

Labor Participation of Married Women in Colombia

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Abstract

A pseudo-panel was built to estimate the determinants of the labor participation decision of married women between 1984 and 2000. Past participation decisions, education level, labor income taxes, children between 1 and 2 years of age, and the presence of other people unemployed at home are the main explanatory variables of married women's labor participation in Colombia. The interest rate variable does not offer any insight into that decision.

JEL classification: C21, C23, C25, J22, J13.

Key words: married women, labor participation, state-dependence, fertility.

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1. Introduction

The decision to join to the labor force is a topic of long-standing tradition in economics (see Heckman, 1993; Blundell and Macurdy, 1999; Pencavel, 1986). Noticeably, an important portion of the research in this area has been devoted to the study of the participation of married women (see Mincer, 1962; Gronau, 1973; Killingsworth and Heckman, 1986; among many others). This is because such a decision of married women has represented some important challenges to researchers that have sometimes been adequately captured by both economic and econometric models. Among these challenges are the proxies that have been used for the potential market wage (human capital acquisitions, experience, age, probability of transitory leaves for fertility decisions, etc.) and the reservation wage (non-labor income, including the husband's wage, fertility decisions, in particular, the presence of young children and the cost of child care, etc.).

Labor participation in Colombia has been studied, from a static point of view, using the independent cross-sections data provided by the National Housing Survey (*NHS*) (see López, 2001; Santamaría and Rojas, 2001; Tenjo and Ribero, 1998; and, Arango and Posada, 2005). Intertemporal models of labor supply have been implemented to capture the behavior of participation within a life-cycle framework (MaCurdy, 1981; Altonji, 1986; Heckman and MaCurdy, 1980) taking into account aspects related to interest rates, labor income taxes, and fertility. For Colombia, unfortunately, there is a lack of research that focuses on the life-cycle behavior of the extensive margin of the labor supply regardless of the advantages of this approach. The explanation lays in the fact that there is no panel data in Colombia on household labor market supply. In spite of this weakness of Colombian statistics, Sánchez and Núñez (2002) undertook a pseudo-panel approach to study some household behavior characteristics including labor force participation.

In this work, following Deaton (1985) a pseudo-panel is conformed in order to observe some life-cycle properties of labor force participation. Independent cross-sections, based on the quarter stages of *NHS* for the seven biggest cities between 1984 and 2000, are transformed into population cohorts; the sample mean of each cohort is computed and used as a panel. Then different models of participation for married women (or those in common-law unions) are estimated to assess the main determinants of the labor participation decision.

The model attempts to capture the behavior of labor participation over time, the main recent findings related to fertility decisions (see Nakamura and Nakamura, 1992; Carrasco, 2001; Chun and Oh, 2002; Attanasio *et al.* 2004, etc.), and memory of labor participation decisions (true state dependence) (Heckman, 1981; Hyslop, 1999; Carro, 2003; etc.). The results of the regressions are in line with the theory, intuition, and findings in other countries.

This article develops as follows: Section 1 is this introduction. Section 2 establishes the model. Section 3 shows the characteristics of the cohorts and some stylized facts derived from the pseudo-panel. Section 4 explains the empirical approach and presents and discusses the results. Finally, Section 5 draws some conclusions.

2. A model for labor participation over time

The aim of this paper is to check the power of some potential determinants of married women's labor participation when they make this decision during the course of their lives. Among the determinants are interest rates, labor income taxes, education level, age, non-labor income, and the cost of child care, this latter factor being neatly connected to fertility decisions. This section develops a model in which these variables appear as determinants of the extensive component of the labor supply¹.

Consider a married woman whose problem is to maximize the present value of discounted utility over a finite lifetime:

$$\Omega = \sum_{t=0}^T \alpha^t u(c_t, l_t; x_t) \quad (1)$$

where Ω is a monotonically increasing function, $u(\cdot)$ is the periodic utility flow, α is the discount factor, c_t is consumption at age t , total hours available for the woman are normalized to 1 and used to work in the market, n_t , or leisure time, l_t , such that $1 = n_t + l_t$, and, x_t is a vector of characteristics of the family in period t , which accounts for observed and unobserved heterogeneity both over time and across families. If the woman decides to work she will undergo a welfare loss but, on the other hand, the labor income will allow her to increase consumption. If she decides to work, her after-tax income net of the costs of childcare and some others is:

¹ This model compiles elements of Carrasco (1998), Hyslop (1999), and Attanasio *et al.* (2004).

$$w_t(1-\tau_t)n_t - \delta_t w_t(1-\tau_t)(1-n_t) + y_t - \phi_t n_t - \lambda_t(1-n_{t-1}) = w_t(1-\tau_t)[n_t - \delta_t(1+n_t)] + y_t - \phi_t n_t - \lambda_t(1-n_{t-1}) \quad (2)$$

where w_t is the wage, y_t the non-labor income, τ_t the labor income tax rate, δ_t the fraction of the wage's present value that she undergoes in the future if she decides not to work in the present; that is, δ_t is the depreciation rate of human capital², ϕ_t the cost of substituting direct child attention for indirect attention, and λ_t the job search cost. The specification in (2) means that if the married woman decides not to work in period t her income will be: $y_t - \delta_t w_t(1-\tau_t) - \lambda_t(1-n_{t-1})$.

The objective is to maximize (1) subject to the constraint:

$$\{w_t(1-\tau_t)[n_t - \delta_t(1+n_t)] - \phi_t n_t - \lambda_t(1-n_{t-1}) + y_t + b_t - c_t\}(1+r_t) = b_{t+1} \quad (3)$$

where b_t is the asset at the beginning of period $t+1$ and r_t is the interest rate. This restriction assumes that the woman can save and acquire debts³.

The solution to the problem implies that she is indifferent to participation or nonparticipation at the corner where $1=l_t$, if the wage that she would receive in the labor market w_t is equal to the reservation wage, \bar{w}_t , plus the job search cost. In other words, an interior solution will exist if $w_t > \bar{w}_t + \lambda^* n_{t-1}$.

The period t decision, conditional on current and future realizations of the exogenous variables, can be defined by⁴:

$$n_t = 1(w_t > \bar{w}_t + \lambda^* n_{t-1}) \quad (4)$$

where $1(\cdot)$ is the indicator function that is equal to 1 if the expression is true and 0 otherwise⁵. Empirically the model considered for woman i in period t is:

$$n_{it} = 1(n_{it}^* > 0) = 1(X'_{it}\beta + \lambda^* n_{it-1} + \mu_{it} > 0) \quad (i = 1, \dots, N; t = 1, \dots, T) \quad (5)$$

where X_{it} is a vector of observed variables as family composition of woman i , education level, and demographic aspects while μ_{it} represents the effect of unobserved determinants that

² This term could also be associated to the indirect effects of fertility explained by Nakamura and Nakamura (1992).

³ The usual terminal conditions that rule out suboptimal decisions are assumed to hold.

⁴ Take into account the reparameterization we have made to express search costs in terms of participation (or hours) rather than in terms of leisure. Now we have λ^* instead of λ .

⁵ Notice that the 1 of the indicator function, $1(\cdot)$, is not the same of time availability: $1 = n_t + l_t$.

might affect the participation decision. The unobserved heterogeneity term μ_{it} might be composed by two elements. One which is time invariant that would reflect heterogeneity among individuals possibly originated in human capital and other cohort factors denoted by φ_i and one associated to random transitory movements in wages denoted by ν_{it} . This term could be serially correlated but independent of X_{it} for consistency.

The specific relationship between fertility and labor participation of married women is not that obvious. Econometricians have tried to overcome any potential endogeneity among these variables through the use of instruments. However, the instruments currently used are not satisfactory (Nakamura and Nakamura, 1992) and, consequently, the correct set of instruments remains as an open question.

Another issue that we try to capture is the memory of current labor participation; that is, we try to answer the question whether the contemporaneous decision on participation depends or not on previous decisions about participation in the labor market. This memory could be due to both serial persistence and state dependence of female participation. Heckman (1981) has made distinctions between serial correlation and state dependence being the latter associated to persistent individual heterogeneity (see also Hyslop, 1999). The restriction in expression (3), where past participation decisions are present, allows our model to introduce the concept of decision memory into play⁶.

3. Data construction and empirical facts

In Colombia there is no panel survey on household labor supply statistics. Thus, to explore the life-cycle implications of the neoclassical model the construction of an artificial panel is required. This pseudo-panel was built with the information from all stages (quarters) of the National Housing Survey (*NHS*), which are independent cross-sections applied between 1984 and 2000 to compile labor market information⁷. With this pseudo-panel data analysis it is possible to track cohort means (supposedly pertaining to a particular married woman) over time while it is not possible with independent cross-sections.

⁶ Apart from search costs and human capital accumulation and depreciation, imperfect information would give rise to the presence of memory in both the theoretical and empirical specification (see Heckman 1981).

⁷ Since the year 2000, the National Agency of Statistics (DANE) has been capturing information from the labor market through another mechanism called the Continuous Housing Survey.

To construct this artificial panel we invoke the proposal of Deaton (1985) in which the population is divided into different groups, or cohorts, to figure on a representative (average) agent for each group. Thus, instead of observing different true individuals over time we track cohort means⁸.

In our particular case, for studying the labor participation decisions of married women in Colombia we focus on six specific groups of women who were born between 1941 and 1970 as presented in Table 1.

Table 1. Composition of age cohorts

Group (cohort)	Women born between		Average year	Average number of observations per quarter	Maximum number of observations in a quarter	Minimum number of observations in a quarter	Standard deviation of observations number per quarter
1	1941	1945	1943	1053	2173	521	341
2	1946	1950	1948	1434	2899	818	469
3	1951	1955	1953	1771	3167	980	447
4	1956	1960	1958	2080	3272	1215	374
5	1961	1965	1963	2001	2579	1299	321
6	1966	1970	1968	1364	2513	166	650
Average				1617			

Source: Authors' calculation based on the National Housing Survey (DANE-ENH)

In other words, we end up with six cohorts of married women who are observed through the period of the *NHS*; that is over 68 quarters, between 1984 and 2000. Summary statistics are presented in Table 2 where the simultaneous increase of participation rate and years of education and the reduction of wealth is noteworthy. It is also important to observe that the number of children increases as long as women are younger; for example, the number of children of age between 0 and 1 is higher and gets bigger for women of cohorts 4 to 6.

A number of other salient features of the Colombian labor market can be accounted for. This is the case of participation over time shown in Figure 1. As predicted by the life-cycle model, the rate of participation over time shows an inverted-*U* behavior: at an early age a woman participates less in the labor force, but as long as age and education levels increase, participation also increases. After that some other forces start to intervene in the decision; for example, the presence of young children, the level of wealth already acquired, and the non-labor income

⁸ Collado (1997) argues that when the cohort sample means are used as panels these are subject to measurement errors. The Monte Carlo simulations that she ran show that the measurement-error correction seems to be important in terms of the bias reduction of the corrected estimators. However, that correction is not undertaken here.

(income of their husbands) reduce the probability of participation. There are, on the other hand, forces, like experience, that increase the probability of labor participation.

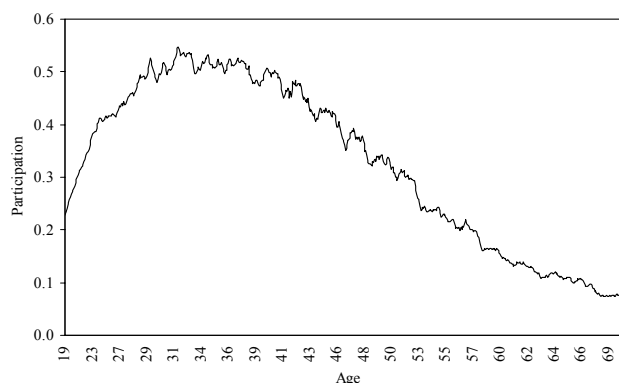
Table 2. Some characteristics of cohorts

Group (cohort)	Participation rate	Age	Years of education	Wealth	Children between:					
					0 – 1	1 – 2	2 – 3	3 – 4	4 – 5	5 – 6
1	0.324	48.89	6.293	0.8253	0.0138	0.0116	0.0163	0.0209	0.0252	0.0080
2	0.415	43.85	6.962	0.7359	0.0403	0.0299	0.0379	0.0462	0.0537	0.0212
3	0.481	38.90	7.632	0.5927	0.0913	0.0610	0.0718	0.0857	0.0925	0.0441
4	0.501	33.94	8.205	0.4351	0.1715	0.1049	0.1190	0.1308	0.1324	0.0728
5	0.479	29.08	8.326	0.2952	0.2841	0.1550	0.1596	0.1570	0.1442	0.0817
6	0.416	24.40	7.919	0.2023	0.3849	0.1697	0.1499	0.1340	0.1096	0.0631
Average	0.4562	35.29	7.729	0.4852	0.1718	0.0993	0.1070	0.1131	0.1110	0.0593

The wealth of the family, as a proxy of non-labor income, is computed as a dummy that takes the value of 1 if the family either owned a house (without any outstanding mortgage debt), or the neighborhood is middle class or higher (according to the official urban classification system), or the family earned \$2,500,000 in real terms (Colombian pesos of December 2000); otherwise it takes the value of 0.

Source: Authors' calculation based on the National Housing Survey (DANE-ENH).

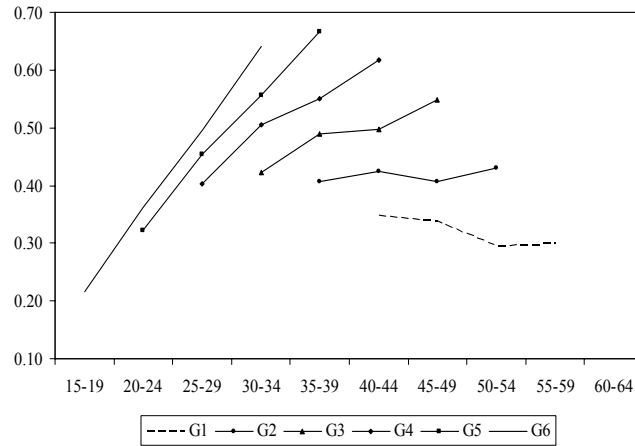
Figure 1. The life-cycle of participation rate



Source: Authors' calculation based on the National Housing Survey (DANE-ENH)

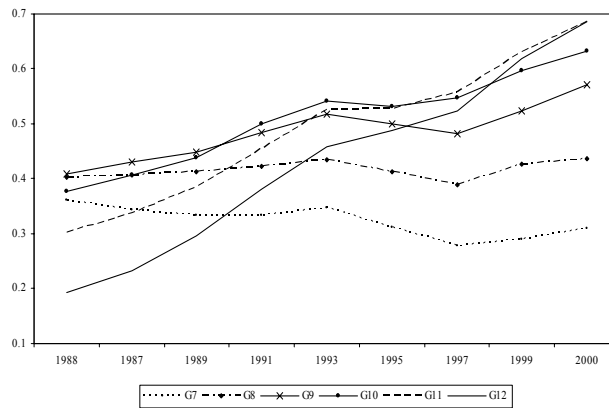
Figure 2 shows the labor participation rate of each group per age. Labor participation is lower for older groups than for younger ones. That is, when people in Group 3 (G3), who were born, on average, in 1953, were between 30 and 34 years old they participated less than those of Groups 4, 5, and 6 at the same ages. At the same time younger married women tend to participate more in the labor force. Figure 3 shows the participation rate of each cohort over time. It is remarkable the rapid increase in participation of G6. These facts might be evidence of a cohort effect that we will try to consider empirically later on.

Figure 2. Mean of participation rate per cohort



Source: Authors' calculation based on the National Housing Survey (DANE-ENH)

Figure 3. Participation rate per group

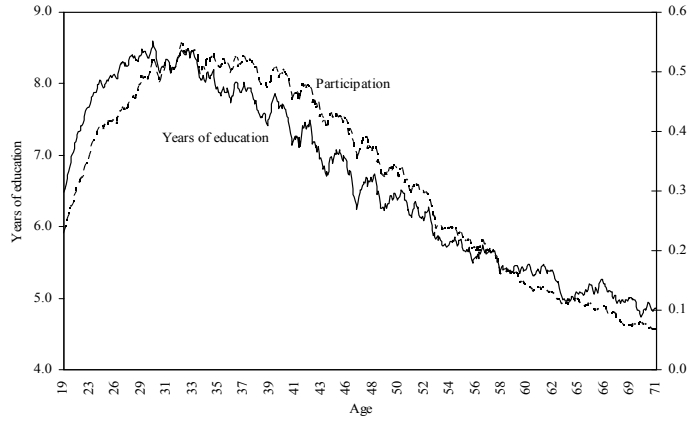


Source: Authors' calculation based on the National Housing Survey (DANE-ENH)

Figure 4 shows the behavior of both the participation rate and the number of years of education. The left vertical axis measures the years of education while the right axis measures the participation rate. Thus, we can observe that, up to a scale, there is a similarity in the movements of the two variables; even more, the peak of education is reached just before the peak of participation rate. Figure 5 presents the relationship of the participation rate and education. It seems clear that participation increases along with the years of education; however, it also seems that two types of women co-exist with education between 4.5 and 8.5 years: one type that participates, on average, more than 12 percentage points than the other type. This difference is

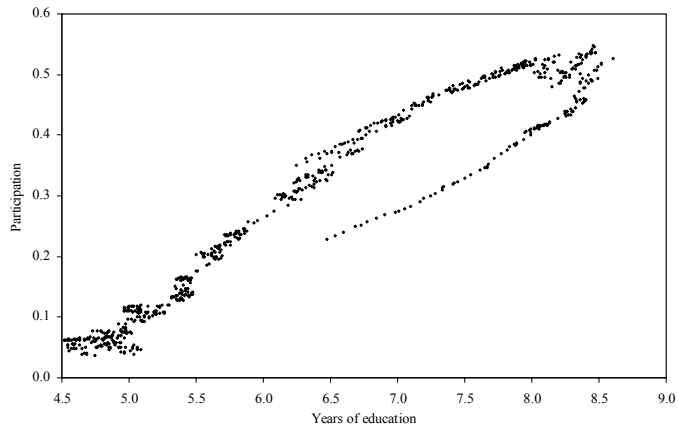
evident between women with 6.5 and 8.5 years of education. The level of wealth is a plausible candidate to explain such a behavior.

Figure 4. Behavior of education and participation rates over time



Source: Authors' calculation based on the National Housing Survey (DANE-ENH)

Figure 5. Education and participation rates



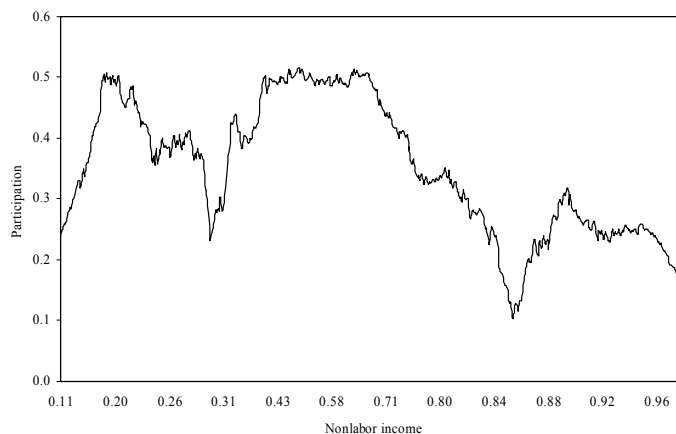
Source: Authors' calculation based on the National Housing Survey (DANE-ENH)

Another typical determinant of labor force participation is the wealth or non-labor income usually regarded as a principal component of the labor opportunity cost or the reservation wage. The wealth of the family is set as a dummy that takes the value of 1 if the family either owned a house (without any outstanding mortgage debt), or the neighborhood is middle class or higher⁹, or the family earned \$2.500.000 in real terms (Colombian pesos of December 2000); otherwise it takes the value of 0. Figure 6 shows the relationship between the participation rate

⁹ According to the official urban classification system.

and our definition of wealth. The probability of participation in the labor market is very small when the probability of having wealth is higher than 0.6.

Figure 6. Participation rate and wealth (or nonlabor income)



Source: Authors' calculation based on the National Housing Survey (DANE-ENH)

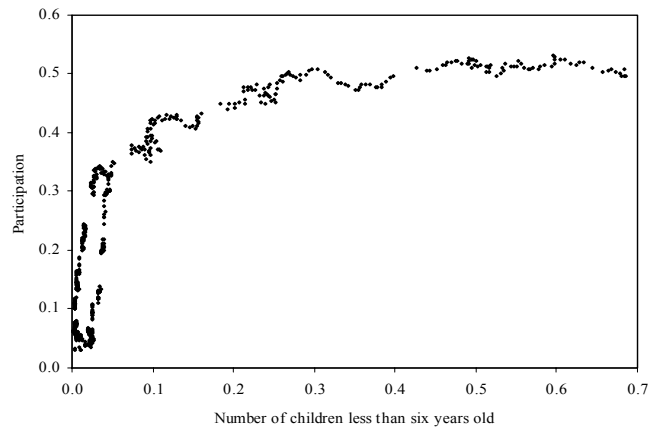
One of the most interesting aspects of the female participation has to do with costs of childcare and fertility decisions. Figure 7 shows the participation of married women ordered according to the number of children they have under 6 years of age. From that picture is clear that participation is lower when the number of children is also low. This pattern suggests a positive relationship among the variables, contrary to that postulated by the theory. To disentangle this counterintuitive fact we decompose the children under age six into six categories: children between age 0 and 1, between 1 and 2, 2 and 3, 3 and 4, 4 and 5 and, finally between 5 and 6.

Figure 8 shows the number of children classified according to age. Thus, 19-year-old mothers have, on average, 0.536 children between ages 0 and 1, 0.182 children between ages 1 and 2, and so on. The conclusion is that younger mothers have younger children.

Fertility poses a challenge in the analysis of labor participation since endogeneity might be present (Nakamura and Nakamura, 1992). That is, labor participation might affect current or future fertility decisions and vice versa. Given the evidence obtained from Figures 9, 10 and 11, we observe some potential to this point. Figure 9 presents the labor participation behavior of mothers who have at least one child between ages 0 and 1 and no children at any other age. This Figure also shows the labor participation of mothers who have at least one child between ages 1 and 2, and the labor participation of mothers who have at least one child between ages 2 and 3. It

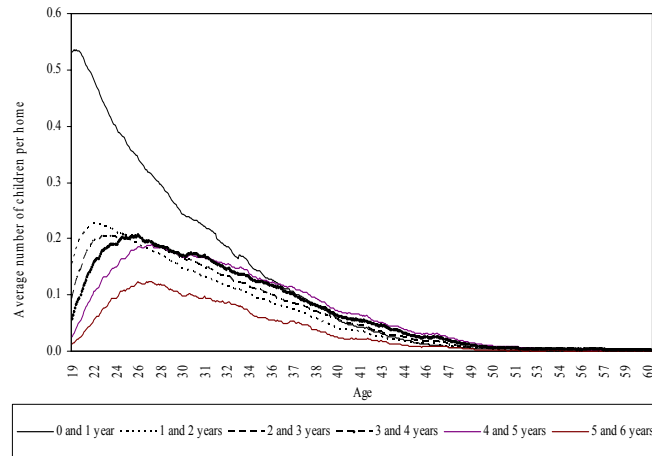
seems evident that the labor participation rate of mothers who have children only between ages 0 and 1 is always lower than that of mothers who have children only between ages 1 and 2, and with children only between ages 2 and 3. This result is the same for mothers with children only between ages 5 and 6. At this children's age their mothers decide to reduce labor participation (Figure 10).

Figure 7. Number of children under 6 years of age and mother's participation



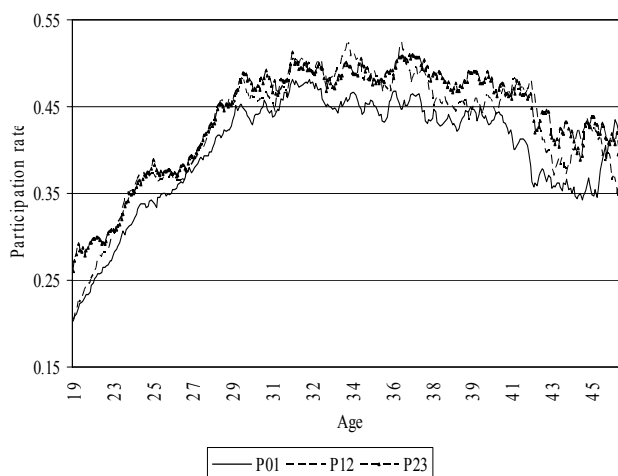
Source: Authors' calculation based on the National Housing Survey (DANE-ENH)

Figure 8. Number of children per mother and mother's age



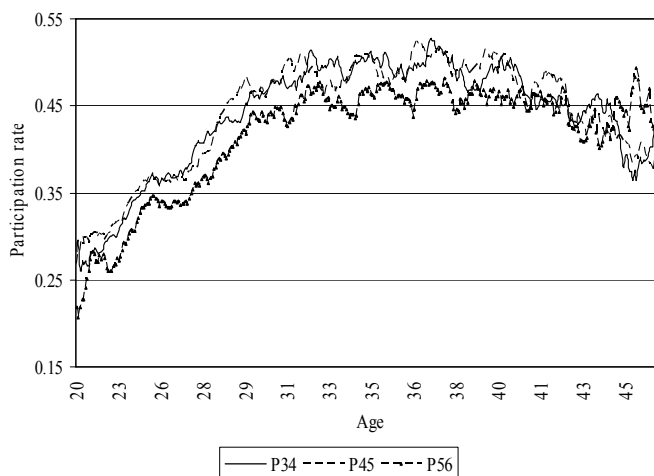
Source: Authors' calculation based on the National Housing Survey (DANE-ENH)

Figure 9. Participation rate of mothers with at least one child at ages 0-1, 1-2 and 2-3.



Source: Authors' calculation based on the National Housing Survey (DANE-ENH)

Figure 10. Participation rate of mothers with at least one child at ages 3-4, 4-5 and 5-6.



Source: Authors' calculation based on the National Housing Survey (DANE-ENH)

In Figure 11 we observe that the participation of mothers with children only between ages 0 and 1 and between ages 5 and 6 is similar up until the mother is about 35 years old; for mothers older than that, the participation rate is slightly higher for those who have only children between ages 5 and 6. Both of them are lower than total participation. That is, participation is negatively related to fertility decisions: participation rate of married women with children aged between 0 and 1 is less than any other participation rate. Also noticeable, the participation rate of married women declines over time; this is why participation of mothers with children who are older than 5 but younger than 6 is also lower than other participation rates.

Figure 11. Participation rate of mothers with at least one child at ages 0-1 and 5-6 and total participation.



Source: Authors' calculation based on the National Housing Survey (DANE-ENH)

4. Econometric issues, results and discussion

The theoretical model of Section 2 (appended to the facts showed in the previous section) gives rise to some hypothesis that one might verify¹⁰. The econometric exercises carried out in this work can be divided into three parts. First, we focus on interest rates and labor income taxes as determinants of participation rates. Second, a probit pooling (static) regression is adjusted in order to analyze the determinants within this set where unobserved heterogeneity becomes more relevant. Third, panel data estimations are carried out. In the latter case we use not only the linear probability model to observe the signs and magnitudes of marginal effects under the fixed effects estimator, but also the random effects probit estimator.

With the linear regressions of each cohort in isolation we verify the power of the interest rate factor as well that of labor income taxes¹¹ to explain the labor participation decision over time. Both elements are always present in the Euler equation generated by an optimization process. The empirical counterpart we define is given by:

$$n_t = 1(n_t^* > 0) = 1(X_t' \beta + \lambda^* n_{t-1} + \mu_t > 0) \quad (6)$$

¹⁰ Following Deaton (1985), given that cohorts are very different in size each observation has been weighted by square root of the cohort size.

¹¹ The series of labor income taxes was kindly provided by L. Fergusson which was first presented in Fergusson (2003).

Hence, we use the model and include the past probability of participation (the latent probability¹²) which is denoted in Table A1 in the Appendix as lagged participation. The rest of the variables in Table A1 are interest rates, labor income taxes, years of education, non-labor income (or wealth) defined as a dummy variable that takes the value of 1 if the family holds the conditions mentioned above and 0 otherwise, presence of other people unemployed at home which is a dummy variable that takes the value of 1 when there are people undergoing unemployment episodes and 0 otherwise, squared age (our proxy of human capital depreciation), and the number of children under age 6. The regressions in Table A1 focus on Groups 3 to 6 given the variability of the dependent variable.

The estimates corresponding to past latent participation and presence of other unemployed people at home are significant for most of the groups. But the lack of significance of interest rates, labor income taxes, and the number of children under age 6¹³ is noticeable.

To check again the relevance of our intuition, we disaggregate the variable children under age 6 to verify the explanatory power of fertility. This is replaced by children between ages 0 and 1, between ages 1 and 2, 2 and 3, 3 and 4, 4 and 5, and 5 and 6. In this case we have disregarded the variable “age” since the inclusion of children at different ages could induce some collinearity between these variables. Table A2 presents the results of these regressions which are, again, focused on Groups 3 to 6 given the variability of the dependent variable¹⁴. There are two regressions which differ only because the first includes children between ages 0 and 1 while the second does not.

The results in Table A2 (see the Appendix) show that past latent participation probability is not significant for Groups 3, 4, 5, and 6. This is also the case with interest rates and labor income taxes, but interestingly, and irrespective of the significance, the corresponding coefficients of those variables take different signs showing different dominance of substitution and income effects depending on the group we are looking at. With respect to children, now disaggregated by age, there is a gain since for each group we can observe which of them affect the labor participation decision. However, no interesting pattern arises from these regressions given that sometimes the coefficients are not significant and sometimes the sign of those

¹² Instead of using the past observed decision (which takes the value 0 or 1) we use the latent or underlying probability of participation.

¹³ The coefficients corresponding to interest rates and taxes could exhibit any sign depending on the dominance of income and substitution effects that each variable might generate in turn.

¹⁴ The dependent variable of Groups 1 and 2 takes always the value of 0.

coefficients is different from the expected one. In summary, the time series approach to the labor participation decision is not illuminating enough about its determinants during the sample period for the artificial cohorts we have built.

A second exercise we undertake is a probit pooling regression without any dynamics to analyze the effect of unobserved heterogeneity. The model is:

$$n_i = 1(n_i^* > 0) = 1(X_i'\beta + \mu_i > 0) \quad (8)$$

The results of this regression are included in the first two columns of Table 3. Some of the estimated probit coefficients have the expected sign. This is the case of education, labor income taxes, non-labor income, other people unemployed at home, squared age, children of between ages 0-1, 1-2, 4-5, and 5-6. However, the coefficients of children of between ages 2-3 and 3-4 do not correspond to the predictions of the theory. As we mentioned above, both labor income taxes and interest rates can generate substitution and income effects. According to the sign, the former dominates in the case of the two variables.

Table 3. Pooled Probit

Variables	Sample: 1984:2 – 2000:4		Sample: 1990:1 – 2000:4	
	Coefficient	Marginal effects	Coefficient	Marginal effects
Constant	-5.6304 (3.1974)		-3.4845 (3.4372)	
Interest rate	-0.0026 (0.0012)	-1.02e-06 (0.0000)	-0.0023 (0.0012)	-0.0005 (0.0004)
Labor income taxes	-0.0009 (0.0027)	-3.57e-07 (0.0000)	-0.0020 (0.0028)	-0.0004 (0.0006)
Education	0.1228 (0.0271)	0.00004 (0.0001)	0.1065 (0.0295)	0.0228 (0.0114)
Non-labor income (wealth)	-0.1100 (0.0829)	-0.00004 (0.0001)	-0.1313 (0.0840)	-0.0281 (0.0310)
Others unemployed at home	0.9972 (0.2976)	0.0003 (0.0010)	0.9534 (0.2985)	0.2043 (0.1090)
Squared age	-0.0004 (0.0001)	-1.76e-07 (0.0000)	-0.0003 (0.0001)	-0.0008 (0.00003)
Children 0-1	-0.8185 (0.3871)	-0.0003 (0.0008)	-0.9492 (0.4176)	-0.2034 (0.1519)
Children 1-2	-1.7663 (0.6714)	-0.0006 (0.0019)	-1.7992 (0.7971)	-0.3855 (0.2538)
Children 2-3	0.7649 (0.5933)	0.0002 (0.0009)	0.6457 (0.6035)	0.1383 (0.1705)
Children 3-4	0.3613 (0.5666)	0.0001 (0.0004)	0.8269 (0.6505)	0.1772 (0.1793)
Children 4-5	-1.0105 (0.5284)	-0.0003 (0.0010)	-0.9440 (0.6123)	-0.2023 (0.1565)
Children 5-6	-0.6620 (0.6391)	-0.0002 (0.0008)	-0.1148 (0.7520)	-0.0246 (0.1627)
Log likelihood	-32.3275		-28.8619	
pseudo R ²	0.8690		0.8265	

Note: standard errors are in parenthesis.

However, not all coefficients are significant. This is most noticeable in the cases of taxes, non-labor income, and children between ages 2-3, 3-4 and 5-6. Based on the coefficients, the probit model seems to be close to the theory and give some importance to unobserved heterogeneity since coefficients linked to fertility are now significant. However, regardless of having the signs predicted by the theory, the marginal effects analysis suggests that no variable is really significant in the model for the whole sample period. However, for a shorter period of time (1990:1-2000:4), education and others unemployed at home, as evidence of the “additional worker effect”, are significant on the grounds of marginal effects.

Then, we turn to panel analysis. Participation decisions of married women pose some problems given the treatment of unobserved heterogeneity either as fixed or random, the incidental parameters problem, the potential endogeneity of fertility decisions¹⁵, the serial persistence-state dependence phenomena, and the initial conditions for the dynamic process given the intrinsic nonlinearity of a probit model.

Consider again Equation (5) which is written here for convenience:

$$n_{it} = 1(n_{it}^* > 0) = 1(X_{it}'\beta + \lambda^* n_{it-1} + \mu_{it} > 0) \quad (i = 1, \dots, N; t = 1, \dots, T) \quad (5)$$

where the term μ_{it} referred to unobserved heterogeneity is composed by two elements as we stated above: φ_i and v_{it} . The first represents heterogeneity among individuals originated in factors such as human capital and other cohort factors and the second associated to random transitory movements in wages. The fixed effects probit model regards φ_i as parameters to be estimated together with β since this procedure does not require any assumption about the distribution of φ_i given X_{it} . Unfortunately the joint estimation of φ_i and β generates the problem of incidental parameters. This difficulty arises because of the nonlinear underlying nature of the probit model which leads to inconsistent log-likelihood estimation of β with T fixed and $N \rightarrow \infty$ (see Wooldridge, 2002, chapter 15). In other words, the estimation of β could change as long as new observations are added to the sample.

The dynamics of the labor participation, observed through the high degree of memory, is an important characteristic of this individual's decision. Associated to the memory of participation are the problems of initial conditions and persistence-state dependence. The former

¹⁵ This problem is not addressed here on the grounds that the set of instruments currently used in the literature is not satisfactory (Nakamura and Nakamura, 1992). However, children between ages 0 and 1 are not included in the regressions when state dependence is explicitly considered.

arises since the participation process is not observed at the moment of entrance to the labor age (which takes place in Colombia when people are at least 12 years old) and, as a result, something must be assumed about the first decision of labor participation (n_{i0}) and its relationship to other determinants. A misspecification of the initial conditions will also lead to inconsistent estimates of β . To deal with this issue, given the random effects approach used, we follow the procedure of Wooldridge (2002) which decompose μ_{it} into φ_i , n_{i0} , X_i and ζ_{it} .

As for the serial persistence problem, the literature recognizes a difference between state dependence and persistence. The former is explained on the basis of human capital accumulation and job search costs¹⁶; these are reasons to observe that individuals, with some observable characteristics, decide for an option with higher probability when they have made the same decision in the past. The latter might be caused by persistent individual heterogeneity through which there is a high probability to take a labor participation decision but without regard to previous choices.

Then, focusing on the estimation, if we assume for the moment that ν_{it} is serially uncorrelated, it could be of some interest to consider the fixed effect linear probability model which has the appeal that, as stated above, does not make any assumption on the distribution of φ_i . This model controls for any arbitrary correlation between φ_i and X_{it} and can help to eliminate the incidental parameters due to the form of controlling for unobserved heterogeneity which consists of differencing the processes. A disadvantage of the linear probability model is that one can account for the fact that its forecasts are not restricted to the $[0, 1]$ interval. For this exercise we restrict ourselves to the shorter sample period and use the variables that (according to previous exercises) have been more promising. At the same time, to avoid the problem of potential endogeneity between the labor participation decision and fertility we discard the children between 0 and 1 years of age taking into account that past participation probability has been included as an explanatory variable. Results in Table 4 suggest that the performance of this model is rather poor in terms of significance of the estimated coefficients and the sign of the coefficient corresponding to education. For the fixed effects model, the ρ coefficient is high enough (0.3813) which might be an indication that the variability explained by the fixed component of the model is important to some extent.

¹⁶ Non-separability of preferences is also a possible source of state dependence.

Table 4. Linear Probability Model (1990:1-2000:4)

Variable	First differences	Levels
Constant	0.4523 (0.0350)	-0.9332 (0.1919)
Past participation probability	0.0292 (0.0235)	0.0450 (0.0128)
Education	-0.0018 (0.0024)	0.0017 (0.0014)
Labor income taxes	-0.00009 (0.00147)	0.0003 (0.0002)
Non-labor income (wealth)	-0.0034 (0.0036)	-0.0077 (0.0035)
Others unemployed at home	0.0431 (0.0325)	-0.0060 (0.0131)
Children 1-2	-0.0610 (0.0572)	-0.0780 (0.0236)
Seasonal 1	-0.0002 (0.0024)	0.0055 (0.0012)
Seasonal 3	-0.0003 (0.0017)	0.0020 (0.0012)
R ²	0.0366	0.6619
ρ (fraction of variance due to φ_i)	0.5361	
σ_φ	0.3813	
Correlation (φ_i, X_{it})	0.0849	
σ_v	0.3547	0.2732

Note: standard errors in parenthesis.

Then we estimate a linear probability model assuming that φ_i is not correlated to X_{it} , or that μ_{it} is a correlated random effect (model in levels in Table 4). In this case, not only the significance but also the sign and the magnitude of the estimates coefficients change with respect to the fixed effect linear probability model. The random specification suggests that, after controlling for seasonal effects, past participation, non-labor income, and children between ages 1 and 2 are the main determinants of married women's participation (see Table 4). However, the results must be interpreted with some caution given the length of time (T) versus the size of individuals (N).

Under the assumption that μ_{it} is a correlated random effect we can use probit models. This kind of models parameterize the distributions of φ_i . Table 5 shows that, controlling for initial conditions and seasonal effects, there is evidence of true state-dependence, all variables have the sign predicted by the theory and all of them, except for non-labor income, are significant. Nevertheless, according to the ρ coefficient, there is no panel effect so that the model is equivalent to a pooled probit. The marginal effects are significant for all variables and have the expected sign, which suggest that the variables are relevant.

Table 5. Panel Probit: Random Effects (1990:1-2000:4)

Variable	Coefficient	Marginal effects
Constant	-16.7284 (4.1734)	
Past participation probability	0.6992 (0.2004)	0.2247 (0.0735)
Initial participation probability	-0.3191 (0.0969)	-0.1026 (0.0391)
Education	0.0608 (0.0240)	0.0195 (0.0077)
Labor income taxes	-0.0093 (0.0037)	-0.0030 (0.0013)
Non-labor income (wealth)	-0.0713 (0.0529)	-0.0229 (0.0171)
Others unemployed at home	0.5690 (0.1843)	0.1829 (0.0619)
Children 1-2	-1.4366 (0.4503)	-0.4618 (0.1623)
Seasonal 1	0.0713 (0.0176)	0.0229 (0.0052)
Seasonal 3	0.0225 (0.0112)	0.0072 (0.0035)
ρ	8.32e-07	
σ_ϕ	0.0009	
Log likelihood	-32.24067	

5. Conclusions

This paper analyzes the labor participation decision of married women in Colombia within a life-cycle framework. By employing the information of the *NHS* we built a pseudo-panel and end up with 6 groups that we regard as 6 different women. Given the difficulties posed by this topic we undertake an exploratory tour by using different specifications that allow us to arrive at some significant conclusions.

Some important facts can be sketched directly from the data. This is the case of the behavior of participation curve which takes the form of an inverted-*U* as age of women increases. Another finding is related to higher participation rates in the labor market of younger women a fact possibly linked to their higher education level. The data also suggests a negative relationship between participation and wealth and an effect of fertility on the participation decision.

Within a neoclassical framework, variables such as interest rates, labor income taxes, education, wealth (non-labor income), presence of others unemployed at home, squared age, and fertility, represented by children of ages from 0 up to 6 are used to model the participation decision of married women (or in common-law unions).

Children under age 6, when considered as a whole, are not significant. The same conclusion is obtained with wealth; however, this variable appears most of the time with the

expected sign. Intertemporal decisions based on the behavior of interest rates are not relevant for the participation decision.

After controlling for seasonal effects, memory of decisions about labor participation is an important variable as well as education, labor income taxes, the presence of other people unemployed at home, and children between ages 1 and 2. Once this set of explanatory variables is included into the model, unobserved heterogeneity does not play any role in determining the participation of married women.

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Appendix : Time series regressions for participation decision of married women

Table A1. Coefficients of models of group participation over time

Cohort	Coefficient	Standard error	Coefficient	Standard error
Constant				
G3	-0.6363	0.8107	-0.1406	0.7413
G4	0.3010	0.5145	0.5149	0.5255
G5	1.6099	0.4579	1.6191	0.4558
G6	-0.1608	0.1957	-0.2016	0.1819
Past (latent) participation probability				
G3	0.1315	0.0594	0.1030	0.0566
G4	0.0695	0.0329	0.0521	0.0333
G5	0.0656	0.0264	0.0729	0.0243
G6	-0.0412	0.0271	-0.0519	0.0238
Interest rate				
G3	0.0000	0.0003	0.0002	0.0003
G4	-0.0000	0.0001	0.0000	0.0001
G5	-0.0001	0.0001	-0.0001	0.0001
G6	-0.0001	0.0001	-0.0001	0.0001
Labor income taxes				
G3	-0.0025	0.0014	-0.0033	0.0013
G4	0.0004	0.0007	0.0000	0.0007
G5	-0.0008	0.0007	-0.0004	0.0006
G6	0.0024	0.0009	-0.0018	0.0007
Education				
G3	0.0088	0.0077	0.0006	0.0053
G4	0.0002	0.0045	-0.0067	0.0035
G5	-0.0102	0.0039	-0.0082	0.0028
G6	-0.0021	0.0046	-0.0053	0.0026
Non labor income (or wealth)				
G3	0.1563	0.1003	0.0154	0.0104
G4	0.0008	0.0071	0.0055	0.0071
G5	0.0047	0.0070	0.0032	0.0067
G6	0.0034	0.0096	0.0061	0.0091
Presence of other unemployed people at home				
G3	0.1407	0.0603	0.1644	0.0586
G4	-1.0119	0.0365	-0.0510	0.0304
G5	-0.1167	0.0307	-0.1222	0.0297
G6	0.0609	0.0539	0.0474	0.0513
Age				
G3	-0.0040	0.0028		
G4	-0.0053	0.0022		
G5	0.0016	0.0023		
G6	-0.0024	0.0029		
Squared age				
G3	0.0000	0.0000	2.08e-06	0.0000
G4	0.0001	0.0000	0.0000	0.0000
G5	0.0000	0.0000	0.0000	0.0000
G6	0.0000	0.0000	0.0000	0.0000
Children				
G3	0.0061	0.0177	-0.0004	0.0172
G4	0.0116	0.0120	-0.0034	0.0105
G5	-0.0119	0.0096	-0.0089	0.0086
G6	-0.0014	0.0092	-0.0035	0.008
R ² 3	0.8339	Df = 57	0.8319	Df = 58
R ² 4	0.8065		0.7879	
R ² 5	0.8532		0.8518	
R ² 6	0.8339		0.8319	

Table A2. Coefficients of models of group participation over time

Cohort	Coefficient	Standard error	Coefficient	Standard error
Constant				
G3	0.0203	0.7957	0.1574	0.7738
G4	1.0150	0.4600	1.0060	0.4497
G5	1.1299	0.5031	0.9523	0.4853
G6	-0.2570	0.2307	-0.3146	0.2274
Past (latent) participation probability				
G3	0.0702	0.0617	0.0889	0.0568
G4	0.0449	0.0310	0.0439	0.0295
G5	0.0628	0.0255	0.0572	0.0252
G6	-0.0572	0.0251	-0.0613	0.0250
Interest rate				
G3	0.0003	0.0003	0.0003	0.0003
G4	-0.0001	0.0001	-0.0001	0.0001
G5	-0.0003	0.0001	-0.0003	0.0001
G6	-0.0000	0.0001	-0.0001	0.0001
Labor income taxes				
G3	-0.0041	0.0017	-0.0034	0.0015
G4	-0.0004	0.0009	-0.0005	0.0008
G5	-0.0005	0.0007	-0.0009	0.0006
G6	0.0026	0.0009	0.0021	0.0008
Education				
G3	0.0036	0.0066	0.0029	0.0066
G4	-0.0056	0.0038	-0.0057	0.0038
G5	0.0000	0.0033	-0.0009	0.0033
G6	-0.0021	0.0038	-0.0045	0.0033
Non labor income (or wealth)				
G3	0.0149	0.0110	0.0144	0.0109
G4	0.0015	0.0070	0.0015	0.0070
G5	0.0060	0.0061	0.0073	0.0061
G6	-0.0087	0.0103	-0.0048	0.0099
Presence of other unemployed people at home				
G3	0.1685	0.0567	0.1795	0.0548
G4	-0.0774	0.0327	-0.0790	0.0296
G5	-0.1054	0.0305	-0.1181	0.0289
G6	-0.0264	0.0808	-0.0370	0.0808
Squared age				
G3	8.70e-06	0.0000	-6.64e-06	0.00004
G4	0.0000	0.0000	0.00004	0.00003
G5	8.90e-06	0.0000	0.00003	0.00003
G6	0.0000	0.0000	0.00007	0.00004
Children 0-1				
G3	0.1183	0.1499		
G4	-0.0065	0.0547		
G5	-0.0395	0.0315		
G6	-0.0395	0.0314		
Children 1-2				
G3	-0.3289	0.1780	-0.2584	0.1534
G4	0.1515	0.0774	0.1493	0.0746
G5	0.0102	0.0598	-0.0130	0.0572
G6	-0.0715	0.0582	-0.0792	0.0582
Children 2-3				
G3	0.4018	0.1478	0.4364	0.1406
G4	0.1614	0.0798	0.1577	0.0727
G5	-0.0605	0.0750	-0.0726	0.0747
G6	0.0413	0.0611	0.0214	0.0594
Children 3-4				
G3	-0.1433	0.1851	-0.1092	0.1794
G4	-0.0881	0.0706	-0.0914	0.0644
G5	0.0797	0.0452	0.0691	0.0446
G6	0.1065	0.0649	0.1006	0.0651
Children 4-5				
G3	-0.1105	0.1296	-0.1241	0.1280
G4	-0.1629	0.0647	-0.1630	0.0641
G5	-0.0681	0.0529	-0.0593	0.0527
G6	-0.1967	0.0734	-0.1704	0.0708
Children 5-6				
G3	0.0017	0.1898	0.0273	0.1863
G4	-0.1374	0.0754	-0.1356	0.0731
G5	-0.1565	0.0459	-0.1457	0.0453
G6	-0.0266	0.0598	0.0054	0.0545
R ² 3	0.6642		0.6603	
R ² 4	0.8635		0.8634	
R ² 5	0.9016		0.8986	
R ² 6	0.8560		0.8517	
		Df = 53		Df = 54