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Income Incentives to Labour Participation and Home Production

The Contribution of the Tax Credits in the Netherlands

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Abstract in English

We set up a reduced form model of labour-market participation for young women who have to balance their career with motherhood. The model accounts for the occurrence of future uncertain events, like child birth and early retirement, and includes time spent in home production; however it does not require the estimation of a dynamic programming model. We claim that the careful implementation of institutions can return optimal life patterns of participation without the need of a structural approach. The weaker theoretical framework is more than compensated by the rich spectrum in policy simulations that may be performed. As illustrations, we simulate the effect of two policy options regarding tax credits on the hazard rate out of work.

Abstract in Dutch

In dit onderzoek presenteren we een herleide-vorm-model voor de arbeidsmarktparticipatie van jonge vrouwen. Het model houdt rekening met een aantal onzekere factoren die de toekomstige participatie kunnen verstoren, zoals de geboorte van een kind of vervroegde pensionering. Nieuw is dat het model ook tijd besteed aan thuiswerk (eng: home production) meeneemt.
We claimen dat ons model geen schatting van een (dynamisch) structureel model vereist. De zorgvuldige toepassing van de instituties geeft al voldoende informatie om optimale participatiebeslissingen over de levensloop te kunnen modelleren.
De zwakkere theoretische modellering wordt ruimschoots gecompenseerd door het brede scala aan beleidssimulaties die uitgevoerd kunnen worden. Ter illustratie simuleren we het effect van twee beleidsopties; afschaffing en verhoging van de arbeidskorting en de combinatiekorting. Afschaffing hiervan verkleint het verschil in levensloopinkomen tussen werken en niet-werken en zal mogelijkerwijs de prikkel tot participatie verminderen.

Contents

Summary

This study presents a reduced form model of labour-market participation for women who need to balance their career with motherhood. The model accounts for uncertain future events, like child birth and early retirement, and also includes home production. However, the model does not need a dynamic programming framework to be estimated, as careful implementation of the institutional setting is able to provide information on optimal patterns of labour participation over the life-cycle. This is an advantage, as it provides a more accessible computational framework. We refer to the Dutch institutions, as we dispose of data concerning the Netherlands, that are particularly convenient to this study. The lack of a structural approach, which is a disadvantage, is more than compensated by the rich spectrum in policy simulations that may be performed. These can reach from retirement to income policy, include home production or fertility dynamics. As illustration, we simulate therefore the effect of two policy options regarding tax credits, and therefore lifetime income profiles, on the hazard rate out of work. We measure the effect of changes in the Earned Income Tax Credit (EITC) and the Tax Credit to Employed Parents (TCEP) on the labour-market participation of young cohabiting Dutch women. These tax reductions (known as “arbeidskorting” and "combinatiekorting" in the Netherlands) are respectively an incentive to work to participating individuals and participating individuals with children. The changes in these credits have consequences for the residual life-cycle income and consumption profiles of women, that in turn may affect labour-market participation decisions.

In the Netherlands, women are in general arranging their life time patterns of labour participation depending on the timing of arrival of children. In order to gain these insights, we have to combine different data sets, since no panel exists containing information on time use, retirement arrangements and work history, which are necessary to this analysis.

This very special labour-market behaviour of Dutch women allows us to estimate a dynamic hazard model that incorporates probabilistically the uncertainty due to potential future child birth at young ages, re-entrance into the labour market and the event of early retirement at later ages. We extend the standard model up to including the value of home production in the definition of life-cycle income. This specification returns plausible results and indicates that our hazard model can be employed for relevant policy simulations.

Since the model postulates that income incentives play a role in determining participation, it is suitable for the above quoted simulation. These tax facilities amount on average to approximately 4-5% of a two earners household income. The reduction to zero of the EITC increases female hazard rate out of work by 4% points, from about 12% to about 16%. The effect of the elimination of the TCEP is lower, about 0.7%. Doubling the value of both the tax credits decreases the hazard rate by about 3% points. This finding is robust to different values of the individual discount rate below 30%. The lower reaction to income increases relative to income

decreases of the same magnitude may indicate a relative preference for the state out of work as income rises. However it holds only for the model with home production. The standard model with market consumption returns no significant effect of the income incentive on the hazard. An interesting future extension of this research should include directly savings and consumption in the model. Dutch panel data sets are not yet a promising base to such developments.

1 Introduction

In the Netherlands, women arrange their life-time patterns of labour participation depending on the timing of arrival of children (Bloemen and Kalwij (2001)). Before the birth of the first child women have labour participation levels and wages that are comparable to the ones of their cohabiting counterparts (Kalwij (2003)). Upon the arrival of children most women stop working. Those who continue, do so by reducing their labour supply by about 40%. When children enter the household women begin to spend more time home-producing goods, and this arrangement is only relaxed when children grow older. In the data available, only the cross-sectional evidence testifies of this partial return to the labour market. The panel, shows no evidence of substantial re-entrances as it does no track women long enough over time to observe their return to the labour market[1].

This paper is largely inspired by the home production literature concerned with household life-cycle consumption and savings (Apps and Rees (2000)). Despite the promising results of initial studies (Apps and Rees (2001), Apps (2003) and Apps and Rees (2003)), recently others have found this explanation insufficient to account, for instance, for the well known puzzle of the drop in consumption upon retirement (Banks et al. (1998)). Haider and StephensJr (2004) find that after retirement there is a drop in consumption both for home produced food and market purchased food in the United States. Hurd and Rohwedder (2003) report that the amount of time spent by women in home production activities hardly changes before and after retirement. Despite these criticisms, we believe that “home production” is worth exploring[2]. We will use a dynamic model that takes into account the endogeneity between fertility and work decisions in a simple way. Solution of this problem would otherwise require a structural model (see Francesconi (2002)). There is however a drawback to our approach, since time use data, necessary to include home production in the model, are not present in our main data source. We will impute them out of our sample[3].

[1] This is noted also by Kalwij (2003). In our model, we will show that this may be due to panel attrition. The possible explanation is that since participation in the panel is conditional on residence, upon child birth all those who move to a new house may “get lost” for data collectors, therefore leaving a selected group of households in the panel. This means that if the birth of a child implies need for new housing and stopping work at the same time, the drop out of the panel (and consequent unobservable re-entrance) may be selective.

[2] Several studies have found that the presence of children is a strong determinant of (income and) consumption profiles over the life-cycle. These findings own to the so called “demographic” explanation of the standard model (e.g.: Attanasio and Browning (1995), Browning and Ejrnaes (2002)). Also for the Netherlands it is found that the timing of arrival of children strongly affects income, consumption and saving behaviour of households (Kalwij (2003)). This evidently calls for models that explicitly take this into account. The present study will not go back to the puzzling results from the consumption-saving literature. We want to introduce the timing of birth and the consequent value of home production in our life-time consumption measures.

[3] Computations are based on an out of sample imputation, since we assume that all the observed characteristics included in the imputation model are strictly exogenous. More sophisticated methods, like instrumental variables, split sample techniques, are proposed (see Angrist and Krueger (1994)) and may well be applied to our problem in case, we want to enlarge the set of characteristics included.

In order keep the model empirically tractable, we treat as exogenous three relevant stochastic events that may affect labour participation and earnings of women. These events are the arrival of a child, women's re-entrance into the labour market and eligibility to early retirement at a given age. This means that we are going to present a 'probabilistic model' in which we compute the expected full income[4] profiles associated to the two states we consider: employment and non-employment. Exogenous determination of arrival of children is also used in Apps and Rees (2003) while for early retirement in the Netherlands see Mastrogiacomo et al. (2004).

This paper contributes to the literature in different regards. First, we explicitly include the perspective of future child birth in the determination of the expected labour supply of women and therefore on income patterns of a household (rather than on income patterns directly). Second, we disclose the relevance of home production for women in the Netherlands, an area that to our knowledge is hardly ever explored. Third, we illustrate the evaluation of the tax credits policy in a life-time context and compare the results of this evaluation when we include home production in the model or not. Finally, we enquiry the relevance of attrition bias in looking at young households, who are more likely to leave their houses, and therefore the panel, upon child birth, when they are also more likely to (temporarily) leave the labour market.

The rest of this study is organised as follows. The data sets used are described in the second Section. In the third we present the model. In the fourth, we show some results and simulate two policy options. Five appendixes are added, those extend on the tax credits, the imputation of the probability distribution of a birth event and early retirement, re-entrances into the labour market after child birth, our income incentive measure to participation and home production.

[4] Full income is the sum of the value of hours supplied on the market (wage) plus the value of hours reserved for home production. We impute this second value on the base of the time spent in home production paid at the hourly wage of home assistants. We therefore follow the so called 'input approach' to the evaluation of home production (see for instance Kerkhofs and Kooreman (2003)).

2 Data

As anticipated above no panel data set exists for the Netherlands that includes information on a large and representative sample of the Dutch population, where time use data, retirement arrangements and a large set of background characteristics are available at the same time. Therefore we combine several sources.

We use the Social Economic Panel (SEP) administered by Statistics Netherlands (CBS) to extract the representative sample and the relevant background characteristics, including earnings. From the CERRA data 1993 (Centre for Economic Research on Retirement and Aging), administered by Leiden University, we extract information concerning individual retirement arrangements. Finally the Time Use Survey 1995 and 2000 (TBO- Tijdbestedingonderzoek) is used to derive information on time employed in housework. This last data set is a repeated cross-section administered by the Social and Cultural Planning Office (SCP), without a longitudinal dimension. It takes place every 5 years. All 3 data sets use a sampling procedure based on area code and interview a representative sub sample of the Dutch population.

2.1 SEP and the arrival of children

In order to organise the data, we loosely follow Apps and Rees (2001). We divide the life-time of the household in different phases. In the first the adult household members live together, are of working age, fertility age (woman < 45), and have no children. In the second the household has children of pre school age (0-3). Women's labour participation in phases 1 and 2, and their hazard rate out of work, is the object of the present study. In the third the household has children of school age (4-18). In the fourth the children are older than 18 and at least one spouse is of working age (therefore younger than 65), or the household has no children and the woman is 45 plus. Women in phases 3 and 4 are included in the sample in order to impute the probability distribution of age of delivery of a baby. In the last phase both adults are retired (65 plus). This last group is selected out of the CERRA data, in order to impute the probability distribution of early retirement age. We select from the SEP a panel with 15 waves in the period 1987-2000. Table 2.1 shows the stages of the sample selection. Most observations are lost because of the age selection and because we exclude the self employed. Since we study yearly labour-market transitions it is important to have a panel that is continuous over time. We are left with approximately 14,000 observations. These individuals are interviewed from 2 to 14 times. About 7,000 observations are in the first two phases of the household life-cycle, that constitute our main sample. We select women employed in $t-1$ and looked at their employment status in t. We have also discarded all those who, non employed in $t-1$, return to work in t (absorbing state assumption), as these appear to be a very small and selected group. This means that we only model transitions out of work and renounce to model re-entrances in the labour market. Though this may seem a very selective approach for young women, inspection of the data suggests that we cannot do otherwise. This is evident from the selection procedure reported in table 2.1 and in the panel as reported in Table 2.2, where women are followed over time and on average not directly observed returning to work (though in the table we only show the net effect of drops and re-entrances). We do not give up considering re-entrances completely and bring this option in our measure of the expected income profiles of those out of work (see section 3.3.3). When out of work, women are assumed to have a probability of re-entrance in the labour market that increases with the age of their children and diminishes as women approach the old age (we extract this information looking at women's participation with older children, not withstanding whether the birth event or their re-entrance is observed or not). This means that even though we exclude the possibility of a re-entrance (we model therefore only the hazard rate out of work, consistently with the absorbing state assumption) we allow women to include this possibility into their expected income profile (which in our analysis is an explanatory variable) conditional on the age of their children.

Table 2.1 Sample selection

Unbalanced panel period 1987-2000	51442	
Reason for removal	Observations dropped	Share %
Age selection (18-64)	7812	15
Panel inconsistencies	2031	4
Self employed	4553	9
Non realistic wage rate	6204	12
Absorbing state assumption violations	2126	4
Housewives	11934	23
Not informative for model estimation	2225	4
Total	14557	
In phase 1	5248	36
In phase 2	2194	15
In phase 3	4061	28
In phase 4	3054	21

Explanatory note: Panel inconsistencies refer to non time-consistent aging of children or spouses. We exclude the self-employed because we cannot rely on wage profiles to impute their future earnings. Wage rates below the minimum wage and above 200 guilders per hour are considered non realistic. “Housewives” are those who have no records of labour-market participation ever. Non informative are all observations of non employed women that follow the first observed transition out of work.

Source: SEP, own computations.

The gain of this approach, which at first sight may appear peculiar, is that we don't need to bother about modelling transitions from non employment to employment in the main model.

Table 2.2 Household situation around the time of first birth for women

Years from/since birth	Time spent in home production	Hours of employment	Partici-pation rate %	Yearly wage	Hourly wage	Age	Obs
− 11	14	38	100	29025	15	23	6
− 10	15	35	100	30612	17	24	10
− 9	15	34	100	30413	17	24	14
− 8	15	35	96	31597	17	25	24
− 7	15	36	100	32932	18	25	40
− 6	15	35	94	30858	18	25	81
− 5	15	35	92	32865	20	25	137
− 4	16	35	92	32280	19	26	221
− 3	16	35	91	32759	19	27	300
− 2	17	34	87	32865	20	27	409
− 1	18	33	79	30444	21	28	532
0	40	26	41	22707	24	29	532
1	40	22	33	18938	24	30	443
2	39	22	27	19254	25	31	364
3	39	22	28	20553	26	32	296
4	32	21	27	19575	28	33	220
5	32	22	23	20388	27	34	168
6	33	21	23	21422	29	35	133
7	33	20	23	18143	29	36	91
8	33	20	17	17390	28	37	70
9		20	24	16561	27	38	49
10		21	24	19775	26	39	29
11		23	25	26441	34	39	16
12		26	30	38511	43	40	10

Explanatory note: Only a few households are followed long after giving birth. The dimension of the sample is therefore extremely small already 5 years after and before the birth of the first child, which makes these figures only indicative. Time spent in home production is imputed out of the TBO data.
Source: SEP and TBO, own computations.

This would be based on very few observations and therefore unreliable. But we also avoid assuming no perspective of re-entrance in the computation of the future income profiles, which we may justify only because of a deficiency of the data, and is not in line with anecdotic evidence concerning the Netherlands (Vlasblom and Schippers (2005)). [5].
Following Kalwij (2004), we also look at those households participating in the panel observed before and after child birth. In tables 2.2 and 2.3, we see that after child birth labour participation of women drops and stays low for a very long period. Those who keep on working

[5] Details about the imputation of re-entrance probabilities are in Appendix C.

Table 2.3 Household situation around the time of first birth for men

Years from/since birth	Hours of employment	Partici-pation rate %	Yearly wage	Hourly wage	Age	Obs
− 11	39	100	35918	18	26	6
− 10	39	100	36818	18	27	10
− 9	39	100	40377	20	27	14
− 8	39	96	37772	19	28	24
− 7	38	95	38519	20	28	40
− 6	37	93	38712	20	27	81
− 5	38	93	41417	21	28	137
− 4	38	90	41983	21	28	221
− 3	38	92	43062	22	29	300
− 2	37	89	44815	23	30	409
− 1	37	89	46486	24	30	532
0	36	90	49214	26	31	532
1	37	91	51758	27	32	443
2	38	92	56005	29	33	364
3	37	90	57532	30	34	296
4	38	93	59069	30	35	220
5	39	93	60824	30	36	168
6	39	92	65164	33	38	133
7	40	97	66411	32	38	91
8	40	97	70136	33	39	70
9	40	96	73370	36	40	49
10	39	90	71671	35	41	29
11	42	100	65614	31	40	16
12	40	90	69528	31	41	10

Explanatory note: Only a few households are followed long after giving birth. The dimension of the sample is therefore extremely small already 5 years after and before the birth of the first child, which makes these figures only indicative.

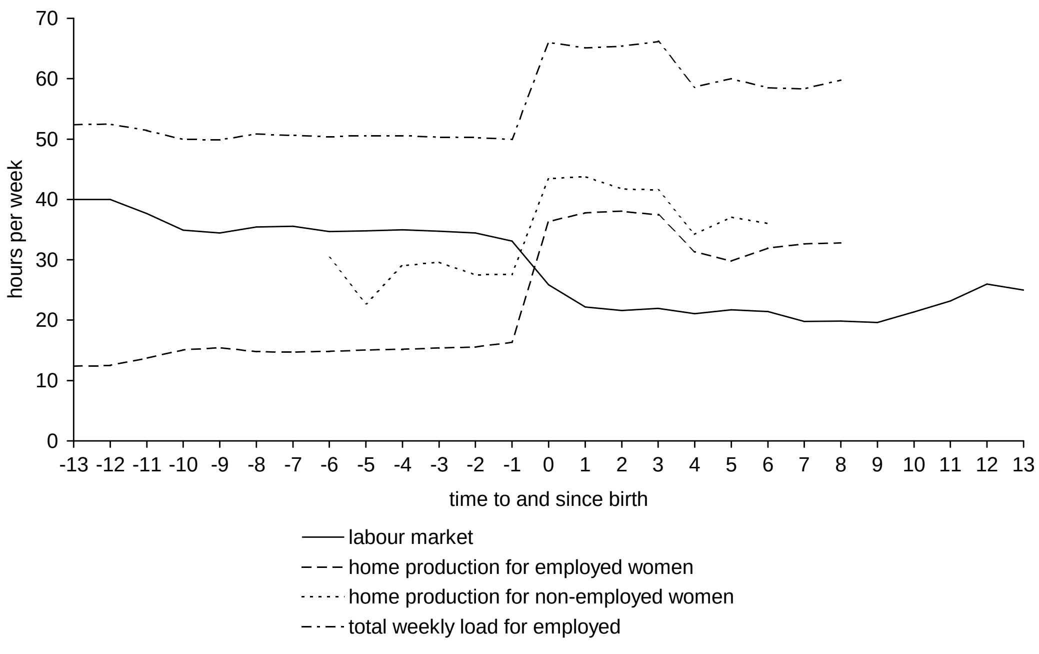
Source: SEP, own computations.

diminish substantially their labour supply. The wage rate for those employed keeps on rising. This is also the case for men. Men however do not modify their participation and their labour supply and immediately after birth are still, on average, in full time employment. This shows the need to explicitly bring into our hazard model the timing of arrival of children. We do so by employing information about all women in the SEP, since those with children report the age at which birth events occurred. This allows us to estimate the probability distribution of a birth event according to the age of the mother (see Appendix B).

2.2 TBO and CERRA

As mentioned in the introduction, women's drop in participation when giving birth may be more properly viewed as a substitution between hours supplied on the market and hours spent on home production. Information concerning time use is present in the TBO data. We extract data on hours spent in home production from the joint cross-sections 1995 and 2000, and impute it in our sample of women in phases 1 and 2 of the SEP. Details on this procedure can be found in Appendix E. In figure 2.1, we do not report results on the basis of our main sample, but of a different sample that only includes women who are observed shifting from phase 1 to phase 2, therefore giving birth to a child. This group is smaller, and therefore selective, but shows some interesting implications that may have general descriptive validity. The figure reports on the horizontal axis the time to and since the birth of the first child (some points are missing because of problems of sample size). On the vertical axis, we set the amount of hours per week. In this figure, we also make a distinction between employment and non employment in order to gain insights of how women allocate their time over the household life-cycle. We observe that the labour supply for those who keep on working drops by about 40% after the birth of the first child.

Figure 2.1 Time use around child birth.



Sources: SEP and TBO, own computations.

When the first child is about 10, women increase again their labour supply (however we only have about 50 observations for ages larger or equal to 10 which may be unreliable). This tendency is not even strong, as also the average figures in table 2.2 suggest. The amount of weekly hours spent on home production, differs substantially according to whether a woman is employed or not. This difference between employed and non employed women, however, diminishes after the birth of the first child, when time in home production sharply increases both for those women who remain employed and for those non employed. The amount of time spent in home production is allowed to depend on the age category of the child, and therefore diminishes after the child is 9. This different impact of the (value of) time spent in home production according to whether a first child is present in the household or not, and according to whether his mum is employed or not, will be used to construct the future (full) income profiles.

From the last data set introduced above, CERRA, we only extract data concerning the pension replacement rate and the age of eligibility to the early retirement schemes. We refer to other work for a comprehensive description of the main trends for these variables (Heyma (2001)). Here (see figure B.1 in Appendix B) we only show the frequencies associated to the age of eligibility to early retirement and the probabilities that we impute in the SEP with a procedure that is similar to the one used for child birth in figure B.2, also in the same Appendix.
The last main element affecting the future income profiles of women is the probability to re-enter the labour market when non-employed. As evident from table 2.2 the panel shows no general increase in labour participation. Looking into the panel, we notice that this is due to the fact that few cases of re-entrances are observed.

In Appendix C, we show that the unbalanced panel can give some indication of re-entrance patterns, that may suggest that women consider the option of re-entrance in forming future income expectations. These effects are small, consistent with our choice to model only exits from the labour market.

3 Model and implementation

3.1 Theoretical model

In order to model the hazard rate out of work, we refer to a standard dynamic utility model. We assume that the observed decision to join the labour force or not is optimal and motivated by the comparison of consumption/income streams associated to employment and non-employment. This means that if we observe employment as a choice variable, the individual has compared the lifetime utility derived from continued work, versus the one derived from withdrawal; and that the first is larger than the second. Households solve a utility maximisation problem of the form:

$$\max_{y_{i,t}} E_t \sum_{t=1}^{T_i} u_t^i(c_{i,t}; y_{i,t}) \tag{3.1}$$

where c stands for (market or full) consumption and y for labour-market participation of women. We maintain a no savings assumption and therefore in our model the budget constraint is implicit[6].

If we select those women employed in $t-1$, this problem is similar to the solution of a standard option value model. The associated Bellman's equation is

$$V_{i,t} = \{u_{i,t}^* + \delta E_t \max_{y_{i,t}}[V_{i,t+1}]\} \tag{3.2}$$

with δ as an individual discount factor. This generates two possible value functions, one for employment ($y_{i,t} = 1$) and the other one for non-employment ($y_{i,t} = 0$):

$$\begin{aligned} V_{i,t}^{y_{i,t}=1} &= u_{i,t}(1) + \delta E_t \max\nolimits_{y_{i,t}}[V_{i,t+1}(1)] \\ V_{i,t}^{y_{i,t}=0} &= u_{i,t}(0) + \delta E_t \max\nolimits_{y_{i,t}}[V_{i,t+1}(0)] \end{aligned}$$

The choice rule for the individual that intends to continue working will be:

$$V_{i,t}^1 > V_{i,t}^0 \tag{3.3}$$

where

$$V_i = E(u^i(c_i; y_i)) \tag{3.4}$$

Evidently in order to easily implement this model empirically, we need to make some assumptions on the determination of $V_{i,t+1}(\cdot)$. For the case of non-employment the values associated to $V_{i,t+1}(0)$ will be based on the combination of the value of future income in case of (probabilistic) re-entrance and the unemployment benefit. In the same fashion we will also simplify the determination of $V_{i,t+1}(1)$ (using a wage equation) without having to face the

[6] Kalwij (2004) has shown significant presence of excess sensitivity of consumption to income in the Netherlands, which makes our substitution of consumption with income less of a severe problem as it may seem.

complexity of its dynamic programming solution. Previous research that has looked at the implicit taxation in the Dutch early retirement schemes (Lindeboom (1999)), at the plans of Dutch employees (Heyma (2001)) and the generosity of the Dutch early retirement schemes (Lindeboom (1998), Kerkhofs et al. (1999)) shows that individuals, in great majority, tend to work up to the moment in which they will become eligible to early retirement and then retire. Mastrogiacomo (2004) has estimated a reduced form model in which retirement age is integrated out of the dynamic maximisation problem. We follow this approach and use this evidence as a behavioural assumption. We employ the probability distribution of eligibility age to compute the expected maximum value of $V_{i,t+1}(1)$. A further complication that we bring in the computation of the income/consumption profile for those who continue working ($V_{i,t+1}(1)$) is that upon the (probabilistic) arrival of a child (first or second child) women will participate less into the labour market[7]. At each future moment in time this will depend on the age (probabilistic again) of the child. At birth the drop will be of about 40% that reduces to 20% when the child is above 12.

We opt for the following specification of the utility function 3.1, that is additive and separable:

$$u_t^i(c_{i,t};y_{i,t}) = v(c_{i,t}) + v(y_{i,t}) \tag{3.5}$$

where $v(\cdot)$ takes a logarithmic form and home production enters the model by augmenting consumption. We introduce home production in the following way:

$$v(c_{i,t}) = v(c_{i,t} + P_{i,t}) \tag{3.6}$$

that brings "full consumption" in the model as the sum of the values of market consumption and home production $(P_{i,t})$.

Before continuing to the empirical implementation, we will summarise again the main assumptions:

1. Utility is additive and separable
2. No savings: households consume all their household income.
3. The expected income of those who stop working takes re-entrance probabilities into account.
4. Those who choose to continue working will work less when a child is born, depending on how old the child is, and will stop at the age of eligibility to early retirement.

This last assumption allows us to solve the model in reduced form, and is supported by the precise implementation of the Dutch retirement institutions.

[7] How much less is established on the basis of the computations in figure 2.1. This means that we assume a strict proportionality between hours worked in $t-1$ and t if in t child birth is expected. This is a very strong assumption since it assumes a (stochastic) drop in participation that is actually what the model may aim to explain. As will be clear later, we will introduce the presence of children in the initial condition equation that will be therefore the exclusion restriction explaining observed participation at the first observation in time. The proportional drop in participation plays a role exclusively in determining the expected pattern of future income and participation, of course not the observed choices (that are indeed the revealed preferences in the model).

3.2 Empirical implementation

Equation 3.5 is very general and in this section, we will try to find a tractable empirical version. Due to the fact that, we only select those employed in $t-1$ and observe their choice in t (therefore excluding shifts from non-employment to employment), we cannot freely specify this function. To illustrate this, we can also state this data selection in mathematical terms. Let $y_{i,t} = 1$ if the respondent i works in period t, and $y_{i,t} = 0$ if she is out of the labour force. The selection implies that

$$y_{i,t} = 1 \Rightarrow y_{i,t-1} = y_{i,t-2} = ... = y_{i,1} = 1 \tag{3.7}$$

$$Pr(y_{i,\tau} = 0 \mid y_{i,t} = 0) = 1, \quad if \quad \tau > t \tag{3.8}$$

If we apply this selection on the data, we have to give up all these observations in which she is observed returning into the labour market. Suppose we have a panel of $t = 4$ waves. We observe a woman working in the last period only if she is working also in the previous period. First we rewrite the simultaneous probability $Pr(y_{i,4} = 1, y_{i,3} = 1, y_{i,2} = 1, y_{i,1} = 1)$ as a product of conditional probabilities, e.g.:

$$\begin{aligned}
&Pr(y_{i,4} = 0, y_{i,3} = 1, y_{i,2} = 1, y_{i,1} = 1) = \\
&Pr(y_{i,4} = 0 \mid y_{i,3} = 1, y_{i,2} = 1, y_{i,1} = 1) * \ldots \\
&Pr(y_{i,3} = 1 \mid y_{i,2} = 1, y_{i,1} = 1) * Pr(y_{i,2} = 1 \mid y_{i,1} = 1) * Pr(y_{i,1} = 1)
\end{aligned}$$

Then, we model these conditional probabilities:

$$\begin{aligned}
&Pr(y_{i,t} = k \mid y_{i,t-1} = 1, y_{i,t-2} = 1, \ldots, y_{i,1} = 1) = \\
&Pr(y_{i,t} = k \mid y_{i,t-1} = 1)
\end{aligned}$$

and the 'initial (selection) condition': $Pr(y_{i,1} = 1)$ (see end of the paragraph).

The choice of what function to estimate is strongly depending on this condition. We would like for instance to estimate the impact of habit formation (how dependent are current choices on past choices) in our model. However as the following example shows, there are some complications. Write:

$$u_t(c_{i,t}, y_{i,t}; y_{i,t-1}) = \alpha_{01} y_{i,t-1} y_{i,t} + \alpha_1 c_{i,t} + \alpha_{02} y_{i,t}. \tag{3.9}$$

We are faced with the following:

Lemma 1. *Due to the fact that transitions from non-work to work are discarded, we cannot identify the impact of habit formation.*

Proof 1. *As:* $y_{i,t} = 1 \Rightarrow y_{i,t-1} = 1 \Rightarrow y_{i,t-1} y_{i,t} = 1$. *Moreover,* $y_{i,t} = 0 \Rightarrow y_{i,t-1} y_{i,t} = 0$.

In other words, the variables $y_{i,t}$ *and* $y_{i,t-1} y_{i,t}$ *are observationally equivalent . Therefore, utility* *function (3.9) can be rewritten as follows:*

$$u_t(c_{i,t}, y_{i,t}; y_{i,t-1}) = \alpha_1 c_{i,t} + (\alpha_{01} + \alpha_{02}) y_{i,t} \tag{3.10}$$

Therefore the 'habit formation' utility (3.9) is observationally equivalent to utility function with no lag[8].

This is important to point out in order to interpret the results correctly. We decided to rewrite the above equation as follows:

$$u_t(c_{i,t}, y_{i,t}) = \alpha_1 c_{i,t} + \alpha_2 y_{i,t} + \alpha_3 (c_{i,t} * y_{i,t}) \tag{3.12}$$

where $(\alpha_{01} + \alpha_{02}) = \alpha_2$ and where we also added the interaction (product) between consumption and participation in order to account for possible non separabilities in the utility derived from consumption between participating and non participating women. Other taste shifters will also be added to this specification.

Disposing of a panel, we can add a next step. We observe women revealing their preferences in t between $y_{i,t} = 1$ and $y_{i,t} = 0$. This means that for these individuals working in t and in $t-1$, we can rewrite 3.3 as :

$$u_t(y_{i,t-1} = 1, y_{i,t} = 1) > u_t(y_{i,t-1} = 1, y_{i,t} = 0) \tag{3.13}$$

as we assume this decision to be the result of an optimisation process. The difference in these utility levels is what motivates the labour-market choice. Before operationally specifying these functions let us concentrate on the identification of the parameters included and the likelihood.

Like Blau (1998) we (have to) allow for state dependence (i.e. the parameters of the utility function depend on labour participation choices). In this way, we link the theoretical model sketched above with our implementation. We attach two subscripts j and k to the value function appearing in equation 3.4: $V_{jk}(\tau)$. Subscript $y_{i,\tau} = k$ denotes current-period labour force status ($k = 0,1$) and j the previous period status[9]. We could rewrite the decision problem in a dynamic programming format. We do not solve the dynamic programming problem as part of the estimation, as the Dutch institutions already suggest a pattern of optimality. Instead, we follow the methodology of Blau (1998) and approximate the value function $V_{jk,\tau}$ as follows:

$$V_{jk}(\tau) = Z'_{k\tau}\alpha_j + X'_\tau \beta_{jk} + \gamma_{jk}\mu + \varepsilon_{k\tau} \tag{3.14}$$

[8] We can also change the specification of the intratemporal utility function a bit, e.g. in the following way:

$$u_t^h(c_{i,t}, y_{i,t}; y_{i,t-1}) = \alpha_{01} y_{i,t-1} + \alpha_1 c_{i,t} + \alpha_2 y_{i,t} \tag{3.11}$$

Obviously, the variables $y_{i,t}$ and $y_{i,t-1}$ should not be perfectly collinear. If we write down the function corresponding to within period preferences (3.11), we can show that one identifies separately the impact of habit formation if transitions from non-work to work are allowed. In his model Blau (1998) allows for habit formation. He is able to do that because in the United States a retired person regularly returns to the labour market, while in our panel re-entrances are negligible.

[9] Notice that since we assume retirement as an absorbing state (that implies $y_{i,t-1} = 1 \quad \forall\, i = 1, ..., N,\ t = 1, ..., T$) j is always equal to 1.

where the $X's$ are exogenous variables affecting preferences (taste shifters) and expectations. μ is an unobserved time-invariant individual specific random effect. We assume that μ is independent across individuals and follows a normal distribution with expectation 0 and variance σ_μ^2. $\varepsilon_{k\tau}$ follows an extreme value type I-distribution. We assume that $\varepsilon_{k\tau}$ is uncorrelated over time and across alternatives and will be treated as $\varepsilon_{k\tau} = \eta_i + \zeta_{i,t}$.

The $Z's$ are state-specific 'incentive' variables that incorporate the future consumption and participation profiles introduced above. This means that the alphas are identified because the $Z's$ differ between employed and non employed individuals. For the betas, we need an identification assumption ($\beta_0 = 0$). In equation 3.14, we can also introduce home production. It will be an element of Z since, as shown in figure 2.1, home production varies between employed and non employed.

Suppose that the econometrician knows the value of μ (later on, we will relax this assumption). Model (3.14) implies the following transition probabilities, $\lambda_{jk\tau}(\mu)$, from state j to state k:

$$\lambda_{jk\tau}(\mu) = Pr(V_{jk}(\tau)) > V_{jm}(\tau)(j,1)\forall m \neq k \mid \mu, y_{i,\tau-1} = j) \tag{3.15}$$

This expression boils down to a random effect logit model when ε is taken as an EV type I distribution. By conditioning the estimation on $y_{i,1} = j = 1$, we are implicitly assuming that this selection does not bias our results. To correct this, we add an 'initial condition equation' to the model. This has (if we suppress the individual index i) the logit form:

$$V_1(l) = X_1'\omega_l + \kappa_l\mu + \upsilon_l, l = 0,1 \tag{3.16}$$

$$I_l(\mu) = Pr(y_{i,1} = l) = Pr(V_1(l) > V_1(j)\forall j \neq l) \tag{3.17}$$

and X will include some exclusion restrictions (in particular the presence of children or not).

Notice that the household effect μ appears both in the transition model and the initial condition equation. This establishes a correlation between the two equations since we assume υ_i uncorrelated with $\zeta_{i,t}$ but correlated to η_i(we assume $E\left(\upsilon_i|\eta_i\right) = \rho\eta_i$). The likelihood contribution per household will therefore take into account the probability of being observed into employment in the first period, as well as the probability of remaining employed the next period. It has the following form:

$$\pounds = \int (\sum_{j=0}^{1} d_{j1} I_j(\mu)) \prod_{t=\tau}^{T} \left[\sum_{k=0}^{1} \sum_{l=0}^{1} d_{klt}\lambda_{klt}(\mu) \right] g(\mu) d\mu \tag{3.18}$$

where $d_{klt} = 1$ if the couple moves from state k in period $t-1$ to state l in period t and equal to 0 otherwise. $d_{j1} = 1$ if couple is in state j in the initial period 1, and 0 otherwise. $I_j(\mu)$ is the corresponding probability.

Instead of maximising the likelihood, we estimate the model by means of simulated maximum likelihood (150 draws). In equation 3.2, we have shown that the theoretical model also implies an individual discount factor. We have been silent so far about it because the model does not allow, in this simplified setting, its identification. Though this is a shortcoming of the model, we can show, with sensitivity analysis, that this is no impediment to estimate the impact of the tax credits policy on labour participation.

In the remaining of this section, we clarify some of the elements that determine $V_{i,t+1}(\cdot)$ and that have only been introduced above, namely:

- Specification of income/consumption over the life cycle
- Specification of participation over the life cycle.

3.3 Future consumption and participation

In order to solve the maximisation problem 3.1, we need consumption and participation over the whole life of each individual. Since no panel exists that provides such information, we have to rely on imputations techniques to approximate these random variables for each entry in the data.

Our departure point is that only three stochastic events may perturbate the future life of each woman. The first is the occurrence of motherhood, the second is the re-entrance after (temporarily) leaving the labour market and the third is early retirement. Furthermore in line with previous studies we assume that these events are exogenously determined (and can therefore be integrated out).

Even under such strong simplifications, notice that we do not observe the exact moment of future child birth, nor the exact moment of early retirement or re-entrance into the labour market. We circumvent this problem by employing expected utility theory. In the previous Section we have introduced the imputation of the probability distribution of such events (more details in Appendix B).

3.3.1 Consumption/Income

Our first step is therefore to determine the complete wage rate profile of each individual in the sample. We opted for an autoregressive random effect model. The model is extremely simplified and takes into account cohort effects, differences in human capital and current wage[10]. We have chosen this specification because we find evidence of systematic cohort differentials in wages (probably indicating productivity shocks).

The model we use to project future wages (y) is:

$$y_{it} = \alpha + x_{it}\beta + v_i + \aleph_{it} \qquad i = 1,...,N; \;\; t = 1,...,T_i, \tag{3.19}$$

where $\aleph_{it} = \vartheta \aleph_{i,t-1} + \phi_{it}$ and $|\vartheta| < 1$ and ϕ_{it} is iid with zero mean and variance σ_n^2 while v_i are

[10] Note that we do not aim to estimate a full wage equation, but just to get a reasonable estimate of in order to impute future wages (Burkhauser et al. (2004)) .

Table 3.1 Wage model

	Men Estimate	St. error	Women Estimate	St. error
Wage rate in t-1	0.544	0.006	0.225	0.008
Education	2.978	0.114	2.768	0.148
1967 - 1971 cohort	0.252	0.576	− 0.060	0.503
1962 - 1966 cohort	0.162	0.551	− 0.362	0.510
1957 - 1961 cohort	0.267	0.554	− 0.881	0.537
1952 - 1956 cohort	0.517	0.569	− 1.648	0.569
1947 - 1951 cohort	0.804	0.583	− 1.793	0.617
1942 - 1946 cohort	0.978	0.615	− 3.866	0.688
1937 - 1941 cohort	0.504	0.659	− 1.800	0.857
1932 - 1936 cohort	0.612	0.731	− 3.209	1.241
1927 - 1931 cohort	− 0.852	0.978	− 0.938	1.729
1922 - 1926 cohort	3.369	2.850		
Experience	0.178	0.034	0.296	0.045
Experience square	− 0.002	0.001	− 0.003	0.001
Constant	4.763	0.565	9.553	0.541
Observations	19902		12845	

Explanatory note: The cohort with older individuals is excluded.
Source: SEP, own computations.

fixed parameters that can be correlated to x_{it} if those vary over time. The results of this random effect model (for men) are summarised in table 3.1

3.3.2 Participation

We project current participation and labour supply into the future. This pattern is of course not deterministic. In the data, we observe for instance that participation of women drops on average by about 40% when they give birth and stays lower than initial participation until the child is 12 (20% lower). Also the data from the Research on Family Formation 1998 (OG '98) support the idea that women do not stop working completely after giving birth to the first child and that withdrawal may only be temporary. In that sample 72% of the women interviewed continued working. However, we have a stricter definition of employment (at least 12 hours per week), and we find that only 50% of those employed keep on working more than 12 hours after giving birth (see table 2.2). At later ages the most significant drop in participation takes place after the age of eligibility to early retirement.

Since we don't know exactly (nor does the individual) when these two events will occur, it is reasonable to assume some uncertainty in the model. As mentioned, we use the probability distribution of these events for the future.

Further in the model, we will rely on the evidence emerged from the literature that when one is eligible to early retirement she will stop with work (Heyma (2001), Lindeboom (1999)). Of course when our younger women will be in phase 3 and 4 early retirement will represent the only possible perturbation to their labour participation pattern, since they will be too old to give birth to a child.

Knowing the wage rate and the way individuals expect to take part into the labour market in the future, on the basis of our behavioural assumptions we can construct the 'expected consumption' and 'expected participation' that should enter the utility function.

3.3.3 Utility levels

According to equation 3.13, we must specify a value for the utility of employment and non-employment. In this paragraph, we summarise the options available to the woman who chooses in t whether to stop with work or not, conditional on participation in $t-1$. These utility levels determine the value of continued employment versus immediate retirement under the assumptions sketched above. In the first case, we assume that if a woman decides to continue working, she will receive (and consume because we have a no saving assumption) half of the family wage (that is the yearly wage earned by her partner and herself) in each future year. Since we allow her labour supply to vary if she gets children, at that point her yearly wage will drop, while the yearly wage of the man will not react to the birth event. Her yearly wage will increase again when the child gets older and finally will drop at eligibility to early retirement. Therefore defining p as the indicator for the woman, h as the indicator for the men, $\tau =$ year of observation (e.g 1987) and yob as the year of birth, we can write the utility of continued work as:

$$u(c_{it}^{p}, y_{i,t}^{p}=1) = u_{it}^{1p} =$$

$$\sum_{t=\tau}^{T=64+yob_p} (1+r)^{\tau-t} \left[\alpha_1 \left(C_{it}^{1}\right) + \alpha_2 \left(H_{it}^{1}\right) + \alpha_3 \left(C_{it}^{1} * H_{it}^{1}\right)\right] \tag{3.20}$$

$$C_{it}^{1} = s_{it}^{p} \frac{\pi_{it} w_{it}^{p*} + (1-\pi_t) w_{it}^{p})(e_{it}^{p} R + (1-e_{it}^{p})}{2} + s_{it}^{h} \frac{\left(w_{it}^{h}\left(1-e_{it}^{h}\right) + w_{it}^{h} e_{it}^{h} R\right)}{2} \tag{3.21}$$

$$H_{it}^{1} = s_{it}^{p} \left(\pi_{it} h_{it}^{p} + (1-\pi_t) h_{it}^{p*})(e_{it}^{p} R + (1-e_{it}^{p})\right) \tag{3.22}$$

where C and H represent income/consumption and participation, r is a discount factor, w_{it}^{k} $(k = h, p)$ is the yearly (full) income. s_{it}^{k} are survival probabilities (derived from life expectancy tables of the CBS), w_{it}^{p*} is the yearly (full) income under the assumption that the amount of hours worked after child birth will diminish by a factor of proportionality varying with the age of the child, π_{it} is the probability of a child birth (that takes positive values only between age 20 and age 40), e_{it} is the probability of eligibility to an early retirement benefit (that takes positive values only between age 55 and 64) and R is the replacement rate[11] of the early retirement

[11] Notice that R^{p} does not vary with time since the early retirement schemes, we describe in this paper are non actuarially fair.

benefit ($R = 1$ if $T < 55 + yob$ and $R < 1$ if $T \geq 55 + yob$). In the second term h^p_{it} expresses participation in the range 0 to 1 where unity corresponds to 38 hours employment per week, that is customary in the Netherlands.

The utility associated to the choice to stop working in t is equal to:

$$u(c^p_{i,t}, y^p_{i,t} = 0) = u^{0p}_{it} =$$
$$\sum_{t=\tau}^{T=64+yob_p} (1+r)^{\tau-t} \alpha_1 \left(s^p_{it} \frac{q_{it} WW_{it} + m^p_{it} w^p_{it}}{2} + s^h_{it} \frac{\left(w^h_{it} \left(1 - e^h_{it}\right) + w^h_{it} e^h_{it} R\right)}{2} \right) \tag{3.23}$$

where q_{it} is an indicator that takes value 1 if the woman is eligible to unemployment benefit, WW_{it} is the level of the unemployment benefit[12] and m^p_{it} is a re-entrance probability that is equal to zero in the current period and takes positive values in the future. The difference between 3.20 and 3.23 is depicted in figure D.1 in Appendix D. The option of re-entrance enters therefore only the income profile of those out of work, and is not consider in the hazard model. The absorbing state assumption is justified by the few observations available for women who give birth, exit and re-enter the labour market available in our sample. If we extend the sample to including all women with older children that are not in the sample at the time of birth we have sufficient information to adapt the income profiles.

Notice that child support programs are supplied independently of the choice to stop with work or not, and therefore do not affect the difference among the two choices. Maternity leave is instead accounted for since we do not lower the wage of the mother in the first year after birth. Both utility levels above can also include home production if we add the value of time spent home working (which we have excluded from the formula in order to simplify the exposition).

[12] The duration of the unemployment benefit depends on the amount of years worked before t.

4 Results

We dispose of about 7000 observations. Since we have a panel, we isolate the first entry in time for each household, and we use it for estimating the selection equation (results available from the corresponding author), that is the auxiliary equation of this model. The remaining 4100 observations are used to estimate the main equation (equation 3.20). Table 4.1 shows results for the model with home production. It shows logit coefficients and not marginal effects. These results are estimated for a value of the individual discount rate $r = 0.1$.

The table shows that the effect of consumption (on the probability to stay employed), also derived from the sum of $\alpha_1 + \alpha_3$, is positive and significant (the marginal effect computed at the sample mean is about 0.04). We will act on this element of the model to implement the two policy simulations later on. Significant is also the α_3 alone in models 3 and 4, that indicates differences in the utility of consumption between participating and non participating women. The sign of α_2 indicates disutility from life-time participation to the labour market. The taste shifters (in Models 2 and 4) are in general significant. Women with intermediate education or cohabiting with an intermediate educated man, are less likely to continue their participation into the labour market. The direction of this effect is the opposite in the initial condition equation (which we don't show). This indicates that higher educated women of fertility age are more likely to have a job in the first place, but less likely to continue working as time goes by, relative to elementary educated women. This result was not expected. We have also included a 'macro' indicator, namely a dummy that picks value one in years in which the registered unemployment is relatively high. Surprisingly this takes up a positive value. This may be due to the fact that these years are also the most recent, and over time women participation has been steadily increasing. We also added some selectivity indicators to test whether attrition may bias our results (Verbeek and Nijman (1992)). These are dummy variables that take the value 1 in the last year in which one participates into the survey. These coefficients have a negative sign in each year, indicating that those who will exit the survey are also less likely to remain employed. For values of the discount rate larger than 2, we reject the null hypothesis that these coefficients are jointly equal to zero ($\chi^2_{(11)}$= 25.84). This indicates that attrition may indeed bias our results. We can only speculate that family enlargements at younger ages may imply at the same time the need for a larger house and less women's labour participation. We also have to be clear about the fact that testing for selectivity is not the same as correcting for it. Such correction is beyond the scope of the present study. In the table, we show that ρ and σ_μ did not turn out significant.

The most interesting parameter for this study is evidently the one relative to full consumption. In order to get an idea of its marginal effect we decided to employ the model for some simulations that affect the income/consumption profile of each woman.

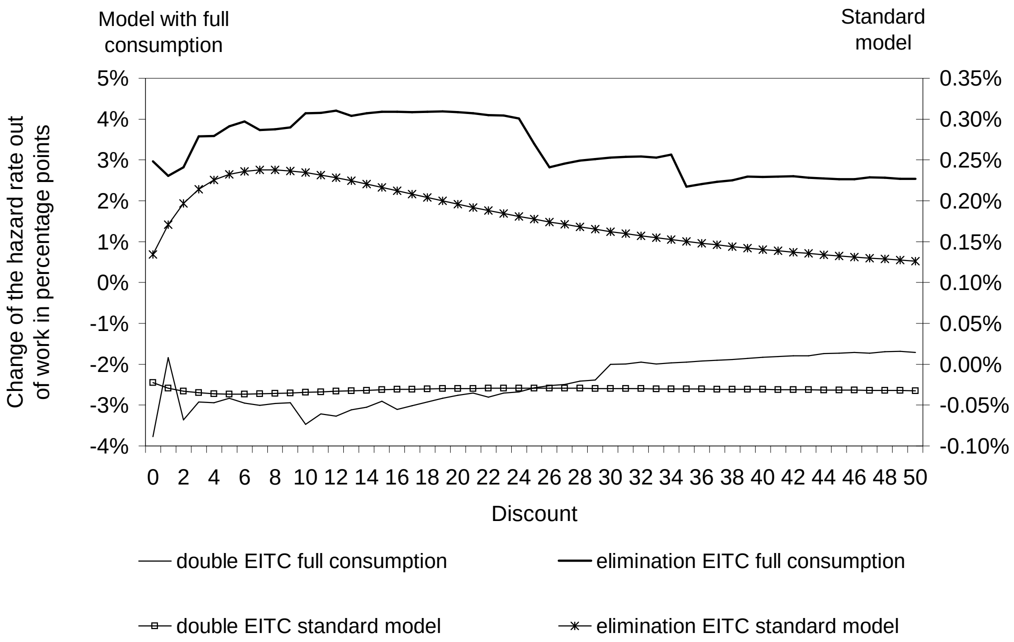
Table 4.1 Estimation results main equation for models with full consumption	Model 1 estimate	Model 2 estimate	Model 3 estimate	Model 4 estimate
Consumption (α_1)	0.18*	0.21*	− 0.08	− 1.13*
Residual life-time participation (α_2)	− 0.28*	− 0.27*	− 0.27*	− 0.29*
Consumption times participation (α_3)			0.25*	1.33*
Taste shifters				
Years of tight labour market		2.06*		2.06*
Woman intermediate education		− 0.20*		− 0.17*
Woman higher education		− 0.07		0.09
Men intermediate education		− 0.15*		− 0.27*
Men higher education		− 0.13		− 0.24*
Woman civil servant		0.08		0.10
Selectivity indicators				
Exit survey in 1989		− 2.38*		− 2.23*
Exit survey in 1990		− 2.74*		− 2.63*
Exit survey in 1991		− 2.38*		− 2.31*
Exit survey in 1992		− 2.43*		− 2.35*
Exit survey in 1993		− 2.32*		− 2.32*
Exit survey in 1994		− 2.49*		− 2.52*
Exit survey in 1995		− 2.41*		− 2.39*
Exit survey in 1996		− 2.23*		− 2.23*
Exit survey in 1997		− 1.17*		− 1.17*
Exit survey in 1998		− 0.79*		− 0.80*
Exit survey in 1999		− 0.47*		− 0.48*
Other statistics				
ρ	0.63	1.96	0.60	1.30
σ	− 0.26	− 0.19	− 0.28	− 0.22
Log likelihood	− 2766	− 2458	− 2706	− 2212
r	0.1	0.1	0.1	0.1

Explanatory note: The selectivity indicators take value 1 if one drops out of the survey in a given year. The discount is set to 0.1. We take the log of consumption and participation. We exclude "Years of labour market with low unemployment", "Elementary education", "Private sector employee". Asterisks indicate significance at conventional level.
Source: SEP, TBO, CERRA: own computations.

4.1 Simulation

In this paragraph, we simulate the effect of the elimination and doubling of two tax credits on the hazard rate out of work(which is defined as $1-\Pr\left(y_t=1|y_{t-1}=1\right)$). Since tax credits have an impact on lifetime income for those who work relative to the non-employed, the value of our consumption variable will also be affected. Because the elimination of the tax credits reduces lifetime income, this will lead to an increase in the hazard rate out of work. Furthermore, because the consumption variable in the full consumption model includes the value of home production and in the standard model it does not, we expect different effects for the different models. For a robustness check, we will estimate it for different levels of the discount rate. We use the estimates of model 2 of the previous section as it produces the most plausible results. Lastly, because we are interested in the possible asymmetry of the response, we simulate both a reduction and an increase in the tax credits of the same amount.

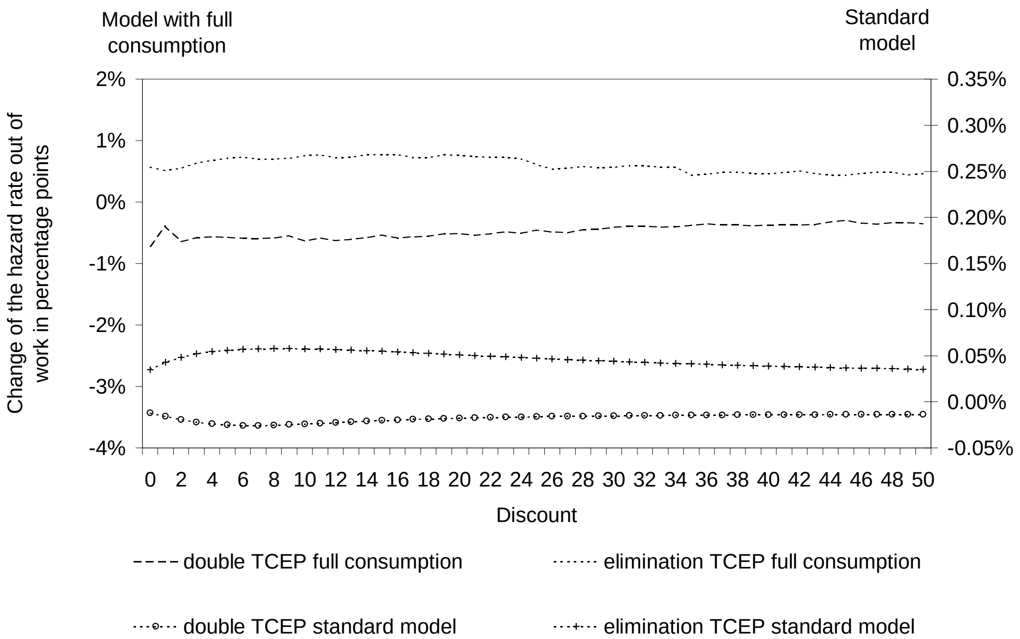
Figure 4.1 Simulated effect of earned income tax credit policy on the hazard rate out of work.



Source CERRA, SEP, TBO: own computations.

The results for the elimination and doubling of the EITC are shown in figure 4.1. In the standard model (line with icons and right axis) eliminating the EITC has a small effect (0,2% points) on the hazard rate out of work, whereas in the full consumption model (left axis) the effect is around 4% points. Doubling of the EITC leads to somewhat smaller results and the negative effect in the standard model is even negligible (0,04%). In the full consumption model the negative effect on the hazard rate is around 3,5% points. For discounts larger than 30% the results do not seem to vary any longer. In figure 4.2, we show the results for the TCEP. Its elimination increases the hazard rate in the full consumption model by 0,75% points. If we compare the effects by increasing the effect of TCEP by almost a factor 6, which is the ratio of the maximum value of the TCEP (214 euro) in comparison with the EITC (1213 euro), then the effects of the TCEP and the EITC are similar. This is not surprising as most working women in the sample already have a child and therefore receive the TCEP. Doubling the TCEP also produces similar negative results, which are of a smaller magnitude then eliminating the TCEP. There seems to be low dependence on the discount rate.

Figure 4.2 Simulated effect of tax credit for employed parents policy on the hazard rate out of work.



Source CERRA, SEP, TBO: own computations.

A few results are worth mentioning. First of all, the small effect in the standard model is implausible because the tax credits amounts to about 5% of a woman's yearly income. The elimination of these tax credits are likely to produce some effect. Furthermore, the large difference in the performance of the two models show the impact of including the value of home production in the consumption variable. The inclusion of home production in the consumption/income profile reduces the difference between lifetime income for employed and non- employed (see figure D.1 in appendix D). A further reduction of this difference by eliminating the EITC has in this model a relatively larger effect. This results in a lower value of the financial incentive to work and a higher increase in the hazard rate out of work in the full consumption model relative to the standard model.

Lastly, the difference in the magnitude of the responses to a reduction versus an increase in the tax credits shows that the effect is non linear. This may reveal a relative preference for homework (e.g. childcare) for these women who already have a job and do not react linearly to extra income as an incentive to more work. Stated differently, we may be facing women with non linear utility functions who have decreasing marginal utility of (full) consumption.

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Appendix A The tax credits

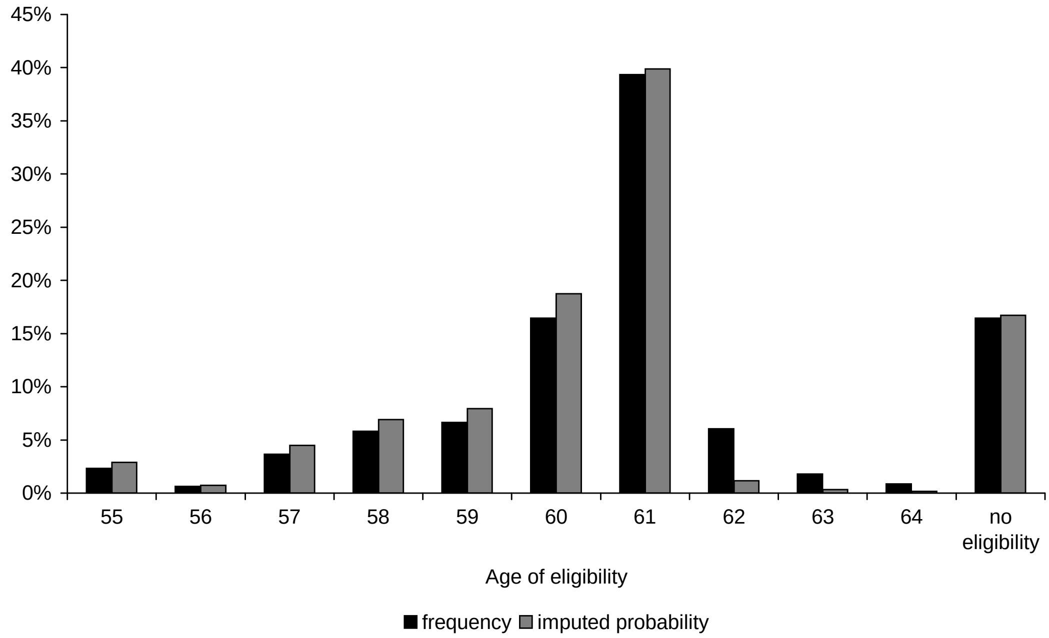
According to the Dutch tax law each (self) employed individual is allowed to receive some tax credits (*heffingskortingen* in Dutch). After income-taxes are levied, the tax credits are deducted. The two credits analyzed in this study are the EITC and the TCEP. Their amount is based on taxable income. In year 2004 individuals with incomes below 8101 euro (minimum wage), could at most expect an EITC of 142 euro (or 1,753% of their income). The EITC is approximately 11% for higher incomes up to a maximum of 1213 euro. In a household with multiple income receivers, each receiver is entitled to this tax credit. TCEP eligibility is stricter since it combines two states: employment and parenthood. It can also be enjoyed by both employed (cohabiting) adults. The child should be below 12. In 2003 the TCEP amounted to 214 euro for incomes larger than 4206 euro.

The correct way to implement these tax credits in our computations requires determining taxable income. One of the main difficulties connected to this computation is the tax-deduction of house-mortgage-payments. The income thresholds to get the maximum credits are very low, and almost all employees tend to receive the full amount. We have therefore simplified the tax system by proportionally reducing the maximum amount to those below the minimum wage.

Appendix B Early retirement and birth event probability distribution

The age of eligibility to early retirement is imputed using the CERRA data. The imputation procedure is a standard out of sample procedure. Figure B.1 shows the well known peaks at ages 60 and 61 present in other studies (Mastrogiacomo et al. (2004)).

Figure B.1 Frequencies of early retirement eligibility age and imputed probabilities.



Explanatory note: these are frequencies for male respondents only. Females are treated separately. Frequencies are derived from the CERRA data and probabilities are imputed in the SEP.
Source: CERRA and SEP, own computations.

For young women without children, we impute the probability distribution of a birth event at any future age. We exploit information about age of delivery within the whole sample. We also observe some common characteristics that will be used to 'transfer' the predicted probabilities to our sub sample of younger women[13].

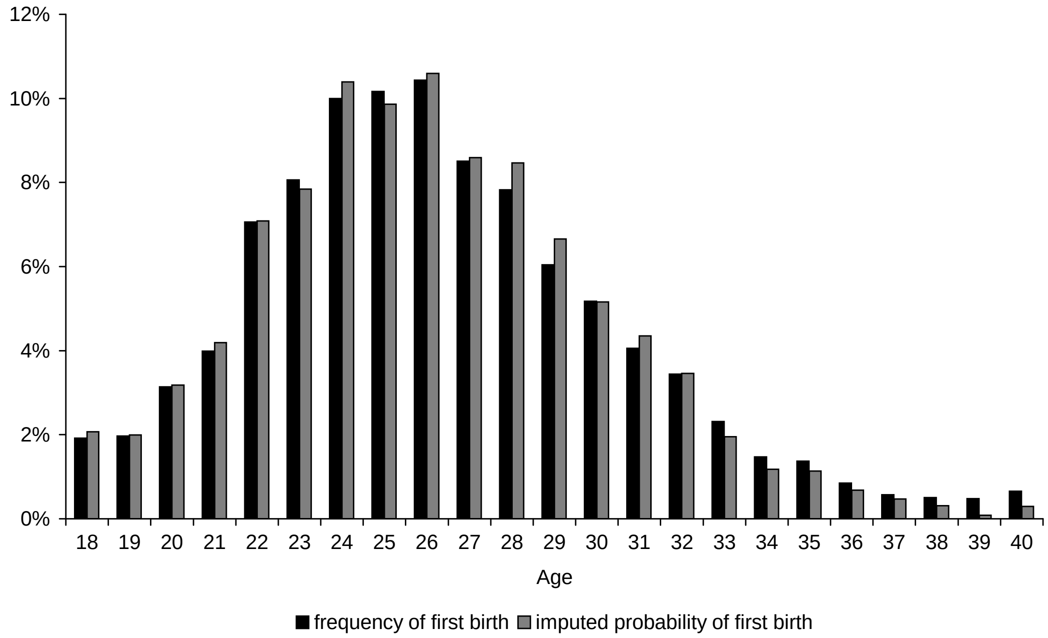
In figure B.2, we compare the frequencies of birth event according to age for older women (not in phase 1), with the out of sample predictions derived by the model for the younger women

[13] By use of a logit model, we can compute the probability that a woman experiences a birth event or not. After we can also compute an ordered logit model to impute the probability that the event occurs at any future (and realistic) age. We estimate probabilities at ages between 20 and 40 (or 43 if women are in phase 2). With these two sets of probabilities, we can compute the probability of birth for each age conditional on the occurrence of a birth event, in this way we also account for the probability that no birth event occurs. Some women enter the sample after age 20. For them the estimated birth probabilities between age 20 and the age of entrance in the sample are not relevant. The birth probabilities for the remaining ages are therefore recomputed conditioning on the probabilities cumulated before the age of entrance in the survey and of course the probability of not giving birth.

without children (therefore in phase 1).

The model corrects for cohort effects, age and education. It also includes current labour-market status as a determinant of fertility, in accordance with the suggestions of Bloemen and Kalwij (2001). A similar procedure, with qualitatively similar results is carried out to impute the probability of a second birth event for women who already have a child.

Figure B.2 Frequency of age of birth of the first child for older women and imputed probabilities of birth event for younger women.



Explanatory note: Frequencies are derived from a sample of older women that is made up by 21854 observations. The imputation is carried out on all women in phase 1. The event of no birth occurs in 28% of the sample of older women. Birth is imputed on base of the 'presence' of children in the household. Therefore the real share of 'no births' should be lower. The model predicts an average probability of 'no birth' equal to 11%.
Source: SEP, own computations.

Notice that these results are consistent with data administrated by Statistics Netherlands (CBS). The share of women who do not give birth is about 15% (Source: OG '98, CBS). The average estimated probability for the same event in our model is 11%. In addition 7% of the women aged 35-39 in the OG data reports that they have no kids and are willing to have one. This corresponds almost perfectly with our estimated probability in that age group.

Appendix C Re-entrances into the labour market

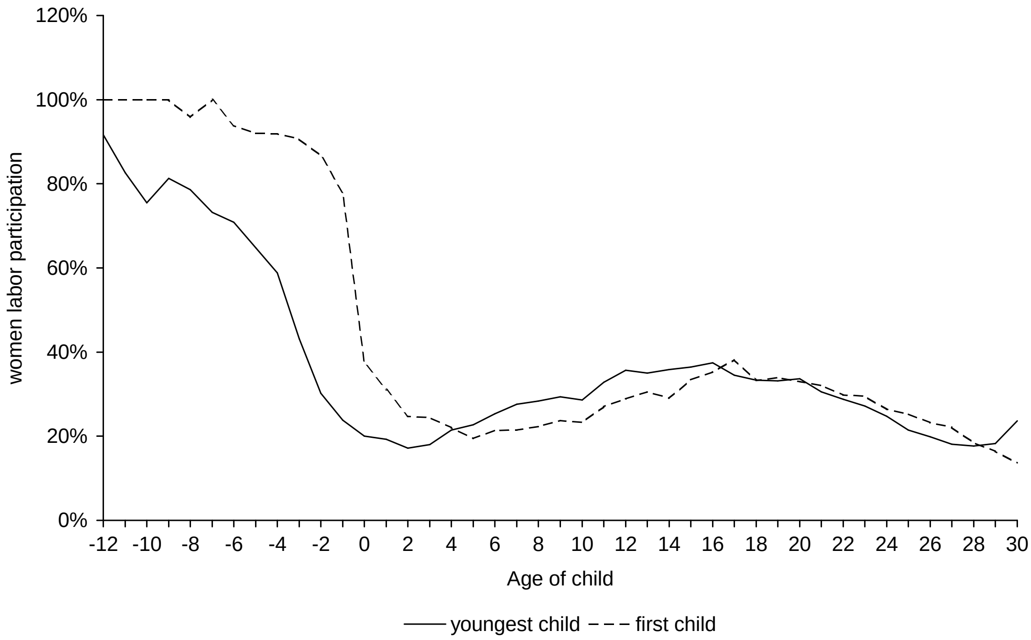
We do not observe re-entrances in our main panel, but we do observe some if we use the broader time series of cross sections. In both cases there are much less re-entrances than common sense and anecdotic evidence would suggest (Ooms and Van Gameren (2005)). When we describe the results of our model we speculate that this may be due to a vicious selection mechanism due to the sampling procedure. To gain a more general understanding of this phenomenon we look therefore in the broader cross section. We observe about 20000 households with children. Their mothers own to different cohorts and their median year of birth is 1955.

Figure C.1 shows their participation over the age of the first or youngest child without distinction for the mothers' cohort or previous labour market status. It shows that when the first child enters primary school, participation increases again. If we follow the first child, we see that the participation of his mum rises from 21% when he is 4 to approximately 36% when he is 16. Further it declines steadily again in the next 10 years, to return to the levels of first-child's pre school age.

In order to impute re-entrances, we need a panel element, in the sense that we need to observe non employed women in $t-1$ returning to work in t. As discussed above the amount of re-entrances in the main panel is about 3% of the sample. This is too few to allow a reliable estimation of the re-entrances, and we therefore decided to estimate a hazard model only for labour exits. It is not troublesome to take re-entrances into account in the estimation of the future expected income profiles.

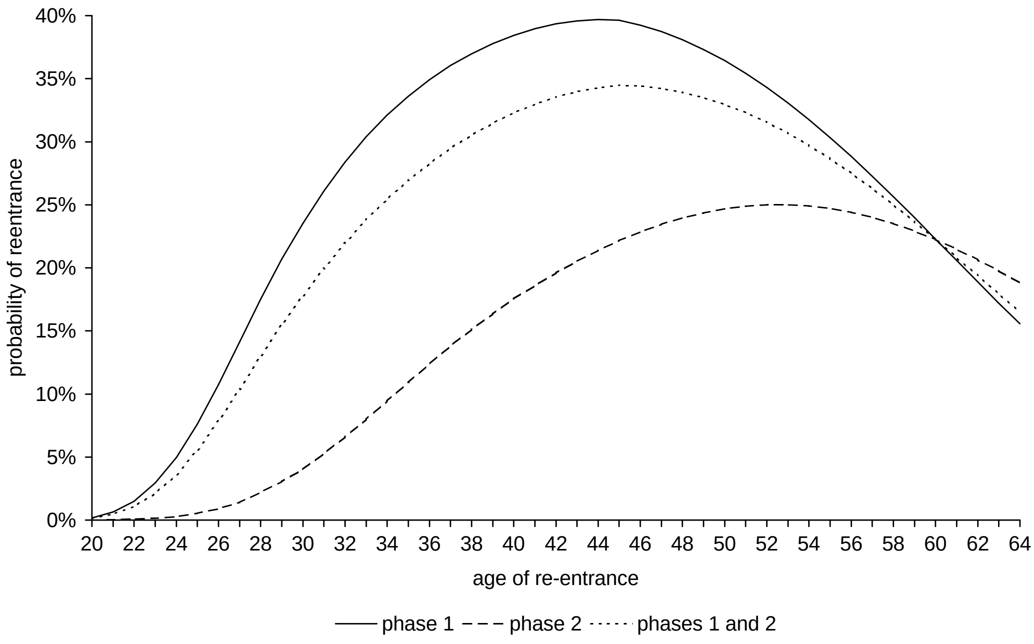
From the time series of cross section, we select a sample of about 15000 women non employed in $t-1$ (most of them discarded when selecting out "housewives") and that may return to employment in t. This happens for about 6% of the selected sample. This unbalanced sample (with at least two repeated observations of labour-market status) has therefore twice as many re-entrances than the main panel (but still very few). On this sample, we estimate a logit model for re-entrances and in figure C.2, we summarise the results of the imputation procedure. The probability of re-entering the labour market varies according to whether women already have children (phase 2) or not (phase 1). It increases until middle age to decline again in the proximity of early retirement age.

Figure C.1 Participation over age



Explanatory note: when the first child enters primary school, participation increases again.
Source: SEP, own computations.

Figure C.2 Imputation of re-entrance's

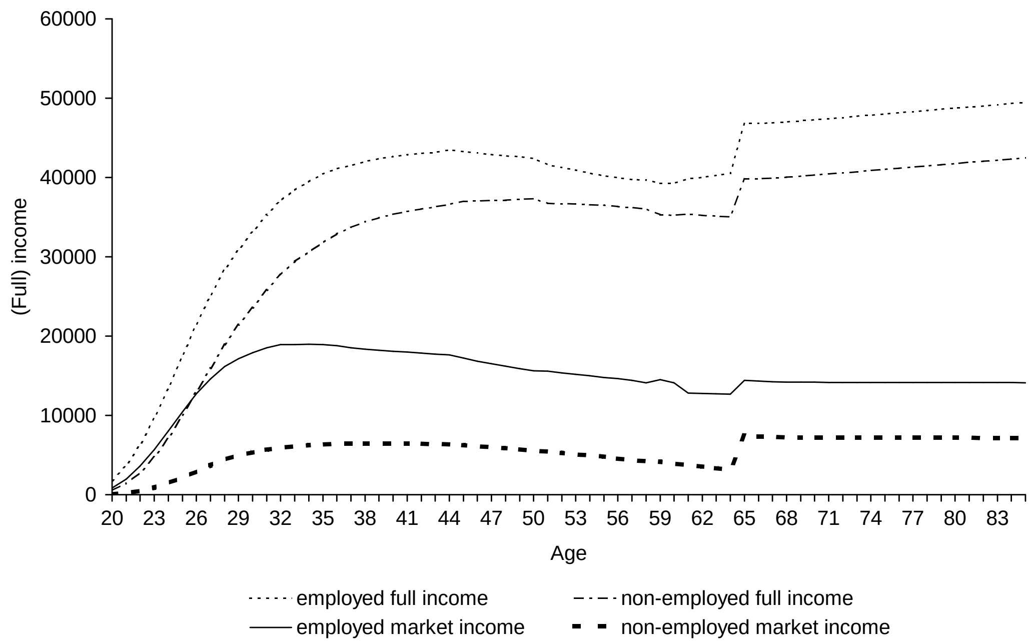


Source: SEP, own computations.

Appendix D Incentives

In figure D.1, we report the average (full) income profiles for employed and non employed women. The area in between the two lines identifies the residual life-cycle incentive to work, versus stopping with work. It shows that the relative difference between employment and non employment is smaller with full consumption. This means that when we consider the value of home production (mostly child care) the incentive to work is relatively smaller.

Figure D.1 Average (full) income/consumption profiles for employment and non employment.



Source: SEP, own computations.

Appendix E Home production

The activities that we include in the definition of home production are listed in table E.1. In order to impute the amount of hours dedicated to home production in the SEP, we have estimated a OLS regression (see table E.2) on a set of characteristics that are available in the SEP also. Using the estimated coefficients and the observed variables in the SEP, we can to impute home production. A similar approach is also used for the imputation of the age of eligibility to early retirement. See Mastrogiacomo et al. (2004) for details.

Figure E.1 summarises the results that we obtained in the SEP and the observed data in the TBO. It reports on the horizontal axis the amount of years on which women form expectations concerning the future profiles of time spent at home production. The weekly hours that women will spend house working is reported on the vertical axis. The figure is therefore not constructed on the base of current observations, but on the base of some imputed future characteristics of each woman for all years subsequent to the current year (see table E.2). Some of these characteristics, such has her age or the age of her partner, evolve deterministically, while others, as the amount of her labour-market hours, the amount of labour-market hours of her partner and the presence of children in a given age group, evolve according to a probabilistic model[14]. The figure also includes the observed TBO patterns according to the age of the child. Note that a woman in the SEP, currently with no children, in two years time has a small probability of having a child of age 2. Therefore while in the observed data, moving on in the future children age deterministically, in the SEP they age 'probabilistically', which means in a 'slower' way, since each year the probability of giving birth is smaller than 1. It is no surprise therefore that for employed and non employed women the imputed values in the SEP are lower than the observed data in the TBO. This is normal since the presence of children, that is the most important determinant of time spent in home production, enters the model probabilistically and each woman has a probability of not giving birth. On the contrary in the TBO children are observed with certainty. This means that no woman in the SEP will expect to spend the full amount of hours of home production that one child needs. As the aim of the imputation in the SEP is only to determine the expected pattern of hours spend in home production by women in the future, we interpret these results as very plausible. Also the reduction in working hours seems plausible, if we consider that in zero women may have any age between 20 and 43. Also the little hump shape after 13 years is realistic, since at that time women are very likely to have a child of schooling age who therefore needs less care.

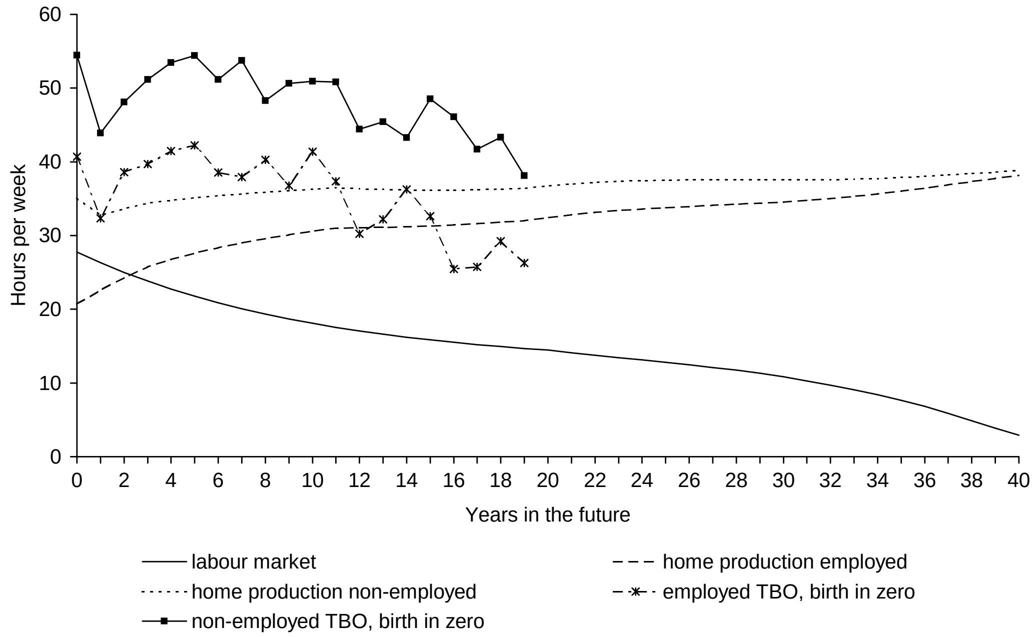
[14] The model includes the probability of giving birth in the future, of re-entering the labour market if non employed and the probability to early retire at each future age if employed, and also the survival probabilities.

Table E.1 TBO variables, activities included in the definition of home production

Cooking	Playing at home with children
Set table	Walk outside with children
Wash (kitchen)	Medical care of children
Vacuum cleaning	Look after children
Cleaning windows and doors	Care use for children
Sweeping the floor	Car reparations for children
Furniture cleanings	Scooter use for children
Setting the bed	Bike use for children
Outside housework	Walking for children
Carwash	Purchasing food in stores
Maintain bike	Purchasing food in shops
Laundry	Pick up meals
Ironing	Visit the market
Cloths reparations	Visit a shopping centre
Gardening	Visit a cloths shop
Other reparations of the house	Visit a ironware shop
Care of pats	Visit the doctor
Care of plants	Visit other shops
Organizing	Visit post office
Car use for housework	Visit bank
Car reparations for housework	Visit council
Scooter use for housework	Visit automatic laundry
Bike use for housework	Waiting
Walks for housework	Car use for shopping
Care of babies	Car reparations for shopping
Care of children	Scooter use for shopping
Helping in housework	Biking for shopping
Reading out for children	Walking for shopping

Source: TBO.

Figure E.1 Time use for future years in the SEP and time spent home production in the TBO data according to the age of the child.



Source: SEP and TBO, own computations.

Table E.2 Model for home production

	Estimate	T-val
Age woman	0.18	2.62
Age man-age woman	0.12	1.32
Child younger than 3	17.87	18.02
Child between 4 and 11	10.85	10.69
Child between 12 and 18	3.12	1.96
Woman intermediate education	− 0.90	− 1.17
Woman higher education	− 0.95	− 0.97
Woman hours in the labor market	− 0.52	− 18.24
Men hours in the labor market	0.09	3.11
Constant term	25.88	9.23

Explanatory note: OLS coefficients in the estimates. Reference case for children's age: women with no children.
Source: TBO.