well as the decreasing trend in the demographic variables. Meanwhile, poverty increased almost ten points between 1996 and 2006. In the following sections we will try to isolate the role that demographic factors have played in poverty and inequality evolution.

Table 3. Poverty, inequality and demographic indicators. 1986, 1996 and 2006

	Poverty incidence	Gini index	Theil index	Nº of children per household	TFR
1986	45,6	0,414	0,302	1,86	3,02*
1996	17,0	0,426	0,319	1,64	2,66
2006	26,8	0,446	0,34	1,51	2,10

*Corresponds to 1985.

Source: based on household surveys, CPV85 and CPV96

2. Methodological aspects: microsimulation technique

Micro-simulation techniques have recently emerged as useful instruments for economic analysis and policy recommendations. The well-known micro-econometric decompositions proposed by Oaxaca (1973) and Blinder (1973) for the study of the labour markets are early examples of the application of this technique. A generalized approach was developed by Bourguignon, Ferrerira and Lustig (1998), and applied in Bourguignon, Forunier and Gurgand (2001), among others. The availability of large and detailed datasets on individual agents and the continuing increases in, and falling costs of computing power, are among the reasons of the intensification in the use of this methods, according to Spadaro and Bourguignon (2006).

We attempt to use this method to assess the importance of fertility decisions on mean income or income distribution, based on household micro data for a specific Latin American country, Uruguay. Examples of micro-simulations for fertility decisions can be found in Ferreira and Leite (2002) and Marchionni and Gasparini (2007). This kind of counterfactual analysis is mainly based in the descriptions of the statistical associations present in the data.

2.1 Micro-simulation model to analyze mean and income distribution

We take the adaptation of micro-simulation techniques proposed by Marchionni and Gasparini (2007) to analyse the role of fertility in Argentina. Following their proposal, D_t is per capita household income distribution corresponding to the N individuals in an economy in time t: [9]

$$D_t = \{y_{1t}, y_{2t}, \ldots, y_{nt}\} \tag{33}$$

where y_{it} is the ratio between Y_h, total income of the household, and N_h, the family size

$$y_{it} = \frac{Y_{ht}}{N_{ht}} \qquad \forall i \in h \text{ in } t \tag{34}$$

Family size is the sum of adults (A_{ht}) and children (Ch_{ht}) in the household:

$$N_{ht} = Ch_{ht} + A_{ht} \tag{35}$$

Per capita household income of individual i is affected by fertility decisions in two ways: the increase in the number of children increases the denominator of the equation and, keeping other things constant, reduces per capita income for all household members. The number of children also affects the labour participation decision of some household members, modifying hours of work or the probability of participating in the labour market, and so affecting the numerator of the equation.

[9] Marchionni and Gasparini (2007) consider equalized household income instead of per capita household income. In the case of Uruguay, there are no official scales of equivalence, and previous evidence shows that results regarding income distribution and even poverty do not change significantly once equivalence adjustment is introduced (Rodríguez and Vigorito, 2003).

Theoretical and empirical economic literature about the links between labour force participation, fertility and education decisions is abundant, as estimating causal relationships among these variables is an extremely challenging empirical problem (Killingsworth and Heckman, 1986; Angrist and Evans, 1998 among others). We do not attempt to address or solve this problem in this research, but just want to make it clear that we are aware of it.

Total household income Y_{ht} is the sum of labour (L) and non labour incomes (NL) of all household members:

$$Y_{ht} = \sum\nolimits_{\forall i \in h} (Y_{it}^{L} + Y_{it}^{NL}) \tag{36}$$

Non labour incomes are exogenously determined, whereas individual *i*'s labour income is the product of the hourly wage rate (w) and the number of hours of work (L).

$$Y_{it}^{L} = w_{it}.L_{it} \tag{37}$$

Labour market decisions can be modelled as originally proposed in Heckman (1974).[10] Labour market reduced form equations are derived from a structural system obtained from a utility maximization problem of labour-consumption decisions. Wages (w^*) are interpreted as marginal valuations of labour. They are a function of hours of work and other personal characteristics, and represent the minimum wage for which the individual would accept to work a certain number of hours. In equilibrium, if the individual decides to work, the number of hours devoted to labour should equate their marginal value w^* with the wage received (w). If the marginal value is greater than the wage offered, given the individual's characteristics, the person chooses not to work.

Then it is possible to model market determinants of wages offered (w) as a function of personal characteristics (standard Mincer equation). In equilibrium, the number of hours of

[10] We follow Gasparini *et al* (2004).

work adjusts to make w=w^*. Under general conditions, it is possible to derive a reduced form for the equilibrium relations in which wages and hours of work are expressed as functions of the exogenous variables. In this way, the model has two equations, one for wages (w^*) and the other for hours of work (L^*). These variables are functions of factors that affect wages (X_1) and hours (X_2), and that may or may not have elements in common. For our specific purposes, the number of children, *Ch*, enters the labour supply equation. ε_1 and ε_2 represent unobservable factors that affect the determination of hours and wages.

For estimation purposes, we observe positive values of w^* and L^* only for those individuals that actually work. So the reduced form model for wages and hours of work for individual *i* can be specified as:

$$w_{it}^* = X_{1it}\beta_t + \varepsilon_{1it} \tag{38}$$

$$L_{it}^* = X_{2it}\gamma_t + \lambda_t Ch_{it} + \varepsilon_{2it} \tag{39}$$

with

$$w_{it} = w_{it}^* \qquad \text{if} \qquad L_{it}^* > 0 \tag{40}$$

$$w_{it} = 0 \qquad \text{if} \qquad L_{it}^* \le 0 \tag{41}$$

$$L_{it} = L_{it}^* \qquad \text{if} \qquad L_{it}^* > 0 \tag{42}$$

$$L_{it} = 0 \qquad \text{if} \qquad L_{it}^* \le 0 \tag{43}$$

It can be assumed that

$$(\varepsilon_{1it}, \varepsilon_{2it}) \sim N(0,0,\sigma_{1t}^2, \sigma_{2t}^2, \rho_t) \tag{44}$$

Then the specification of equations (37) and (38) correspond to the Tobit Type III model in Amemiya (1985). The parameters can be estimated through the estimation of (37) by

Heckman's maximum likelihood method[11], using a censored version of (38) as selection equation, and estimating (38) using a Tobit model.

Fertility decisions, or more precisely the number of children in the household, are determined by some household observable characteristics (Z_{ht}), some unobservable characteristics (ε_{3ht}), and the vector of parameters (η_t) that describe fertility decision:

$$Ch_{ht} = Ch(Z_{ht}, \varepsilon_{3ht}; \eta_t) \qquad (45)$$

In order to simulate the number of children in year *t* if the fertility parameter were that of *t'*, we followed the strategy proposed in Marchionni and Gasparini (2007). They explain that, since the objective is to simulate changes in the number of children as a consequence only in the parameters of fertility, it is necessary to keep unobservable factors fixed. To do this, they characterize each household by the quantile it occupies in the distribution of children in year *t*. The simulated number of children for each household will be the one that places it in the same quantile of the distribution of children with the relevant parameters of *t'*, conditional on the observable characteristics in *t*. This was the strategy adopted in this research. The modelling and estimation of equation (44) is carefully explained in the following section.

The combination of equations (35) to (38) and (44) implies that household income depends on the following variables and parameters:

$$y_{ht} = F\left(Y_{it}^{NL}, X_{1it}, X_{2it}, Ch_{ht}, Z_{ht}, \beta_t, \gamma_t, \lambda_t, \eta_t, \varepsilon_{1it}, \varepsilon_{2it}, \varepsilon_{3ht}\right) \forall i \in h \qquad (46)$$

where *X* and *Z* may have variables in common.

[11] The log likelihood of this regression model combines the classical regression for the non limit observations (positive hours) and the probability of participation for the limit observations (individuals not working) (Greene, 2000).

The change of some of the parameters in this equation allows simulating incomes. In our case, we would like to simulate the number of children that household *h* in year *t* would have if fertility parameters were that of year *t'*, that is $Ch_{ht}(\eta_t^{'})$.

Once the counterfactual number of children $Ch_{ht}(\eta_t^{'})$ is estimated, per capita household income in equation (2) has to be recalculated, as the denominator changes. The change in income distribution resulting of this change in the number of children is called *direct-size effect*. It reflects the contribution of the change in fertility parameters η to the change in income distribution through the direct channel, the change in the number of household members.

The second step consists on estimating the hours of work using the counterfactual number of children. With a different number of children, hours of work of individuals will change and this will imply different individual and household income (numerator of (34)). This implies computing the income that an individual of household *h* would have had at time *t* if the labour market participation decisions had changed in response to the number of children simulated using the fertility parameters of time *t-1*, keeping all other things constant, even the number of people in the household. This simulated individual income allows to compute a simulated household income, and to compute the distributional impact of a change in the hours worked by individual *i* caused by a change in the number of children between years *t* and *t'*. The family size in the denominator is kept constant. This effect is called the *hours-size effect*.

Marchionni and Gasparini (2007) propose a third simulation consisting of considering the counterfactual distribution in time *t* if parameter λ took the value estimated in year *t'*. This parameter reflects the impact of a change in the number of children on individual's hours of work. The distributional impact of changes in these parameters of the hours of work equation is named *hours-parameter effect.*

In order to perform the second and third micro-simulations, results on the simulated hours of work for all individuals, and their predicted wages, are needed. This implies having residuals for the hours of work and the wage equations for all individuals. These residual terms are not available for individuals who are not working at year *t*. To obtain an estimation of residuals from both the hours of work and the wage equation, they were randomly sampled from the distribution of residuals (hours and wage) for working people at time t. If the resulting prediction for year t is not consistent with the participation behaviour of the individual in year t, these residuals were discarded. The process goes on until convergence was achieved.

2.2 Fertility decisions

To perform these simulations it is necessary to estimate fertility and labour income models. In the following paragraphs we discuss the issues related to the modelling of fertility decisions.[12]

The variable *Chi*, that reflects the number of children ever born by woman i (or the number of children in the household in our case), must be a non-negative integer m=0,1,2…… For this reason, the use of count data models for this dependent variable has been recommended in the literature, as they provide better specifications than linear models for demographic data (Winkelmann and Zimmermann, 1994; Wang and Famoye, 1997; Melkersson and Rooth, 2000, among others). In spite of that, some empirical research is based on OLS estimation of fertility equations, as authors argue that results do not differ considerably (Klawon. and Tiefenthaler, 2001; Veloso, 1999; among others)[13]. Multinomial logit specification of fertility decisions is also found in the economic literature (see for example Ferreira and Leite 2002). Nevertheless, count data models are the most extended in the demographic and economic literature.

Among the count data models more often used to model fertility are the standard Poisson and the negative binomial.

The specification of fertility equations through standard Poisson regression has some advantages. First, it captures the discrete and non negative nature of data, and second, it allows inference to be drawn on the probability of event occurrence. In this way, it accounts for the heteroscedastic and skewed distribution inherent in non-negative data, and attributes a non negligible probability to the outcome zero.

[12] Fertility studies also analyze the timing and spacing of births, modelling fertility dynamics. The data requirements for this type of study are high.

[13] Nguyen-Dinh (1997) mentions a review made by Cochrane (1983) that finds dozens of least squares estimations of fertility.

The Poisson regression model specifies that each Ch_i is drawn from a Poisson distribution with parameter ηi, which is related to the regressors Z. The Poisson density can be expressed as:

$$f(ch_i | Z_i \rangle = \exp(-\eta_i)\eta_i^{ch_i} / ch_i! \qquad (40)$$

where $\eta_i = E(Ch_i | x_i)$ is the expected number of children, conditional on individual characteristics of woman (x_i).

The conditional mean is equal to the conditional variance in the Poisson distribution:

$$E(Ch_i | x_i) = V(Ch_i | x_i) = \eta_i \qquad (41)$$

The property of equality of the mean and variance of a Poisson distributed variable results from the assumption of independence among events. The Poisson model is simply a log linear regression and can be estimated by the maximum likelihood method (Greene, 2000).

As mentioned, the main disadvantage of the Poisson regression is that it implies an equi-dispersion condition, which turns out to be very restrictive, as it may not be verified by data of completed fertility. If the variance is not equal to the mean (if events are not independent), the estimates in Poisson regression models are still consistent but inefficient, and so inference based on the estimated standard errors is not valid. Non validity of the equi-dispersion property implies that events do not occur randomly over time, but that occurrences influence the probability of future occurrences.

Deviation from this equi-dispersion property is called over-dispersion when $E(Ch_i | x_i) < V(Ch_i | x_i)$ and under-dispersion when $E(Ch_i | x_i) > V(Ch_i | x_i)$. Over-dispersion is the consequence of positive correlation among events, while negative correlation causes under-dispersion[14].

[14] Nguyen-Dinh (1997) reports that over-dispersion is more common in real data, while under-dispersion is rare. However, he states, researchers using demographic data have found evidence of both under and over dispersion. Winkelmann and Zimmermann (1995) argue that overdispersion is predominant in practical applications.

Because of the restrictive assumption of equi-dispersion of the Poisson distribution, some authors prefer to model fertility through a negative binomial distribution, which is characterized by a greater variance than a Poisson with the same mean. The negative binomial model is the most common alternative to the Poisson model, and arises from a natural formulation of cross-section heterogeneity. The model is a generalization of the Poisson model, where an individual, unobserved effect is introduced into the conditional mean. The distribution of conditioned Ch_i on x_i remains Poisson with the same conditional mean and a higher variance, and the negative binomial model can be estimated by maximum likelihood (Greene, 2000). So the negative binomial is suitable to study count data with over dispersion, and has been used in many empirical analysis of fertility (Cameron and Trivedi, 1986; Winkelmann and Zimmermann, 1995). For a certain parameter, the conditional mean of the negative binomial equals its conditional variance, and the model reduces to the Poisson.[15]

Empirical research has also found an excess of zeros in raw data. For this reason, zero-inflated negative binomial and zero-inflated Poisson models have been estimated. These models assume an extra probability of zero child in relation to what would be predicted by a standard count data model. They are called hurdle count data models, and they allow for a systematic difference in the statistical process governing observations with zero counts and individuals with one or more counts. The formulation of hurdle models has an intuitive appeal because it may be interpreted as a two stage decision process. In a first stage, the individual decides whether or not to have children, and conditional on a positive decision, in a second stage she decides on the quantity (Winkelmann and Zimmermann, 1994).

[15] Other authors prefer to use more general models, which allow greater flexibility. For example, Melkersson and Rooth (2000) estimate a standard Gamma count data model, which allows to obtaining the standard Poisson as a special case. The Gamma count distribution has the same mean as the Poisson, but its variance depends on a parameter α. It is more dispersed for $\alpha<1$ and more concentrated for $\alpha>1$. The additional parameter α has to be estimated, under the restriction of being non negative, and when it equals one, the Gamma is equal to the Poisson. Winkelmann and Zimmermann (1994) developed a generalized event count model which subsumes the Poisson, the negative binomial and the binomial models.

3. The impacts of fertility on inequality

In this section we present our main findings. First, we describe the main results related to the estimation of the fertility equation (3.1). In second place we describe results related to the estimation of labor market equations (3.2) and finally we present the results from micro-simulations (3.3).

3.1 The fertility equation

We estimated a count data model that describes observed fertility patterns in Uruguay. The model was estimated using micro data for 1986, 1996 and 2006. As explained before, the estimation of the fertility equation is a first step for to carry out the micro-simulations. Strictly speaking, our data set does not allow to model fertility per se, so our dependent variable is the number of children in the household. To undertake our analysis, we considered three types of household: lone parents, bi-parental households and other households. Households without children were excluded from the sample.

A first analysis of the data shows that the unconditional mean of the number of children per household for different types of households is lower than the variance for the three years considered, suggesting over-dispersion in the data (Table A.20). Additionally, the sample distribution of the number of children per household shows higher frequency of zeros, especially in the case of lone parent households and other households (Table A.21).

Based on this, we tried to estimate five models for each type of household: linear, Poisson, negative binomial, zero inflated Poisson and zero inflated negative binomial.[16] As it was set, it depends on mother's wage, father's wage and family income. In practice it is difficult to measure female life-time wages, so years of schooling both of the father and the mother are usually included as exogenous variables in empirical research[17]. In our case we included three binary variables, for high, medium and low (excluded) education, for the household head and the spouse. Other exogenous variables are age and age squared of both the

[16] The distribution of household types is presented in table A.22

[17] The variables that reflect educational levels are time constant and do not present the problems of endogeneity that preclude from including household income.

household head and spouse. For lone parent households, independent variables refer to the household head, whereas for the rest of the households, attributes of both the household head and spouse are considered. We included a control variable for the region of residence (binary variable that takes the value one if the household lives in the capital) and another binary variable that reflects the sex of the household head (it takes one if she is a woman). Empirical tests of the cooperative bargaining model usually include individual unearned income and assets as a source of variation for household decisions. We included capital income earned by the household head and the spouse.[18]

Results for households formed by couple and children for 1986 and 2006 are presented in Table 4. For these households, the zero inflated negative binomial regression does not converge in any of the years. The negative binomial model converges to a Poisson both years. The different models estimated yield similar results. The number of children is decreasing with the level of education in the case of spouse (mainly women), reflecting higher cost of opportunity. In the case of household head, only medium level education yields a significant and negative coefficient in 1986. But twenty years later, in 2006, the binary variable distinguishing high level education household heads is also significant[19]. The magnitude of the coefficients for spouse's education is higher than that of the household head, supporting Becker's hypothesis of wife's opportunity costs of having children.

Age of both the household head and the spouse show a significant and non negative effect on fertility. Age squared is also significant and negative, indicating a non linear, inverse U shaped fertility-age profile. The coefficient on region is always significant and negative in 1986, reflecting lower number of children per household in the capital. Nevertheless this variable is not significant in 2006[20]. The sex of the head of the household is not significant in any estimation (less than 1 % of bi-parental households are headed by a woman). Non labour income of the household head (in logs) is only significant, with a positive and small

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[18] Unfortunately, variables reflecting social constraints and norms, and the distribution of contraceptive knowledge, which undoubtedly influence reproductive behaviour, are not available from the household survey database and could not be included in the estimation.

[19] In 1996 this binary variable is weakly significant in some specifications (table A. 27).

[20] In 1996 the binary variable of region is also significant and the coefficient is negative (table A.29).

magnitude, in 2006. Non labour income of the spouse is significant both years, but changes its sign. Whereas in 1986 it yields the expected negative sign, in 2006 it turns positive.

Results of the estimation of the fertility equations for other types of household and for bi-parental households in 1996 s are presented in tables A.23 to A. 29.

Table 4. Estimation of fertility equations. Biparental households. 1986 and 2006

	1986				2006			
	OLS	Poisson	Negative binomial	Zero inflated Poisson	OLS	Poisson	Negative binomial	Zero inflated Poisson
Medium educ hh	-0.149	-0.087	-0.087	-0.082	-0.173	-0.124	-0.124	-0.123
	(0.034)***	(0.019)***	(0.019)***	(0.020)***	(0.005)***	(0.004)***	(0.004)***	(0.004)***
High educ hh	-0.003	-0.024	-0.024	-0.024	-0.184	-0.138	-0.138	-0.136
	(0.060)	(0.036)	(0.036)	(0.036)	(0.007)***	(0.006)***	(0.006)***	(0.006)***
Med. educ. sp.	-0.229	-0.149	-0.149	-0.142	-0.267	-0.151	-0.151	-0.148
	(0.034)***	(0.019)***	(0.019)***	(0.020)***	(0.005)***	(0.004)***	(0.004)***	(0.004)***
High educ sp.	-0.215	-0.160	-0.160	-0.154	-0.294	-0.204	-0.204	-0.198
	(0.055)***	(0.033)***	(0.033)***	(0.033)***	(0.007)***	(0.005)***	(0.005)***	(0.005)***
Age hh	0.080	0.070	0.070	0.068	0.026	0.059	0.059	0.052
	(0.010)***	(0.008)***	(0.008)***	(0.008)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Age2 hh	-0.001	-0.001	-0.001	-0.001	-0.000	-0.001	-0.001	-0.001
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Age spouse	0.024	0.180	0.180	0.160	0.045	0.201	0.201	0.172
	(0.010)**	(0.009)***	(0.009)***	(0.010)***	(0.001)***	(0.002)***	(0.002)***	(0.002)***
Age2 spouse	-0.001	-0.003	-0.003	-0.002	-0.001	-0.003	-0.003	-0.003
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Region	-0.193	-0.084	-0.084	-0.067	-0.000	-0.001	-0.001	-0.001
	(0.029)***	(0.017)***	(0.017)***	(0.018)***	(0.001)	(0.001)	(0.001)	(0.001)**
Sex of hh	0.127	0.084	0.084	0.071	-0.018	0.002	0.002	-0.003
	(0.188)	(0.112)	(0.112)	(0.112)	(0.008)**	(0.006)	(0.006)	(0.006)
Non labor inc. hh	0.004	0.002	0.002	0.002	0.011	0.006	0.006	0.006
	(0.002)*	(0.001)	(0.001)	(0.001)*	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Non labor inc. sp.	-0.003	-0.003	-0.003	-0.003	0.012	0.006	0.006	0.006
	(0.002)**	(0.001)***	(0.001)***	(0.001)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Constant	0.767	-3.402	-3.402	-3.044	1.732	-3.372	-3.372	-2.741
	(0.254)***	(0.185)***	(0.185)***	(0.202)***	(0.027)***	(0.029)***	(0.029)***	(0.035)***
Observations	8179	8179	8179	8179	306654	306654	306654	306654

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Performance of alternative models can be assessed on the basis of some measures of goodness of fit. Among the most extended measures of goodness of fit is the Akaike information criterion AIC (Akaike 1973).

Other tests have been proposed to choose between the different count data models, for example the LR ratio and the Vuong test. The likelihood ratio allows to compare the Poisson and the negative binomial models, being the null hypothesis that the parameter of the negative binomial is zero (implying both models are equal).

The Vuong test compares between the zero inflated Poisson model and the standard Poisson model (Vuong, 1989).The statistic (V) must be compared to a critical value from a standard normal distribution (c).[21] The test can also be used to compare zero inflated negative binomial and standard negative binomial.

Table 5 shows the AIC measure for the different models estimated in the three years, for different types of household. In some cases, some of the models could not be estimated as they did not converge, that is indicated in the table as non convergence (nc). According to the AIC criterion, the zero inflated Poisson is the best model for lone parents and for couple and children, the three years considered. The Vuong test confirms the advantages of the zero inflated Poisson over the Poisson.

For other households, there seems to be over dispersion in data, as the null hypothesis of α being zero (implying that the Poisson and the negative binomial are equivalent and there is equi-dispersion) is rejected according to the LR test. For these households, the Vuong test indicates that the zero inflated negative binomial is preferred to the negative binomial in 1986 and 2006, the years for which this hurdle model could be estimated. In 1996 the zero inflated negative binomial regression does not converge, and both the AIC criteria and the LR test indicate that the negative binomial is preferred to the Poisson.

For the microsimulations, we chose the best model for each type of household, according to these criteria.

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[21] If $V>c$, the null hypothesis that the models are the same is rejected in favor of the zero inflated Poisson distribution. If $V<-c$ the null hypothesis that the models are the same is rejected in favor of the standard Poisson distribution. If $|V| \leq c$ the null hypothesis that both models are the same can not be rejected.

Table 6.5. Goodness of fit and tests for choosing among different models

	AIC OLS	AIC Poisson	AIC NB	AIC Zero inflated Poisson	AIC Zero inflated NB	LR test α=0 (Poisson vs. NB)	Vuong test (Zero inf.Poisson vs Poisson)	LR test α =0 (Zero inf. Poisson vs. Zero inf. NB)	Vuong test (Zero inf. NB vs. NB)
Lone parent household									
1986	2,939	2,022	2,023	**2,009**	Nc	0,150	2,46	-,-	-,-
1996	2,672	1,861	nc	**1,848**	Nc	-,-	2,3	-,-	-,-
2006	2,756	1,942	1,942	**1,927**	Nc	0,000	21,4	-,-	-,-
Other households									
1986	3,474	3,063	3,032	3,007	**2,996**	159,020	7,43	56,24	6,820
1996	3,340	2,901	**2,875**	nc	Nc	121,490			
2006	3,365	2,872	2,846	2,805	**2,797**	4200,810	47,88	1370,2	42,930
Couple and children									
1986	3,305	2,889	2,889	**2,886**	Nc	0,000	2,96	-,-	-,-
1996	3,044	2,656	2,657	**2,654**	Nc	0,000	3,62	-,-	-,-
2006	2,979	2,628	2,628	**2,622**	Nc	0,000	24,85	-,-	-,-

Source: based on household surveys

The estimations presented in this section confirm the results relative to the central role of education, and especially of mother's education, to determine the number of children. The different models estimated allowed to choose between the best specification for each type of household and for each year, so that our micro-simulations are based on count data models that describe in the best way observed fertility patterns.

3.2 Labor market equations

Two labour supply equations were estimated, one for hours of work and one for hourly wages. These equations were estimated separately for household heads and spouses (assuming that labour supply of the other members of the household does not depend on the presence of children), and for 1986, 1996 and 2006.

The labour supply equation is estimated using hours of work as the dependent variable, and including among the explanatory variables sex, age, age squared, a binary variable that indicates if the person lives in the capital of the country, a variable that reflects the number of children, a binary variable that indicates if the person is attending school, educational level (three levels: low, medium and high), a binary variable indicating if the person is married (or lives with her partner). For household heads, non labour income was considered as an explanatory variable, whereas for spouses we included a variable reflecting income from the household head.

As discussed in the literature, some caveats may arise from the fact of the possible endogeneity of the number of children and ours of work. On this issue, Cruces and Galiani (2007) find no significant evidence of endogeneity of the number of children on their mothers' labour participation decision. Based on that, Marchinnoni and Gasparini (2007) assume that the number of children is an exogenous variable in the labour market equations. This assumption was also taken in our case.

Results of the estimation using the Tobit method (maximum likelihood estimation) are presented in Table 6. Separate equations were estimated for household heads and spouses, for the years 1986, 1996 and 2006. All coefficients yield the expected signs. In particular, hours of work are higher for men than for women. The relation between hours of work and age shows an inverse U pattern. Living in the capital is associated with higher hours of work, except for household heads in 2006. The presence of children in the household has a negative impact on hours of work both for household heads and for spouses, but the magnitude of the effect is considerable higher for spouses, who are mainly women. Those who are attending school tend to work less hours per week. Hours of work increase with the level of education. The magnitude of the coefficient of these variables is considerably high for spouses. As expected, the binary variable that distinguishes those who are married presents a positive sign for household heads, although it gets weaker as time goes by. For spouses, being married is associated with lower hours of work, as expected according to traditional roles, only in 1986. The coefficient is not significant in 1996 and becomes positive in 2006, with a similar magnitude to that of household heads.

In the case of household heads, higher non labour income is associated with lower hours of work. In the case of spouses, higher income of the household head is associated with lower hours of work, although again the magnitude of the coefficient decreases considerably in time.

Table 6. Labor supply. Dependent variable: hours of work. Tobit estimation						
	Household heads			Spouses		
	1986	1996	2006	1986	1996	2006
Sex	19.465	10.116	17.949	20.565	27.030	28.659
	(1.048)***	(0.984)***	(0.102)***	(6.486)***	(2.740)***	(0.242)***
Age	4.115	3.494	4.605	6.194	6.208	5.098
	(0.142)***	(0.126)***	(0.024)***	(0.298)***	(0.274)***	(0.036)***
Age squared	-0.055	-0.045	-0.058	-0.080	-0.078	-0.063
	(0.001)***	(0.001)***	(0.000)***	(0.004)***	(0.003)***	(0.000)***
Region	6.620	1.298	-1.186	6.513	2.955	2.357
	(0.542)***	(0.483)***	(0.095)***	(1.001)***	(0.900)***	(0.124)***
Children	-0.627	-0.355	-0.567	-2.729	-2.620	-3.326
	(0.194)***	(0.192)*	(0.037)***	(0.367)***	(0.370)***	(0.053)***
School	-13.577	-9.649	-10.952	-8.673	-5.757	-7.673
	(2.692)***	(2.125)***	(0.324)***	(4.521)*	(3.081)*	(0.368)***
Medium education	4.184	4.183	5.195	12.786	12.117	11.166
	(0.604)***	(0.531)***	(0.106)***	(1.110)***	(1.024)***	(0.149)***
High education	4.394	7.886	11.103	31.723	28.891	25.288
	(1.021)***	(0.786)***	(0.147)***	(1.647)***	(1.434)***	(0.198)***
Married	4.964	2.865	0.722	-10.228	2.043	0.897
	(0.982)***	(0.938)***	(0.116)***	(3.466)***	(10.280)	(0.156)***
Non labor inc.	-0.561	-0.904	-0.136			
	(0.050)***	(0.027)***	(0.005)***			
Income of hh.				-5.973	-2.951	-1.952
				(0.688)***	(0.560)***	(0.072)***
Constant	-53.506	-40.445	-65.320	-94.164	-96.617	-74.344
	(3.364)***	(3.037)***	(0.578)***	(6.888)***	(12.108)***	(0.953)***
Observations	14862	13754	445057	11045	9493	366917
Standard errors in parentheses						
* significant at 10%; ** significant at 5%; *** significant at 1%						

The estimation of the wage equation was undertaken using Heckman's proposal. A censored version of the labour supply equation was used as the selection equation. The wage equation was estimated separately for household heads and spouses, considering all households included for the fertility equation estimation. The estimation was done using maximum likelihood.

Hourly wages, in logs, is the dependent variable, and the independent variables are sex, age, age squared, region, three binary variables that indicate educational level (low, medium and high), and a binary variable indicating if the person is married or not. The selection equation includes all the variables included in the labour supply equation. So it adds as selection the number of children, a binary variable that indicates if the person is attending school, and a variable that reflects non labour income (in logs) for household heads, or the income of the household head (in logs) for spouses.

Results for the three years considered are presented in Table 7 for household heads and in Table 8 for spouses. Wages are higher for men, and present the expected inverse U pattern in relation to age. Wages are higher in Montevideo and, as expected, wages are increasing with the level of education. Being married is associated with higher wages for household heads, but with lower wages for spouses.

Table 7. Wage equation estimation with selection correction (Heckman maximum likelihood). Household heads

	1986		1996		2006	
	Hourly wages	Selec. eq.	Hourly wages	Selec. eq.	Hourly wages	Selec. eq.
Sex	0.387	0.592	0.271	0.314	0.281	0.599
	(0.031)***	(0.046)***	(0.032)***	(0.057)***	(0.004)***	(0.005)***
Age	0.047	0.122	0.036	0.123	0.053	0.158
	(0.005)***	(0.007)***	(0.005)***	(0.008)***	(0.001)***	(0.001)***
Age sq.	-0.000	-0.002	-0.000	-0.002	-0.000	-0.002
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Region	0.290	0.259	0.346	0.053	0.184	-0.015
	(0.014)***	(0.027)***	(0.015)***	(0.030)*	(0.003)***	(0.005)***
Med. educ.	0.385	0.218	0.380	0.223	0.416	0.189
	(0.015)***	(0.030)***	(0.016)***	(0.033)***	(0.004)***	(0.005)***
High educ.	0.952	0.344	0.954	0.570	1.208	0.514
	(0.025)***	(0.053)***	(0.023)***	(0.054)***	(0.005)***	(0.008)***
Married	0.199	0.136	0.113	0.035	-0.218	0.017
	(0.026)***	(0.045)***	(0.029)***	(0.056)	(0.004)***	(0.006)***
Children		-0.024		-0.005		-0.006
		(0.009)***		(0.012)		(0.002)***
School		-0.510		-0.331		-0.514
		(0.130)***		(0.133)**		(0.016)***
Non labor inc.		-0.041		-0.052		-0.020
		(0.003)***		(0.002)***		(0.000)***
Income of hh						
Constant	3.249	-1.516	3.761	-1.633	3.093	-2.349
	(0.112)***	(0.165)***	(0.110)***	(0.191)***	(0.030)***	(0.029)***
Observations	14690	14690	13507	13507	438175	438175

Table 8. Wage equation estimation with selection correction (Heckman maximum likelihood). Spouses.

	1986		1996		2006	
	Hourly wages	Selec. eq.	Hourly wages	Selec. eq.	Hourly wages	Selec. eq.
Sex	0.046	0.415	0.291	0.712	0.122	1.047
	(0.153)	(0.185)**	(0.069)***	(0.102)***	(0.008)***	(0.012)***
Age	0.068	0.161	0.077	0.188	0.058	0.176
	(0.009)***	(0.008)***	(0.010)***	(0.009)***	(0.002)***	(0.001)***
Age sq.	-0.001	-0.002	-0.001	-0.002	-0.001	-0.002
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Region	0.420	0.201	0.426	0.157	0.199	0.097
	(0.025)***	(0.028)***	(0.024)***	(0.030)***	(0.004)***	(0.005)***
Med. educ.	0.532	0.389	0.433	0.366	0.453	0.385
	(0.030)***	(0.031)***	(0.030)***	(0.033)***	(0.005)***	(0.005)***
High educ.	1.338	1.313	1.226	1.202	1.229	1.149
	(0.046)***	(0.051)***	(0.044)***	(0.051)***	(0.008)***	(0.008)***
Married	-0.030	-0.280	-0.262	-0.120	-0.092	0.002
	(0.085)	(0.098)***	(0.264)	(0.328)	(0.005)***	(0.006)
Children		-0.049		-0.063		-0.112
		(0.010)***		(0.012)***		(0.002)***
School		-0.325		-0.200		-0.264
		(0.128)**		(0.102)**		(0.014)***
Non labor inc.						-0.114
						(0.003)***
Income of hh		-0.288		-0.198		
		(0.020)***		(0.020)***		
Constant	2.658	-2.214	2.996	-2.092	3.075	-2.392
	(0.226)***	(0.188)***	(0.348)***	(0.386)***	(0.040)***	(0.038)***
Observations	10647	10647	9137	9137	356223	356223

3.3 The microsimulations

To carry out our micro-simulations, we divided the period 1986-2006 in two sub-periods, and considered changes between 1986 and 1996 and changes between 1996 and 2006. Our main results are depicted in Table 6.9. The first two columns present the real values of the indicators, whereas the other three present the value of the indicators constructed on the simulated or counterfactual income. The fertility size effect column shows the value of the different social indicators in 2006 if only the parameters that govern fertility decisions had changed, and had modified the denominator of equation (34). The hours size effect column presents the value of the different social indicators in 2006 if only labour market decisions had changed as a consequence of changes in fertility. The final column shows the value of the social indicators if only the parameters regulating the relationship between hours of work and children in the household had changed.[22]

Table 9. Results from the microsimulations.

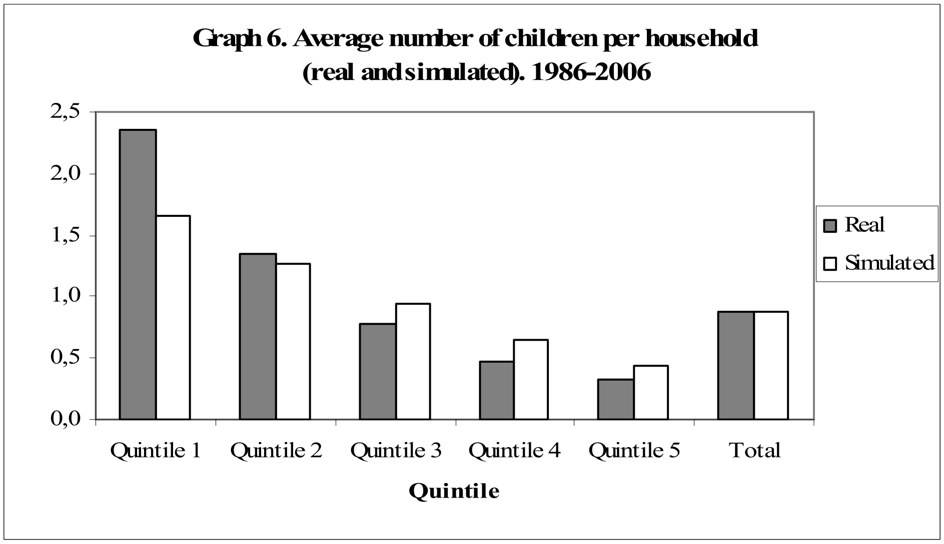
1986-2006	1986	2006	Fertility size effect	Hours size effect	Hours parameter effect
Mean income	5.146	7.068	7.070	7.024	7.161
Poverty incidence	0,471	0,252	0,214	0,255	0,244
Extreme poverty incidence	0,076	0,017	0,011	0,021	0,019
Theil index	0,318	0,361	0,345	0,363	0,359
Gini coefficient	0,415	0,446	0,431	0,447	0,445
1986-1996	1986	1996	Fertility size effect	Hours size effect	Hours parameter effect
Mean income	5.146	8.176	8.176	8.110	8.303
Poverty incidence	0,471	0,172	0,131	0,177	0,167
Extreme poverty incidence	0,076	0,017	0,006	0,025	0,023
Theil index	0,318	0,321	0,300	0,320	0,316
Gini coefficient	0,415	0,424	0,407	0,424	0,421
1996-2006	1996	2006	Fertility size effect	Hours size effect	Hours parameter effect
Mean income	8.328	6.298	6.389	6.297	6.328

[22] The effects are not being accumulated, each one is presented isolated.

Poverty incidence	0,171	0,252	0,221	0,255	0,251
Extreme poverty incidence	0,324	0,361	0,349	0,363	0,362
Theil index	0,481	0,584	0,575	0,587	0,583
Gini coefficient	0,426	0,446	0,435	0,447	0,446
Source: own calculations based on household surveys					

The first step of our micro-simulation exercise consisted on analyzing household income in 2006 if the parameters that govern fertility decisions in 2006 had been those of 1986. In that case, the average number of children per household does not change significantly, although this counterfactual variable presents different behaviours depending on the type of household. In effect, the number of children in lone parent households and other households would have been lower (4 and 9% respectively) (table A.30). This would have implied higher mean income and lower incidence of poverty for these households. In the case of biparental households, although the average number of children would have been higher, the different behaviour along income strata implies that poverty incidence would also have been lower. As a result, poverty would have been lower (21.4% instead of 25.2%), and also extreme poverty would have been lower (1.1% instead of 1.7%). The distribution of income would have been more equal, both inequality indexes would have been around 1.5 points lower. This result indicates that changes in the parameters that govern fertility between 1986 and 2006 have contributed to higher poverty and extreme poverty incidence, as well as higher inequality.

The consideration of the change in the number of children by income quintile illustrates about the process underlying direct counterfactual changes. The main change refers to the lower counterfactual number of children in the first quintile, as a result of the changes in fertility results for the different types of households described above. If the parameters of 1986 had governed the fertility decisions in 2006, households of the first quintile would have had less children that they did. From the third quintile on, the result is the inverse, and explains the considerable impact on inequality. It must be kept in mind that children concentrate in the first two quintiles of population, although the pattern changes considerably under the counterfactual scenario (Table A.31).



Source: own calculation based on household surveys

This direct effect, called fertility size effect, is the higher one. The other two indirect effects have opposite signs and are of very small magnitude. The hours size effect is negligible, it would have implied a slightly higher poverty (25.5% instead of 25.2%) and inequality (the Gini coefficient would have been 44.7 instead of 44.6). Probably these effects are non significant in statistical terms. The hour parameter effect is also very small. If the parameters that govern the relationship between hours of work and number of children have been that of 1986, poverty would have been slightly lower (24.4% instead of 25.2%), as well as inequality (the Gini coefficient would have been 44.5 instead of 44.6). Again, it must be stressed that these changes are also of a very small magnitude. This result is explained by the fact that the number of children in the household had a higher negative effect on hours of work for household heads in 1986 than in 2006. The effect on spouses acted on the other direction, as the coefficient is higher (in absolute terms) in 2006, but the first effect seems to prevail.

Between 1986 and 1996 de decrease in poverty was even more acute that during the whole period, although the change in inequality was smaller, as expected because of the shorter length of the period. Again, the fertility size effect indicates that changes in the parameters that govern fertility have contributed to a higher incidence of poverty and extreme poverty. Again, the effect on inequality is relatively high, if fertility parameters had not changed between 1986 and 1996, the Gini index could have been lower than in 1986. The hour size effect has a negative effect on the incidence of poverty and extreme poverty, but no effect on inequality. As in the whole period, changes due to hours size effect and hours parameter effect are very small in magnitude.

The same pattern is found in 1996-2006, a period of increase in poverty incidence. Change in fertility patterns contributed to that increase in a significant way: they can account for almost 35% of the increase in poverty during the period. Again, the hours size effect acted slightly increasing poverty, and the hours parameter effect had the contrary effect, being the effects in both cases of very small magnitude.

For Argentina (Greater Buenos Aires) Marchionni and Gasparini also find that the increase in the family size in low and middle income households considerable contributed to the observed growth in inequality and poverty during the 80s. On the contrary, this demographic effect reverted during the 90s, where demographic factors have a poverty decreasing effect without affecting inequality. This seems not to have been the case in Uruguay, where during all the period the negative direct effect prevails.

In their case, the weakening in the association between hours of work and the number of children for spouses had a small poverty and inequality decreasing effect, and the hours size effect has a very small impact, that they point as probably non significant. In our case, both the hour size effect and the hour parameter effect are very small, and they tend to cancel out in the case of inequality. In any case, fertility direct size has a non negligible impact, especially in the case of inequality (Table 10).

Table 10. Summary of results from microsimulations.

	1986-1996	1996-2006	1986-2006
Change in poverty	**-0,299**	**0,081**	**-0,219**
Direct size	0,041	0,031	0,038
Hours size	-0,005	-0,003	-0,003
Hours parameter	0,005	0,001	0,008
Total demographic effect	0,040	0,028	0,044
Change in extreme poverty	**-0,060**	**0,000**	**-0,059**
Direct size	0,011	0,004	0,006
Hours size	-0,009	-0,004	-0,004

Hours parameter	-0,006	-0,004	-0,002
Total demographic effect	-0,004	-0,003	0,000
Change in inequality (Gini)	**0,010**	**0,020**	**0,031**
Direct size	0,017	0,011	0,015
Hours size	0,001	-0,002	-0,001
Hours parameter	0,003	-0,001	0,001
Total demographic effect	0,020	0,009	0,014
Source: own calculations based on household surveys			

4. Final comments

Demographic factors seem to have played a role in the evolution of inequality and poverty over the past twenty years in Uruguay. This effect is mainly a direct one, derived from the evolution of the parameters that govern fertility decisions, and so refers to the size of households. Indirect effects, through the labour market, do not seem to have played a central role, as their magnitude is really small. Other indirect but relevant effects, related to investment in human capital, for example, can not be traced with the proposed methodology.

This micro-simulation exercise illustrates about the potentially important direct effect of fertility or demographic factors in the evolution of poverty, and especially on inequality. If the uruguayan population had taken fertility decisions in 2006 according to the parameters that were estimated in 1986, poverty, and specially inequality, would have been lower. Part of the increase in inequality can be accounted for changes in the reproductive behaviour. The non-equalizing trend in the evolution of fertility parameters is a relevant result for the formulation of public policies.

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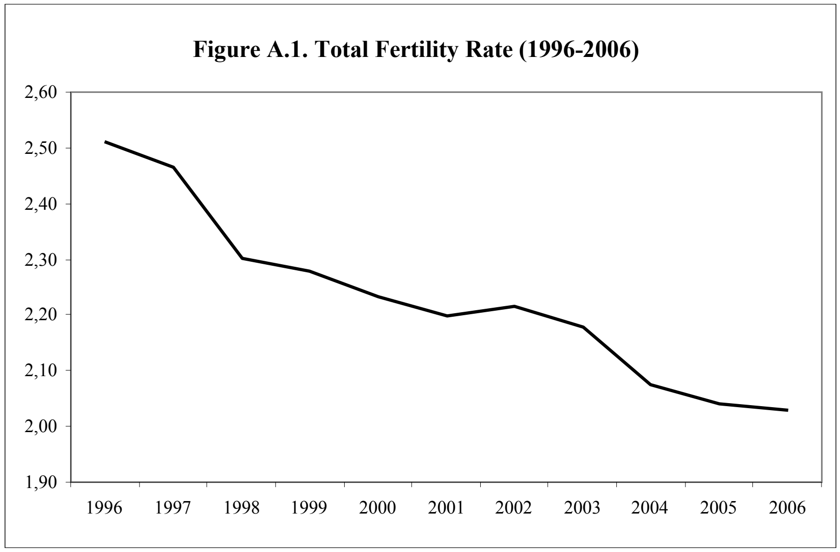
Annex

Figure A.1 Evolution of TFR for Uruguay. 1985-2006.



Source: INE (2008)

Figure A.2 Inequality indexes

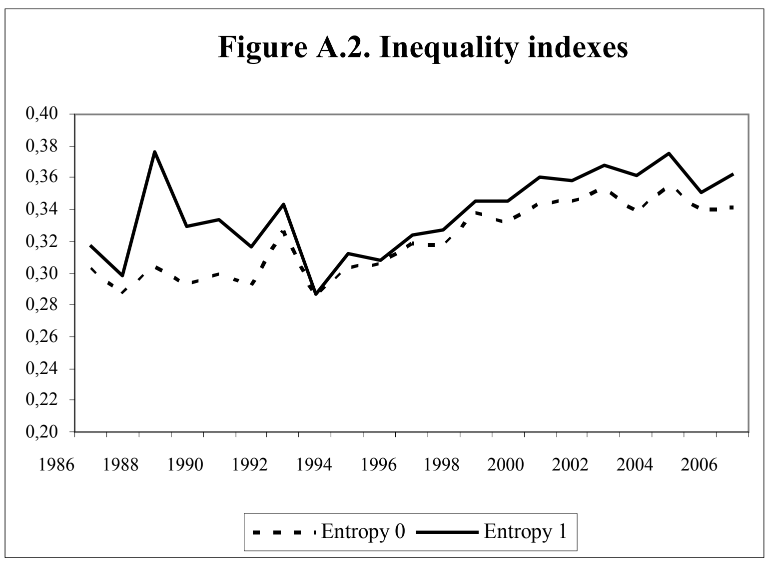


Table A.19 Poverty incidence by age group.1986-2006

	0-5	6-12	13-17	Under 18	18-64	More than 64	Total
1986	62,5	63,3	57,9	61,6	39,7	32,4	45,6
1987	54,1	53,5	46,9	51,9	29,6	20,8	35,5
1988	44,2	43,4	37,3	42,0	21,3	12,4	26,6
1989	43,9	43,4	37,1	41,7	21,4	13,2	26,5
1990	49,6	46,7	41,6	46,0	24,3	15,0	29,6
1991	41,1	39,8	33,0	38,0	19,1	12,5	23,3
1992	37,8	36,6	29,5	34,6	16,1	9,1	20,2
1993	32,5	31,2	26,7	30,1	13,4	7,4	16,9
1994	30,5	28,6	24,0	27,7	11,9	4,1	15,1
1995	34,3	32,1	25,9	30,9	14,0	5,0	17,3
1996	35,3	31,8	25,6	31,0	13,6	4,8	17,0
1997	36,1	30,3	25,6	30,7	14,1	4,8	17,1
1998	34,7	29,2	26,7	30,1	13,1	5,4	16,7
1999	32,9	29,2	23,4	28,4	12,4	6,2	15,7
2000	39,5	35,1	27,6	34,0	14,4	6,0	17,7
2001	38,3	35,4	27,7	34,0	15,3	3,9	18,8
2002	46,5	41,9	34,6	41,1	20,3	5,4	23,6
2003	56,5	50,2	42,8	49,8	27,8	9,7	30,9
2004	56,5	53,7	45,0	51,9	28,7	10,8	32,1
2005	54,1	51,0	42,8	49,4	25,8	9,2	29,4
2006	48,6	47,6	40,0	45,6	22,6	7,7	26,8

Table A.20 Summary statistics for the dependent variable

	1986	1996	2006
Lone parent	0,9580	0,8614	1,0005
Biparental	1,8018	1,5727	1,5520
Other households	1,4153	1,2577	1,2767
Total	1,1455	0,9399	0,8794

Table A.21 Frequency of the number of children in the data

	1986				1996			
	Lone parent	Biparental	Other households	Total	Lone parent	Biparental	Other households	Total
0	52,7	17,6	32,8	46,6	51,9	22,1	35,9	52,4
1	21,2	28,1	27,6	19,9	24,9	30,4	29,9	20,3
2	14,3	30,1	21,3	18,4	14,7	28,0	18,8	15,8
3	6,1	14,0	10,0	8,5	5,1	12,3	9,3	7,1
4	3,0	5,7	4,1	3,5	1,7	4,3	3,2	2,4
5	1,6	2,5	1,9	1,6	1,1	1,8	1,5	1,1

6	0,7	1,0	1,1	0,7	0,2	0,6	0,7	0,4
7	0,2	0,5	0,6	0,4	0,2	0,3	0,4	0,2
8	0,1	0,3	0,4	0,2	0,1	0,1	0,1	0,1
9	0,1	0,2	0,1	0,1	0,1	0,1	0,1	0,0
10	0,0	0,1	0,0	0,0	0,1	0,0	0,0	0,0
11	0,0	0,0	0,0	0,0	0,0	0,0	0,1	0,0
13	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Total	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0

Table A.22. Distribution of household types. 1986, 1996 and 2006			
	1986	1996	2006
Lone parents households	8,1	9,4	11,8
Biparental households	39,8	36,5	34,2
Other	24,6	22,5	17,9
Households without children	27,5	31,6	36,0
Total	100,0	100,0	100,0

Table A.23. Estimation of fertility equations. Lone parent households.1986					
	OLS	Poisson	Negative binomial	Zero inflated Poisson	Inflate
Medium educ hh	-0.308	-0.272	-0.272	-0.254	0.376
	(0.067)***	(0.059)***	(0.059)***	(0.063)***	(0.509)
High educ hh	-0.273	-0.267	-0.266	-0.269	-0.034
	(0.102)***	(0.096)***	(0.097)***	(0.104)***	(0.750)
Age hh	-0.150	0.180	0.179	0.133	1.106
	(0.011)***	(0.020)***	(0.020)***	(0.022)***	(0.308)***
Age2 hh	0.001	-0.003	-0.003	-0.002	-0.008
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.003)***
Region	-0.230	-0.233	-0.233	-0.224	0.025
	(0.053)***	(0.053)***	(0.053)***	(0.060)***	(0.398)
Sex of household head	-0.050	-0.076	-0.079	0.071	15.947
	(0.069)	(0.072)	(0.073)	(0.077)	(894.308)
Non labor inc. hh	0.010	0.011	0.011	0.009	-0.036
	(0.005)*	(0.005)**	(0.005)**	(0.005)	(0.041)
Constant	6.692	-1.703	-1.685	-1.232	-68.144
	(0.325)***	(0.448)***	(0.454)***	(0.476)***	(1,788.639)
Observations	1665	1665	1665	1665	1665
R-squared	0.40				
Standard errors in parentheses					
* significant at 10%; ** significant at 5%; *** significant at 1%					

Table A.24. Estimation of fertility equations. Lone parent households.1996				
	OLS	Poisson	Zero inflated Poisson	Inflate
Medium educ hh	-0.141	-0.186	-0.156	1.064
	(0.051)***	(0.057)***	(0.059)***	(0.553)*
High educ hh	-0.131	-0.204	-0.196	0.361
	(0.069)*	(0.077)***	(0.079)**	(0.782)
Age hh	-0.120	0.185	0.124	1.851
	(0.009)***	(0.018)***	(0.020)***	(0.536)***
Age2 hh	0.001	-0.003	-0.002	-0.013
	(0.000)***	(0.000)***	(0.000)***	(0.004)***
Region	-0.097	-0.106	-0.099	0.124
	(0.045)**	(0.053)**	(0.055)*	(0.461)
Sex of household head	-0.170	-0.253	-0.129	15.536
	(0.060)***	(0.077)***	(0.082)	(990.217)
Non labor inc. hh	0.009	0.010	0.010	-0.003
	(0.002)***	(0.003)***	(0.003)***	(0.029)
Constant	5.845	-1.550	-0.766	-94.039
	(0.270)***	(0.419)***	(0.412)*	(1,980.520)
Observations	1905	1905	1905	1905
R-squared	0.41			
Standard errors in parentheses				
* significant at 10%; ** significant at 5%; *** significant at 1%				

Table A.25. Estimation of fertility equations. Lone parent households.2006					
	OLS	POISSON	Negative binomial	Zero inflated NB	Inflate
Medium educ hh	-0.268	-0.274	-0.274	-0.272	0.282
	(0.007)***	(0.007)***	(0.007)***	(0.007)***	(0.102)***
High educ hh	-0.350	-0.408	-0.408	-0.405	0.342
	(0.009)***	(0.009)***	(0.009)***	(0.010)***	(0.140)**
Age hh	-0.096	0.244	0.244	0.180	1.732
	(0.001)***	(0.003)***	(0.003)***	(0.003)***	(0.183)***
Age2 hh	0.000	-0.004	-0.004	-0.003	-0.011
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.002)***
Region	0.002	-0.001	-0.001	-0.000	-0.032
	(0.001)	(0.001)	(0.001)	(0.001)	(0.019)*
Sex of household head	-0.132	-0.179	-0.179	-0.105	21.139
	(0.009)***	(0.011)***	(0.011)***	(0.012)***	(643.278)
Non labor inc. hh	0.019	0.017	0.017	0.017	-0.033
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.005)***
Constant	5.236	-2.734	-2.734	-1.777	-105.639
	(0.041)***	(0.059)***	(0.059)***	(0.061)***	(1,286.568)
Observations	106003	106003	106003	106003	106003
R-squared	0.43				
Standard errors in parentheses					
* significant at 10%; ** significant at 5%; *** significant at 1%					

Table A.26. Estimation of fertility equations. Other households.1986							
	OLS	Poisson	Negative binomial	Zero inflated Poisson	Inflate	Zero inflated negative binomial	Inflate
Medium educ hh	-0.266	-0.187	-0.192	-0.127	0.537	-0.137	0.559
	(0.050)***	(0.031)***	(0.035)***	(0.033)***	(0.181)***	(0.035)***	(0.207)***
High educ hh	-0.429	-0.371	-0.372	-0.148	1.186	-0.157	1.272
	(0.082)***	(0.059)***	(0.065)***	(0.068)**	(0.247)***	(0.070)**	(0.266)***
Médium educ. spouse	-0.207	-0.122	-0.110	-0.198	-13.899	-0.169	-34.959
	(0.062)***	(0.034)***	(0.040)***	(0.038)***	(526.829)	(0.038)***	(2.142e+09)
High educ spouse	-0.315	-0.176	-0.172	-0.283	-1.988	-0.250	14.788
	(0.108)***	(0.065)***	(0.074)**	(0.074)***	(4.253)	(0.072)***	(20.080)
Age hh	-0.018	0.001	0.001	0.007	-0.006	0.006	-0.017
	(0.008)**	(0.005)	(0.006)	(0.007)	(0.034)	(0.007)	(0.038)
Age2 hh	0.000	-0.000	-0.000	-0.000	0.000	-0.000	0.000
	(0.000)	(0.000)***	(0.000)***	(0.000)***	(0.000)	(0.000)**	(0.000)
Age spouse	0.063	0.043	0.042	0.021	-0.155	0.022	-0.660
	(0.004)***	(0.003)***	(0.003)***	(0.003)***	(0.034)***	(0.004)***	(1.494)
Age2 spouse	-0.001	-0.001	-0.001	-0.000	0.002	-0.000	-0.001
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.032)
Region	-0.376	-0.271	-0.286	-0.176	0.985	-0.199	1.013
	(0.040)***	(0.025)***	(0.028)***	(0.029)***	(0.162)***	(0.029)***	(0.179)***
Sex of hh	0.198	0.191	0.184	-0.121	-1.075	-0.119	-1.198
	(0.065)***	(0.047)***	(0.052)***	(0.064)*	(0.195)***	(0.073)	(0.254)***
Non labor inc. hh	0.005	0.003	0.003	0.001	-0.016	0.002	-0.016
	(0.004)	(0.002)	(0.003)	(0.002)	(0.013)	(0.003)	(0.014)
Non labor inc. spouse	-0.006	-0.004	-0.004	-0.004	0.026	-0.004	-0.035
	(0.003)**	(0.002)**	(0.002)**	(0.002)**	(0.039)	(0.002)***	(0.170)
Constant	1.843	0.221	0.246	0.864	0.513	0.864	-0.016
	(0.209)***	(0.133)*	(0.152)	(0.151)***	(0.880)	(0.160)***	(2.476)
Observations	5066	5066	5066	5066	5066	5066	5066
R-squared	0.16						
Standard errors in parentheses							
* significant at 10%; ** significant at 5%; *** significant at 1%							

Table A.27. Estimation of fertility equations. Other households.1996			
	OLS	Poisson	Negative binomial
Medium educ hh	-0.322	-0.257	-0.265
	(0.048)***	(0.033)***	(0.037)***
High educ hh	-0.532	-0.512	-0.527
	(0.074)***	(0.062)***	(0.067)***
Médium educ. spouse	-0.143	-0.083	-0.075
	(0.062)**	(0.038)**	(0.044)*
High educ spouse	-0.283	-0.146	-0.134

	(0.101)***	(0.069)**	(0.078)*
Age hh	-0.008	0.007	0.006
	(0.007)	(0.006)	(0.006)
Age2 hh	-0.000	-0.000	-0.000
	(0.000)	(0.000)***	(0.000)***
Age spouse	0.063	0.048	0.048
	(0.004)***	(0.003)***	(0.003)***
Age2 spouse	-0.001	-0.001	-0.001
	(0.000)***	(0.000)***	(0.000)***
Region	-0.245	-0.199	-0.206
	(0.039)***	(0.027)***	(0.031)***
Sex of hh	0.272	0.269	0.283
	(0.060)***	(0.047)***	(0.053)***
Non labor inc. hh	0.006	0.005	0.005
	(0.002)***	(0.001)***	(0.002)***
Non labor inc. spouse	0.003	0.002	0.002
	(0.003)	(0.002)	(0.002)
Constant	1.480	-0.028	-0.042
	(0.213)***	(0.155)	(0.174)
Observations	4537	4537	4537
R-squared	0.15		
Standard errors in parentheses			
* significant at 10%; ** significant at 5%; *** significant at 1%			

Table A.28. Estimation of fertility equations. Other households.2006

	OLS	Poisson	Negative binomial	Zero inflated Poisson	Inflate	Zero inflated negative binomial	Inflate
Medium educ hh	-0.364	-0.277	-0.282	-0.237	0.478	-0.246	0.465
	(0.008)***	(0.005)***	(0.006)***	(0.005)***	(0.037)***	(0.006)***	(0.042)***
High educ hh	-0.929	-0.957	-0.967	-0.510	2.247	-0.531	2.459
	(0.012)***	(0.011)***	(0.011)***	(0.012)***	(0.045)***	(0.013)***	(0.052)***
Médium educ. spouse	-0.294	-0.152	-0.146	-0.201	-6.191	-0.195	-3.467
	(0.011)***	(0.006)***	(0.007)***	(0.006)***	(1,299.642)	(0.007)***	(545.463)
High educ s.	-0.408	-0.158	-0.141	-0.319	13.792	-0.310	15.363
	(0.018)***	(0.012)***	(0.014)***	(0.013)***	(1.692)***	(0.014)***	(2.206)***
Age hh	0.013	0.032	0.032	0.027	-0.009	0.026	0.002
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.006)	(0.001)***	(0.006)
Age2 hh	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)	(0.000)***	(0.000)**
Age spouse	0.065	0.044	0.044	0.021	-0.874	0.022	-0.974
	(0.001)***	(0.000)***	(0.001)***	(0.001)***	(0.091)***	(0.001)***	(0.121)***
Age2 spouse	-0.001	-0.001	-0.001	-0.000	0.008	-0.000	0.009
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.000)***	(0.001)***
Region	0.009	0.007	0.008	0.003	-0.065	0.004	-0.067
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.006)***	(0.001)***	(0.007)***
Sex of hh	0.291	0.256	0.271	-0.052	-1.839	-0.046	-2.106
	(0.009)***	(0.006)***	(0.007)***	(0.008)***	(0.038)***	(0.008)***	(0.046)***
Non labor inc. hh	0.023	0.016	0.016	0.013	-0.031	0.013	-0.032
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.000)***	(0.002)***

Non labor inc. spouse	0.014	0.007	0.007	0.007	0.006	0.007	0.004
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.016)	(0.000)***	(0.018)
Constant	1.234	-0.454	-0.506	0.573	2.811	0.556	2.862
	(0.039)***	(0.028)***	(0.032)***	(0.031)***	(0.269)***	(0.033)***	(0.304)***
Obs.	160322	160322	160322	160322	160322	160322	160322
R-squared	0.20						
Standard errors in parentheses							
* significant at 10%; ** significant at 5%; *** significant at 1%							

Table A.29. Estimation of fertility equations. Biparental households.2006

	OLS	Poisson	Negative binomial	Zero inflated Poisson	inflate
Medium educ hh	-0.131	-0.103	-0.103	-0.098	0.786
	(0.031)***	(0.022)***	(0.022)***	(0.022)***	(0.634)
High educ hh	-0.033	-0.072	-0.072	-0.056	2.297
	(0.051)	(0.037)*	(0.037)*	(0.037)	(1.015)**
Médium educ. spouse	-0.126	-0.096	-0.096	-0.099	-0.785
	(0.032)***	(0.022)***	(0.022)***	(0.023)***	(1.159)
High educ spouse	-0.199	-0.140	-0.140	-0.146	-0.965
	(0.048)***	(0.035)***	(0.035)***	(0.035)***	(0.959)
Age hh	0.034	0.064	0.064	0.062	2.124
	(0.010)***	(0.009)***	(0.009)***	(0.009)***	(1.111)*
Age2 hh	-0.001	-0.001	-0.001	-0.001	-0.017
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.009)*
Age spouse	0.027	0.190	0.190	0.170	2.290
	(0.010)***	(0.010)***	(0.010)***	(0.013)***	(1.181)*
Age2 spouse	-0.001	-0.003	-0.003	-0.003	-0.018
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.010)*
Region	-0.140	-0.077	-0.077	-0.063	2.611
	(0.027)***	(0.019)***	(0.019)***	(0.020)***	(2.531)
Sex of hh	0.020	0.034	0.034	0.022	-0.727
	(0.092)	(0.067)	(0.067)	(0.068)	(3.260)
Non labor inc. hh	0.006	0.004	0.004	0.004	0.017
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.025)
Non labor inc. s.	0.007	0.003	0.003	0.004	0.033
	(0.002)***	(0.001)***	(0.001)***	(0.001)***	(0.040)
Constant	1.914	-3.307	-3.307	-2.939	-139.088
	(0.186)***	(0.186)***	(0.186)***	(0.259)***	(58.720)**
Observations	7361	7361	7361	7361	7361
R-squared	0.29				
Standard errors in parentheses					
* significant at 10%; ** significant at 5%; *** significant at 1%					

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A.30. Average number of children (real and simulated) by household type

	1986	1996	2006
Lone parent	0,958	0,861	1,000
Biparental	1,802	1,573	1,552
Other households	1,415	1,258	1,277
Total	1,145	0,940	0,879

A.31 Distribution of children by income quintile. 2006.		
	Real	Simulated
Quintile 1	34,7	25,0
Quintile 2	25,1	23,8
Quintile 3	17,6	20,7
Quintile 4	12,4	17,1
Quintile 5	10,2	13,4
Total	100,0	100,0