Estimating labour supply responses in the Netherlands using structural models

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Abstract

We exploit a very large administrative dataset to estimate labour supply elasticities for a large number of subgroups in the Netherlands. We estimate parameters for a broad set of preference specifications. We find that men and women have similar labour supply elasticities when they are single. When they form a couple men have much smaller elasticities than women, in particular when children are present. We also find that cross elasticities of men's wages on women's labour supply are substantial. Low skilled singles and single parents have much higher labour supply elasticities than high skilled singles and single parents, whereas differences between skill types are less pronounced for couples. For all subgroups we find that the extensive margin (participation) is much more important than the intensive margin (hours per week). Women with children have the highest intensive margin response. Controlling for household type, we do not find a clear age pattern for labour supply elasticities. Most of these results are in line with the findings on labour supply elasticities abroad.

JEL classification codes: C25, C52, H31, J22

Keywords: Labour supply elasticity, discrete choice models, the Netherlands

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1 Introduction

Labour supply elasticities are a crucial parameter for policy analysis. In setting tax rates and benefit levels the government faces a fundamental trade-off between equity and efficiency (Mirrlees, 1971). Redistribution from *e.g.* rich to poor households distorts labour supply, or effort more generally. Redistribution occurs between various subgroups on the labour market, and subgroups may respond differently to this redistribution. Hence, it is important to have good empirical information on the labour supply elasticities of different subgroups.

In this paper we exploit a very large administrative dataset on Dutch households, the *Arbeidsmarktpanel* (Labour market panel) of Statistics Netherlands, to estimate labour supply elasticities. This dataset covers more than a million individuals in households over the period 1999-2005. This allows us to precisely estimate preferences and the corresponding labour supply elasticities for a large number of subgroups on the Dutch labour market. We also consider parameter estimates for a broad set of preference specifications.

We use a discrete choice model for labour supply (Van Soest, 1995, Aaberge *et al.*, 1999, Blundell *et al.*, 2000, Bargain *et al.*, 2011). Discrete choice models have become popular in labour supply analysis because they greatly simplify the analysis of (joint) labour supply decisions when there are kinks and non-convexities in the budget set, due to *e.g.* the tax-benefit system.

The outline of the paper is as follows. We first discuss the labour supply model and the empirical methodology in Section 2. Section 3 then provides information on the dataset we use in the empirical analysis. Section 4 discusses the labour supply estimates for the different subgroups. Section 5 compares these results with the findings of other studies, both for the Netherlands and abroad. Section 6 discusses future research and concludes.

2 Model

2.1 Preferences

We use structural models to estimate the labour supply elasticities. We estimate the two most popular specifications for preferences in discrete choice model: 1) a (log) quadratic specification (used in *e.g.* Van Soest, 1995, Blundell *et al.*, 2000, and Bargain *et al.*, 2011), and 2) a Box-Cox specification (used in *e.g.* Aaberge *et al.*, 1999, Aaberge and Colombino, 2009, and Blundell and Shephard, 2011).

First consider the (log) quadratic specifiction for couples (the specification for singles is similar, but without the terms for the partner). The choice of hours to work is the result of a coordinate decision of the two household members m and f. Define y as household income and l_m and l_f as leisure of the respective partners. Household utility[1], suppressing a household indicator i and a time indicator t, is given by

$$\begin{aligned} U(y, l_m, l_f) \quad &= \quad \beta_1 \; y + \beta_2 \; l_m + \beta_3 \; l_f + \alpha_1 \; y^2 + \alpha_2 \; (l_m)^2 + \alpha_3 \; (l_f)^2 \\ &\quad + \alpha_4 \; y \; l_m + \; \alpha_5 \; y \; l_f + \; \alpha_6 \; l_m \; l_f + \; \delta_m + \; \delta_f + \; \varepsilon. \end{aligned} \tag{1}$$

δ_m and δ_f are fixed costs related to working, which are negative terms for options where the respective person is working only. As shown by *e.g.* Van Soest (1995), fixed costs are necessary to reproduce the low share of individuals that work only few hours per week. Of course there are sound economic to include them. They also play a crucial role in the distinction between the extensive (participation) and intensive (hours per week) response to changes in financial incentives. Furthermore, they have important implications for the regularity conditions of leisure (Heim and Meyer, 2004). Since we do not know what these fixed costs are, we remain agnostic about them. We do not include them in income or leisure, but simply include a dummy in utility metric. ε is an individual and option specific utility term, necessary to reproduce heterogeneous choices for otherwise similar individuals as observed in the data. ε is assumed to be identically and independently distributed across individuals and options according to an Extreme Value Type-I distribution. This results in a convenient multinomial logit specification for the probabilities for observing individuals in particular options (see below).

In the empirical specification below we allow the β's and the δ's to depend on individual and household characteristics, like age, ethnicity and the age of the youngest child if present, in part to relax the indepedence of irrelevant alternatives (IIA) assumption. Furthermore, we also estimated models with random preference heterogeneity, but the results were very similar to the models without random preference heterogeneity, so we do not present them here.[2]

Next, consider the Box-Cox specification

$$\begin{aligned} U(y, l_m, l_f) \quad &= \quad \exp(\beta_1) \left(\frac{y^{\gamma_1} - 1}{\gamma_1} \right) + \exp(\beta_2) \left(\frac{{l_m}^{\gamma_2} - 1}{\gamma_2} \right) + \exp(\beta_3) \left(\frac{{l_f}^{\gamma_3} - 1}{\gamma_2} \right) \\ &\quad + \delta_m + \; \delta_f + \; \varepsilon. \end{aligned} \tag{2}$$

[1]Samuelson (1956) shows that in a unitary model individual utilities can be aggregated to obtain a household utility function.

[2]Details available on request.

This specification is less flexible than the quadratic function, but guarantees that marginal utility of income and leisure remain positive. When the marginal utility of income is negative the optimization problem is not well defined. Theory does not put a priori restrictions on the marginal utility of leisure though. In choosing between the quadratic and Box-Cox specification we face a trade-off between flexibility and an economically meaningful model. It is a priori not clear which function does better empirically. The empirical results will show if negative marginal utility is a problem in the (log) quadratic model, and whether the Box-Cox model generates a poor fit of the data.

2.2 Discrete choice model

We use a discrete choice model to model labour supply decisions. Define h_m and h_f as the discrete number of hours worked per week by men and women. We experimented with a number of discretizations, an interval of 8 hours (a normal working day in the Netherlands) running from 0 to 40 hours gave a good fit to the data and worked well in the estimations. For single men and women we then have 6 discrete options, and for couples we have 6x6 = 36 discrete options.

For the estimation we add an idiosyncratic term to the utility function for each individual in each option. Denote the choice sets for men and women by j and k respectively. We assume, in line with most studies, that the idiosyncratic component follows $\varepsilon^{j,k} \sim EV(I)$, which implies a multinomial logit form of the probabilities in the model. Notice that the idiosyncratic term depends on the combined choice in the household.

Evidently if we observe households making choices j, these must deliver a higher utility then any other choice $k = 0, ..., M$. That is: $U\left(y, h_m^j, h_f^j\right) + \varepsilon\left(h_m^j, h_f^j\right) > U\left(y, h_m^k, h_f^k\right) + \varepsilon\left(h_m^k, h_f^k\right)$, or $U^{jj} + \varepsilon^{jj} > U^{kk} + \varepsilon^{kk}$, thus $U^{jj} - U^{kk} > \varepsilon^{kk} - \varepsilon^{jj}$. Given the distributional assumptions about the ε term, using capital letters for the observed choice, we find

$$\Pr\left(h_m = J, h_f = K\right) = \frac{\exp\left(U^{J,K}\right)}{\sum_{j=1}^{M}\sum_{k=1}^{M}\exp\left(U^{j,k}\right)}.$$

This means that in the denominator we sum all choices for the different categories, while in the numerator we only have the one category being chosen.

All the elements within the utility function can be prepared separately, outside of the likelihood function, by predicting the income for non-employed.[3] In the Appendix we show results of the panel data method that we have selected, among different other methods,

[3] Wages could also be jointly determined within the likelihood function. However for reasons of computational time we preferred to impute these beforehand using two steps methods.

to impute wages of non-employed. For employed we use observed wages, while for non-employed we draw the error term $r = 1, ..., R$ times to determine its empirical distribution, and integrate it out of the likelihood function.

If we define X as being the vector of the elements in the utility functions that do not include income, Z as the income related vector and we also add a to indicate unobserved heterogeneity, then the probability that category j is chosen can be written as:

$$\Pr\left(J, K | X_{it}\gamma, Z_{r,it}^{j,k}\zeta, a_i\right) = \frac{\exp\left(X_{it}\gamma + Z_{r,it}^{J,K}\zeta + a_{r,i}\right)}{\sum_{j=1}^{M}\sum_{k=1}^{M}\exp\left(X_{it}\gamma + Z_{r,it}^{j,k}\zeta + a_{r,i}\right)}. \tag{3}$$

As the choice probabilities are conditioned on the R draws of the error term in income and on a_i, we must integrate over the distribution of the unobserved heterogeneity. Notice that we have assumed an equal amount of draws both for the income and unobserved heterogeneity term. This technical assumption is easy to relax, but abandoning it results in much longer computational time. The likelihood for the multinomial logit with random intercept boils down to:

$$L = \sum_{i=1}^{N}\int_{-\infty}^{+\infty}\prod_{t=1}^{T}\prod_{j=1}^{M}\prod_{k=1}^{M}\left\{\frac{\exp\left(X_{it}\gamma + Z_{r,it}^{J,K}\zeta + a_{r,i}\right)}{\sum_{j=1}^{M}\sum_{k=1}^{M}\exp\left(X_{it}\gamma + Z_{r,it}^{j,k}\zeta + a_{r,i}\right)}\right\} d_{ijt} f(a)\, da \tag{4}$$

where d_{ijt} is a dummy variable $= 1$ if respondent i chooses category j at time t. For identification we define a reference category (whose estimates are therefore equal to zero). Most studies assume a to be normally distributed and independent of X. Integration over the distribution of a is not straightforward, in the sense that there is no analytical solution for expression 4.

The approach we follow is to maximize a simulated likelihood. We draw R times values of imputed income errors and of a from a normal distribution, compute the likelihood, and average it out over the R draws. So we do not estimate the exact likelihood but a simulated one, namely:

$$L = \sum_{i=1}^{N}\frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T}\prod_{j=1}^{M}\prod_{k=1}^{M}\left\{\frac{\exp\left(X_{it}\gamma + Z_{r,it}^{J,K}\zeta + a_{r,i}\right)}{\sum_{j=1}^{M}\sum_{k=1}^{M}\exp\left(X_{it}\gamma + Z_{r,it}^{j,k}\zeta + a_{r,i}\right)}\right\} d_{ijt}. \tag{5}$$

3 Data

The data we use for the analysis is from the *Arbeidsmarktpanel* of Statistics Netherlands. The *Arbeidsmarktpanel* is an administrative household panel dataset covering about 1.1

Table 1: Number of individuals and households

	Individuals	Households
1999	137056	89822
2000	147611	96703
2001	160665	105403
2002	166007	109267
2003	161241	106920
2004	154511	103274
2005	135815	91798
Total observations	1062906	703187
Number of unique records 1999 - 2005	320329	225332

million individuals, aged 15 and over, over the period 1999-2005. The dataset combines information from the *Gemeentelijke Basisadministratie* (data from municipalities) 1999-2005 on e.g. demographics and household characteristics, the *Sociaal Statistisch Bestand* (Social Statistical Panel) 1999-2005 on e.g. wage income and hours worked, and *Enquete Beroepsbevolking* (Labour Force Survey) 1996-2005 on e.g. education.[4]

Entry into the panel occurs mostly because people turn 15 or immigrate, exit from the panel occurs mostly because people die or emigrate. We make a selection from this dataset. We drop all individuals under 20 years old and over 57 years old. The maximum age is set at 57 years old, because we do not want outcomes to be influenced by the changes in early retirement benefits in the dataperiod. This would require a dynamic tax-benefit calculator, and a dynamic discrete choice model, which we do not have at the moment. We also drop students. We further drop households for which we have incomplete demographic information (e.g. the age of the children is missing) or households for which we have incomplete partner information. Finally we drop all households for which we do not have information on the gross wage of the partner. When there is a timegap for a household we only keep the longest period. In the end we are then left with 320 thousand individuals and over one million observations, see Table 1. The number of individuals is lowest in the first and last year since these years have the highest chance of being dropped in case of a timegap. Descriptive statistics for the sample are given in the Appendix.

To estimate the discrete choice model we need to calculate net income y at each discrete choice. We assume that gross hourly wages are constant in the number of hours

[4] And the *Centrale Registratie Inschrijvingen Hoger Onderwijs*, data on individuals participating in higher education. However, we do not use these data in this study.

worked. Gross wages for the unemployed are imputed using estimates for workers, see the Appendix for details. We calculate net household income corresponding to the gross incomes of the two partners using the MIMOSI model of CPB (see Romijn *et al.*, 2008). MIMOSI is, among other things, a very detailed (non-behavioural) tax-benefit calculator for the Netherlands. It takes into account all (country level) taxes, subsidies and benefits for individuals in households.

4 Results

Given the specifications for preferences above, and with net incomes for all possible choices we then estimate the preference parameters for the following key groups on the labour market: i) singles, ii) single parents, iii) couples without dependent children and iv) couples with dependent children. For all these groups we estimate the preference parameters for different utility functions. We first present the estimated preference parameters of the models, then consider the fit and conclude with the labour supply elasticities. The labour supply elasticities are simulated using an impulse on gross hourly wages of 10 percent.

4.1 Singles

4.1.1 Estimated preferences

We first estimated preferences for single men and women separately. This yielded very similar results to when we pooled single men and women together. Below we present the results for the pooled regressions. Furthermore, we used a subsample of the full dataset, estimates with larger datasets generated similar results.[5] Table 2 gives the estimated preference parameters for different preference specifications for singles.

The first column gives the results for the quadratic utility function. We find positive but diminishing marginal utility of income, the linear term is positive and the quadratic term is negative. For none of the chosen options in the data we find negative marginal utility of income, as required for the optimisation problem to be well defined. We also find positive and diminishing marginal utility of leisure. The coefficients of the interaction term between leisure and (age – 38) suggests that older singles have a higher marginal utility of leisure than younger individuals workers, whereas the interaction term between leisure and (age – 38)^2 suggests that both the very young and the 'very' old (up to 58) individuals have a higher preference for leisure. For 38% of the chosen options we find a negative marginal utility of leisure. However, this is not a problem per se, theory does

[5]Details available on request.

not require it to be positive. Working more hours may have benefits beyond income. Furthermore, with fixed costs of work, the marginal value of leisure is harder to interpret anyway (see also Bargain *et al.*, 2011). The coefficient on the interaction term between income and leisure is positive, but the coefficient is not significant. The coefficient on fixed costs of work, a dummy that is 1 when individuals are working, is negative. Fixed costs of working are higher for singles with only elementary education, but lower for natives (compared to immigrants). All in all, the quadratic utility function does rather well in economic terms.

Column 2 gives the results for the log quadratic utility function. Again we find positive but diminishing marginal utility of (log)income. Both the linear and quadratic term of log leisure are negative, resulting in more individuals having a negative marginal value of leisure (52%) in the chosen option. Older workers again have a higher marginal value of leisure, as do the youngest and the oldest singles in the sample. For the log quadratic specification the interaction term of income and leisure has a negative sign, and is significantly different from zero. Fixed costs of working again reduce the utility from working, and the more so for singles with elementary education and immigrants.

Column 3 then gives the results for the Box-Cox 1 specification. This specification restricts the marginal utility of both income and leisure to be positive (which is indeed what we find). We find that the parameter γ_1 is very close to 0. In this case, the Box-Cox specification converges to the log specification in income. The β parameter of leisure (in the exponential term in front of leisure) has a very large negative number (-43.43). This shows that the Box-Cox specification is restricting the marginal value of leisure from becoming negative. Fixed costs of working again reduce the utility fom working, and the more so for singles with elementary education and immigrants.

Finally, in Column 4 we add an interaction term between leisure and income, which is significant. In economic terms, the results are quite similar to the results from Column 3. Again, we see the β parameter of leisure going to minus a big negative number. The results for fixed costs are similar.

4.1.2 Fit

Figures 1-4 give the respective fit for the models with the different utility functions. The black bars are the observed frequencies in the data (averages over the period 1999-2005), and the grey bars are the frequencies predicted by the model.

The quadratic model fits the data quite well. Due to the fixed costs parameters, the model reproduces the low frequencies at few working hours. At high working hours the frequency in the data levels off, and the quadratic specification predicts too many singles

Table 2: Estimated preference parameters: singles

	Quadratic	Log quadratic	Box-Cox 1	Box-Cox 2
Income	0.650***	4.292***	1.617***	1.478***
Income^2	-0.0584	-2.100***		
γ_1			–0.0628	0.0693
Leisure	127.3***	-22.29***	–43.43	-36.36***
x (Age – 38)	1.064***	1.084***	0.278***	1.170**
x (Age – 38)^2	2.027***	1.626***	–0.00847	–0.445*
Leisure^2	-80.03***	-97.54***		
γ_2			–178.1	–148.1
Income x leisure	0.851	-16.53***		-36.28***
Fixed costs	-4.169***	-4.245***	-2.386***	-2.373***
x Elementary education	-0.814***	-0.808***	-0.747***	-0.755***
x Native	0.920***	0.886***	0.831***	0.833***
Observations	24000	24000	24000	24000
Log likelihood	–5691	–5655	–5687	–5687
Chosen options with $u'_y < 0$	0%	1%	0%	0%
Chosen options with $u'_l < 0$	38%	52%	0%	0%

*** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Quadratic

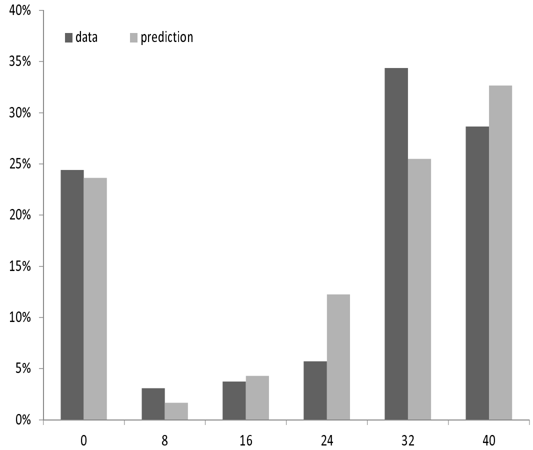


Figure 2: Log quadratic

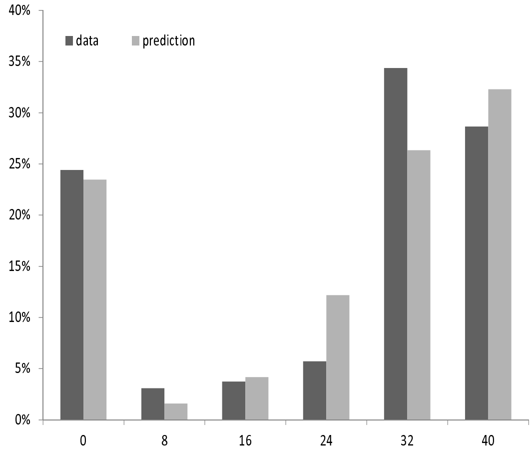


Figure 3: Box-Cox 1

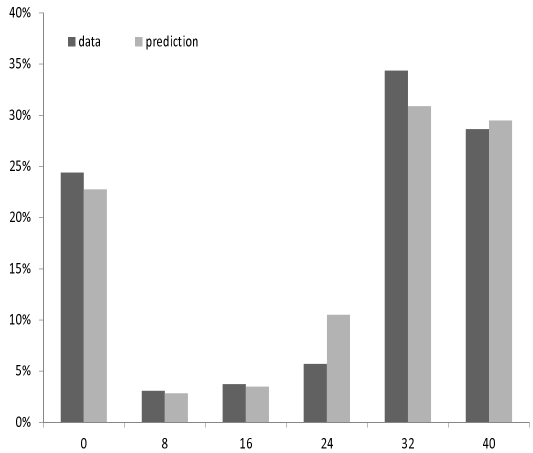


Figure 4: Box-Cox 2

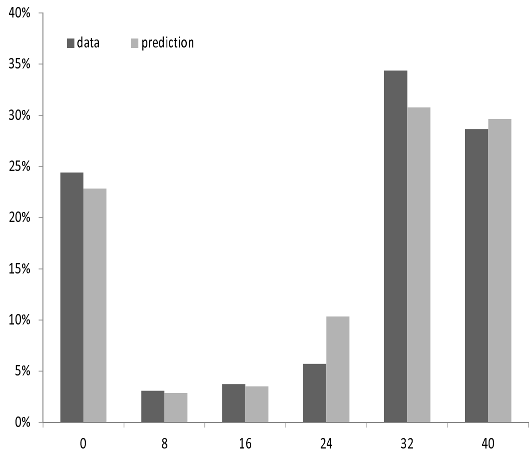


Table 3: Labour supply elasticities: single women[a]

	Quadratic			Log quadratic			Box-Cox 1			Box-Cox 2		
	Total	Ext.	Int.	Total	Ext.	Int.	Total	Ext.	Int.	Total	Ext.	Int.
Full sample	0.46	0.37	0.08	0.47	0.39	0.08	0.64	0.52	0.11	0.62	0.52	0.10
Age 20–28	0.48	0.37	0.11	0.55	0.43	0.11	0.74	0.58	0.15	0.70	0.56	0.14
Age 28–40	0.31	0.24	0.07	0.32	0.26	0.06	0.55	0.45	0.10	0.53	0.44	0.09
Age 40–57	0.54	0.45	0.08	0.50	0.43	0.07	0.62	0.52	0.09	0.62	0.52	0.09
Lower educ.	0.82	0.68	0.13	0.97	0.82	0.14	1.21	1.00	0.19	1.17	0.97	0.18
Higher educ.	0.36	0.28	0.07	0.33	0.26	0.06	0.47	0.38	0.09	0.46	0.37	0.09

[a] Simulated labour supply elasticities following an impulse of 10% in gross hourly wages. Total is the elasticity of total working hours, ext. is the participation elasticity, int. is the hours per worker elasticity.

Table 4: Labour supply elasticities: single men[a]

	Quadratic			Log quadratic			Box-Cox 1			Box-Cox 2		
	Total	Ext.	Int.	Total	Ext.	Int.	Total	Ext.	Int.	Total	Ext.	Int.
Full sample	0.39	0.32	0.06	0.39	0.33	0.06	0.54	0.45	0.09	0.53	0.44	0.08
Age 20–28	0.45	0.35	0.10	0.50	0.40	0.10	0.69	0.55	0.13	0.65	0.53	0.12
Age 28–40	0.03	0.00	0.04	0.33	0.27	0.05	0.10	0.05	0.05	0.51	0.44	0.07
Age 40–57	0.41	0.36	0.05	0.37	0.32	0.05	0.46	0.40	0.06	0.46	0.40	0.06
Lower educ.	0.75	0.63	0.11	0.87	0.74	0.11	1.13	0.95	0.16	1.10	0.93	0.15
Higher educ.	0.29	0.24	0.05	0.27	0.22	0.05	0.39	0.32	0.07	0.38	0.31	0.07

[a] Simulated labour supply elasticities following an impulse of 10% in gross hourly wages. Total is the elasticity of total working hours, ext. is the participation elasticity, int. is the hours per worker elasticity.

at 40 hours and too few singles at 32 hours. However, also at high working hours the differences are not big, and the precise pattern of the frequency data is sensitive to the choice of discrete points in this region. Overall, the quadratic specification does quite well in predicting the observed frequencies.

The fit for the log quadratic model is quite similar to the fit of the quadratic model. Despite differences in estimated parameters for leisure and the interaction term of leisure and income between the two models they still lead to similar predictions.

The Box-Cox specifications do rather well in terms of fit, although the specification is restrictive regarding the differences in the marginal value of leisure. The Box-Cox specifications actually do a better job than the quadratic and log quadratic specifications at the 32 and 40 hours points.

4.1.3 Labour supply elasticities

Table 3 gives the labour supply elasticities for single women corresponding to the estimated preferences above. Table 4 gives the results for single men. Preferences for both groups are assumed to be the same,[6] but wages and personal characteristics differ. As is common in the discrete choice labour supply literature (see *e.g.* Bargain *et al.*, 2011), these labour supply elasticities are simulated by comparing the predicted base frequencies with the predicted frequencies when we increase gross wages. We increase gross wages by 10%. We present results for the total hours worked elasticies and the two components that make up this total hours worked elasticity, the participation elasticity and the hours per worker elasticity. Furthermore, we also present results for elasticities by age groups of singles and for lower and higher educated singles.

For the quadratic utility function we find a total hours worked elasticity for single women of 0.46. By far most of the response is on the participation or extensive margin, with only a small response on the hours per worker or intensive margin. This is a common finding in the empirical labour supply literature (see *e.g.* Heckman, 1993, Blundell and MaCurdy, 1999 and Bargain *et al.*, 2011). Furthermore, we find a U-shape for the age pattern in elasticities for single women, with the highest elasticities for both younger and older single women, and the lowest elasticities for middle-aged women. Also, the differences across age groups are mostly due to differences in the extensive margin response. This is in line with the findings of Blundell *et al.* (2011) for the US, the UK and France. The labour supply elasticities are much higher for lower educated single women than higerh educated single women, the difference is mostly due to a difference in the extensive margin response.

[6] Which is not restrictive, details available on request.

The resulting elasticities for the log quadratic specification for single women. are quite similar to the quadratic specification. The resulting elasticities for the Box-Cox specifications are somewhat higher due to a somewhat higher extensive margin reponse. We still find a U-shape for the age pattern, and for both Box-Cox specifications, the labour supply elasticity of lower educated single women is much higher than for higher educated single women.

For single men we find comparable yet somewhat smaller total hours worked elasticities in all specifications, due to both a somewhat smaller extensive and intensive margin response. For single men we also find the U-shape for the age pattern, and much higher elasticities for lower than for higher educated, in all specifications.

4.2 Single parents

4.2.1 Estimated preferences

Table 5 gives the estimated preferences for the same four preference specifications for preferences but now for single parents rather than singles. Both the quadratic and log quadratic specification do rather poorly in economic terms. The linear term in (log) income is negative. As a result, 33% and 70% of the single parents has a negative marginal utility in chosen options in the quadratic and log quadratic specification respectively. Since this implies that these specifications do a bad job in explaining behaviour in economic terms we skip the discussion of the other coefficients and turn to the Box-Cox specifications instead.

In the Box-Cox specifications, we find a significant positive coefficient for income. For the Box-Cox 2 specification, with interaction term between income and leisure, we find γ_1 close to zero, hence close to the log specification. The coefficient on the exponent in front of leisure is a large negative number, bringing it close to zero. The value of leisure seems to fall somewhat in age. Having a youngest child aged between 0 and 3 years old significantly raises the value of leisure time, as does having a child aged between 4 and 11 years old. The interaction term between income and leisure in Box-Cox 2 is significantly negative. Fixed costs of working significantly reduce utility, and even more so when the single parent has only elementary education and when the single parent is an immigrant. Having a small child also significantly raises the fixed costs of working, in particular when the youngest child is 0 to 3 years old.

Table 5: Estimated preference parameters: single parents

	Quadratic	Log quadratic	Box-Cox 1	Box-Cox 2
Income	-2.714***	-5.559***	1.713***	1.185***
Income^2	0.116***	2.636***		
γ_1			–0.452	–0.0194
Leisure	233.6***	-55.91***	–50.96	-54.75***
x (Age – 38)	-3.387***	-2.999***	-0.260***	-0.729***
x (Age – 38)^2	2.685***	2.327***	0.0161	–0.137
x Youngest child 0 – 3	4.823***	3.914***	0.399**	11.77***
x Youngest child 4 – 11	5.752***	4.841***	0.405***	11.72
Leisure^2	-148.6***	-111.6***		
γ_2			–206.9	–175.7
Income x leisure	2.202**	7.129**		-43.13***
Fixed costs	-5.373***	-5.011***	-1.036***	-1.035***
x Elementary education	-1.649***	-1.659***	-1.399***	-1.400***
x Native	0.465***	0.469***	0.464***	0.467***
x Youngest child 0 – 3	–0.283	–0.373	-1.613***	-1.600***
x Youngest child 4 – 11	0.679***	0.608***	-0.379***	-0.378***
Observations	24000	24000	24000	24000
Log likelihood	–5157	–5152	–5378	–5374
Chosen options with $u'_y < 0$	33%	70%	0%	0%
Chosen options with $u'_l < 0$	72%	73%	0%	0%

*** p<0.01, ** p<0.05, * p<0.1.

Figure 5: Quadratic

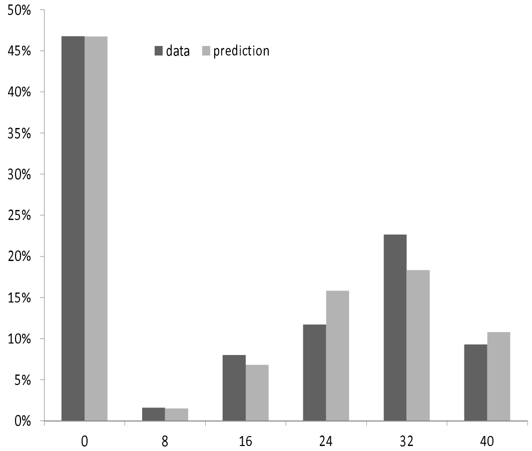


Figure 6: Log quadratic

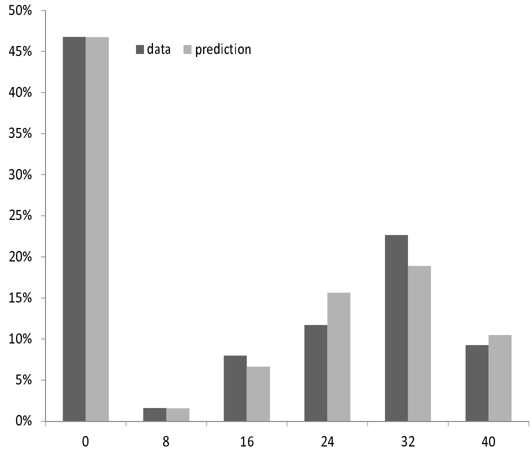


Figure 7: Box-Cox 1

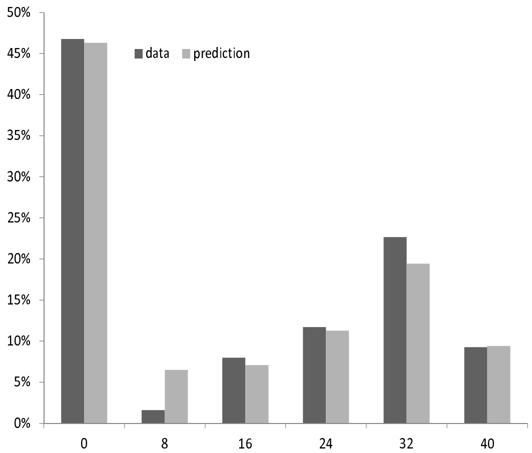


Figure 8: Box-Cox 2

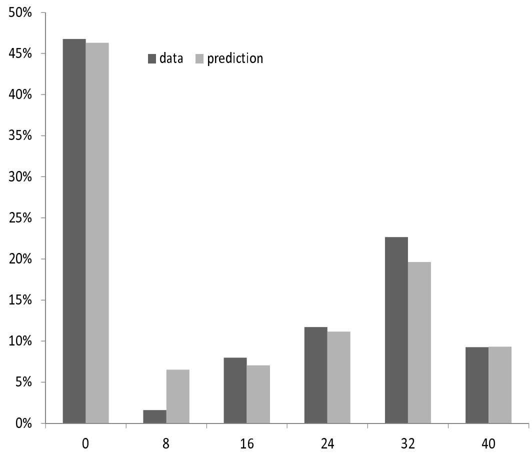


Table 6: Labour supply elasticities: single parents[a]

	Single mothers						Single fathers					
	Box-Cox 1			Box-Cox 2			Box-Cox 1			Box-Cox 2		
	Total	Ext.	Int.	Total	Ext.	Int.	Total	Ext.	Int.	Total	Ext.	Int.
Full sample	0.62	0.43	0.18	0.62	0.43	0.18	0.43	0.31	0.11	0.45	0.32	0.12
Age 20–28	1.02	0.75	0.25	1.01	0.74	0.25	0.83	0.63	0.19	0.62	0.43	0.18
Age 28–40	0.69	0.49	0.19	0.69	0.49	0.19	0.55	0.41	0.13	0.85	0.75	0.09
Age 40–57	0.53	0.36	0.16	0.53	0.36	0.16	0.41	0.29	0.11	1.01	0.82	0.17
Lower educ.	1.00	0.72	0.26	0.97	0.70	0.25	0.93	0.71	0.21	0.92	0.71	0.20
Higher educ.	0.47	0.31	0.15	0.48	0.32	0.15	0.32	0.23	0.10	0.35	0.24	0.11

[a] Simulated labour supply elasticities following an impulse of 10% in gross hourly wages. Total is the elasticity of total working hours, ext. is the participation elasticity, int. is the hours per worker elasticity.

4.2.2 Fit

Figures 5-8 gives the fit of the different utility specifications for single parents. Figures 5 and 6 show that a poor economic model can still give a good fit. More importantly, Figure 7 and 8 show that the Box-Cox models also give a good fit of the data, though they overpredict individuals at the 8 hours point to some extent.

4.2.3 Labour supply elasticities

Table 6 gives the labour supply elasticities for single parents for the different specifications. We only give elasticities for the economically meaningful models Box-Cox 1 and 2.[7]

Single mothers are by far the largest group of single parents, 81% of single parents was female in the Netherlands.[8] The elasticity of single mothers is substantial: 0.62 for the

[7] The quadratic and log quadratic specifications yielded elasticities close to 0, unsurprisingly given that the marginal utility of income is negative for these specifications for a large part of the data. Details available on request.

[8] Statistics Netherlands.

total hours worked elasticity. The intensive margin response is somewhat more important for single mothers than for single women, and amounts to a bit less than a third of the total response. We find a monotonically declining age pattern. Just like for single women, single mothers with a lower education level have a much higher elasticity of labor supply than those with a higher education level.

The elasticity of single fathers is also substantial, though somewhat smaller. The age pattern depends on the specification. Lower educated single fathers have a much higher elasticity than higher educated single fathers.

4.3 Couples without children

4.3.1 Estimated preferences

Table 7 gives the estimation results for the utility functions for couples without children. The quadratic function now distinguishes between the leisure of the man and the woman, includes interaction terms between income and leisure of both partners, and we have two separate fixed costs for both partners.

First consider the results for the quadratic specification. The linear term in income is slightly negative, and so is the quadratic term in income, but this is dominated by the positive interaction term with leisure. In the end, all chosen options have positive marginal utility of income. The linear term in leisure is positive both for the men and the women, while the quadratic term is negative. For both men and women this results in a negative marginal value of leisure for the majority of chosen options. However, this is not a problem per se, in particular when the model also has fixed costs of working (see above). For females we find significant age dependence, with women at the lower and upper end of the age distribution having a higher elasticity. The interaction term of leisure for couples without children is positive, suggesting they prefer to spend more time together *ceteris paribus*. The interaction terms of income and leisure are small. For both men and women we find significant fixed costs of working, which rise when the person has only elementary education and when the person is an immigrant.

The log quadratic specification also has a negative linear income term, but a positive quadratic term and a positive interaction term with leisure. Again, all chosen options have positive marginal utility of income. Both the linear and quadratic terms in leisure are negative for both partners, all chosen options have negative marginal utility of leisure. The age pattern is quite similar to the quadratic form for preferences. Males and females still prefer to spend time together, and there is a positive relation between income and leisure for both partners. For both men and women we again find significant fixed costs of working, which rise when the person has only elementary education and when the person

Table 7: Estimated preference parameters: couples without children

	Quadratic	Log quadratic
Income	–0.116	-9.730**
Income^2	–6.59e-07	1.993***
Male leisure	94.97*	-134.2***
x (Age – 38)	0.268	0.313
x (Age – 38)^2	–0.491	–0.302
(Male leisure)^2	-91.21***	–24.03
Female leisure	207.0***	-90.48***
x (Age – 38)	5.966***	4.869***
x (Age – 38)^2	2.187***	2.120***
(Female leisure)^2	-137.7***	-46.70***
Male leisure x Female leisure	28.08**	5.248***
Income x male leisure	0.197*	12.74***
Income x female leisure	–0.00803	4.521
Male fixed costs	-8.134***	-7.623***
x Elementary education	-0.381*	–0.291
x Native	1.199***	1.337***
Female fixed costs	-3.869***	-3.244***
x Elementary education	-0.384*	-1.006***
x Native	0.814***	0.337***
Observations	72000	72000
Log likelihood	–4999	–4930
Chosen options with $u'_y < 0$	0%	0%
Chosen options with $u'_l < 0$ males	96%	100%
Chosen options with $u'_l < 0$ females	57%	100%

Table 8: Fit quadratic model for couples without children (obs. frequencies in brackets)

	Hours males					
Hours females	0	8	16	24	32	40
0	3.7%	0.0%	0.3%	2.1%	8.4%	18.8%
	(4.0%)	(0.3%)	(0.6%)	(0.5%)	(9.6%)	(18.7%)
8	0.2%	0.0%	0.0%	0.2%	0.9%	2.1%
	(0.1%)	(0.0%)	(0.2%)	(0.1%)	(1.1%)	(1.9%)
16	0.5%	0.0%	0.1%	0.7%	2.8%	6.3%
	(0.4%)	(0.1%)	(0.1%)	(0.2%)	(4.1%)	(7.7%)
24	0.6%	0.0%	0.2%	1.3%	5.2%	11.5%
	(0.4%)	(0.1%)	(0.3%)	(0.3%)	(5.6%)	(8.1%)
32	0.7%	0.0%	0.2%	1.5%	5.7%	12.5%
	(0.8%)	(0.2%)	(0.5%)	(0.6%)	(10.0%)	(12.4%)
40	0.4%	0.0%	0.1%	0.9%	3.6%	8.1%
	(0.6%)	(0.0%)	(0.2%)	(0.2%)	(2.9%)	(8.4%)

Table 9: Fit log quadratic model for couples without children (obs. frequencies in brackets)

	Hours males					
Hours females	0	8	16	24	32	40
0	3.7%	0.0%	0.3%	2.0%	8.9%	18.2%
	(4.0%)	(0.3%)	(0.6%)	(0.5%)	(9.6%)	(18.7%)
8	0.2%	0.0%	0.0%	0.2%	1.1%	2.1%
	(0.1%)	(0.0%)	(0.2%)	(0.1%)	(1.1%)	(1.9%)
16	0.4%	0.0%	0.1%	0.7%	2.9%	5.8%
	(0.4%)	(0.1%)	(0.1%)	(0.2%)	(4.1%)	(7.7%)
24	0.6%	0.0%	0.2%	1.3%	5.4%	11.1%
	(0.4%)	(0.1%)	(0.3%)	(0.3%)	(5.6%)	(8.1%)
32	0.7%	0.0%	0.2%	1.4%	6.1%	13.1%
	(0.8%)	(0.2%)	(0.5%)	(0.6%)	(10.0%)	(12.4%)
40	0.4%	0.0%	0.1%	0.8%	3.5%	8.3%
	(0.6%)	(0.0%)	(0.2%)	(0.2%)	(2.9%)	(8.4%)

Table 10: Labour supply elasticities couples without children: quadratic utility[a]

	Male own			Female cross			Female own			Male cross		
	Total	Ext.	Int.	Total	Ext.	Int.	Total	Ext.	Int.	Total	Ext.	Int.
Full sample	0.05	0.05	–0.01	0.04	0.04	0.00	0.22	0.17	0.05	–0.02	0.00	–0.02
By characteristics of:	males						females					
Age 20–28	0.03	0.03	0.00	0.02	0.01	0.00	0.10	0.05	0.05	–0.03	–0.01	–0.02
Age 28–40	0.03	0.04	–0.01	0.02	0.02	0.00	0.13	0.08	0.06	–0.05	–0.02	–0.03
Age 40–57	0.05	0.06	–0.01	0.07	0.06	0.01	0.35	0.27	0.07	–0.01	0.00	–0.01
Lower educ.	0.07	0.08	0.00	0.06	0.06	0.00	0.26	0.21	0.05	0.00	0.01	–0.01
Higher educ.	0.04	0.04	–0.01	0.04	0.04	0.00	0.21	0.16	0.05	–0.03	–0.01	–0.02

[a] Simulated labour supply elasticities following an impulse of 10% in gross hourly wages. Total is the elasticity of total working hours, ext. is the participation elasticity, int. is the hours per worker elasticity.

Table 11: Labour supply elasticities couples without children: log quadratic utility[a]

	Male own			Female cross			Female own			Male cross		
	Total	Ext.	Int.	Total	Ext.	Int.	Total	Ext.	Int.	Total	Ext.	Int.
Full sample	0.07	0.07	0.00	–0.03	0.00	–0.02	0.27	0.22	0.05	–0.02	–0.01	–0.02
By characteristics of:	males						females					
Age 20–28	0.04	0.04	0.00	0.00	0.01	–0.01	0.11	0.06	0.05	–0.04	–0.02	–0.02
Age 28–40	0.06	0.05	0.00	–0.02	0.00	–0.02	0.14	0.08	0.06	–0.06	–0.03	–0.02
Age 40–57	0.09	0.08	0.00	–0.04	–0.01	–0.03	0.43	0.35	0.08	–0.01	0.00	–0.01
Lower educ.	0.10	0.10	0.00	0.05	0.07	–0.01	0.42	0.37	0.05	0.00	0.01	–0.01
Higher educ.	0.07	0.06	0.00	–0.04	–0.02	–0.03	0.23	0.17	0.05	–0.04	–0.02	–0.02

[a] Simulated labour supply elasticities following an impulse of 10% in gross hourly wages. Total is the elasticity of total working hours, ext. is the participation elasticity, int. is the hours per worker elasticity.

is an immigrant.

We also tried to estimate the Box-Cox specifications for couples without children, but they did not converge.

4.3.2 Fit

The predicted and observed frequencies of the two specifications are given in Table 8 and 9. The observed frequencies are in brackets.

The quadratic specification has a good fit, the notable exceptions being the (32,32) and (24,40) combination for women and men. Here the density is close to 4 percentage points short of what is observed in the first cell, and close to 3 percentage points too high for the second cell. The same is true for the log quadratic specification, with the same notable exceptions at (32,32) and (24,40), where the discrepancies with the data are now somewhat smaller.

4.3.3 Labour supply elasticities

Tables 10 and 11 give the labour supply elasiticities. First, we consider the own labour supply elasticity of men when we increase their gross hourly wages by 10%. Second, we consider the cross elasticity of women when we increase the gross hourly wage of men by 10%. Third, we consider the own labour supply elasticity of women when we increase their gross hourly wages by 10%. And finally, fourth, we consider the cross elasticity of men when we increase the gross hourly wage of women by 10%.

For the quadratic case we find low own elasticities for men. The own total hours worked elasticity is 0.05 for the full sample, with all of the response on the extensive margin. There is a slight monotonic increase in this elasticity with age. Furthermore, the elasticity for lower educated men is almost double the elasticity of higher educated men, though the numbers are still small for lower educated men in couples without children. Turning to the cross elasticities for women, we find negative cross elasticities which are substantial when compared to the own wage elasticities of men. Hence, a large part of the positive labour supply response of men is nullified by the negative cross effect on the labour supply of women.

The own labour supply elasticity is higher for women in couples without children than for men. Most of the response is on the extensive margin. The elasticity increases with age, and is somewhat higher for lower educated women than for higher educated women. The cross elasticities for men are almost zero.

The own and cross elasticities for the log quadratic specification are a bit higher than for the quadratic specification. For the rest, qualitatively the results are quite similar.

4.4 Couples with children

4.4.1 Estimated preferences

Table 12 gives the estimated parameters for two specifications for preferences for couples with children: the log quadratic and the Box-Cox 1 specification (without interaction term for income and leisure).

For the log quadratic case we find a positive and slightly increasing marginal utility of income. For all chosen options marginal utility of income is positive. The marginal value of leisure is negative for a large fraction of the chosen options. Having a youngest child 0 to 3 years old and 4 to 11 years old raises the value of leisure. The linear interaction term between age and leisure is positive, but the second order interation term is negative.

The interaction term of leisure is close to zero, they do not prefer to spend time together *ceteris paribus*. For men, leisure is a normal good. For both men and women we find significant fixed costs of working, which are higher for persons with elementary education and immigrants.

Turning to the Box-Cox 1 specification, the marginal utility of income is positive, and again income seems to be close to a log form. The marginal value of leisure for men is small. However, for women it is substantial. Fixed costs are significant for both men and women, and rise when they have a small child.

4.4.2 Fit

The log quadratic specification has a good fit, see Table 13. The largest difference between the predicted and observed frequency is 3 percentage points, for the option where the man works 24 hours and the woman 40 hours. The Box-Cox specification also has a good fit, see Table 14.

4.4.3 Labour supply elasticities

Table 15 gives the results for the labour supply elasticities of couples with children assuming log quadratic preferences. For couples with children we find larger elasticities for both men and women than for couples without children. The own elasticity is much larger for women than for men. There is also a substantial cross-elasticity for women, whereas the cross-elasticity for men is still close to zero. For both the men and the women, there is no clear relation with age. Lower educated have a higher elasticity than higher educated, and this is particularly true for men. Most of the response is on the extensive margin. The intensive margin is small, also for women with small children. Furthermore, there is no clear relation with the age of the youngest child.

Table 12: Estimated preference parameters: couples with children

	Log quadratic	Box-Cox 1
Income	3.415	2.264***
Income^2	0.253	
γ_1		-0.168*
Male leisure	-67.81***	-43.43***
x (Age – 38)	2.342***	9.758***
x (Age – 38)^2	-1.506**	-4.752**
x Youngest child 0 – 3	1.150	–12.68
x Youngest child 4 – 11	0.575	–16.06
(Male leisure)^2	-89.72***	
γ_2		9.589***
Female leisure	–20.97	1.236***
x Male higher education		0.100
x Native		0.342**
x (Age – 38)	0.176	
x (Age – 38)^2	1.653***	
x Youngest child 0 – 3	3.545***	
x Youngest child 4 – 11	3.774***	
(Female leisure)^2	-109.3***	
γ_3		-12.48***
Male leisure x Female leisure	–0.0819	
Income x male leisure	5.314	
Income x female leisure	–0.711	
Male fixed costs	-8.368***	-4.948***
x (Age – 38)		0.728***
x (Age – 38)^2		–0.0983
x Youngest child 0 – 3		–1.382
x Youngest child 4 – 11		-1.811*
x Elementary education	–0.0238	
x Native	1.520***	
Female fixed costs	-2.931***	-2.087***
x Male higher education		-0.790***
x Elementary education	-0.817***	
x Native	0.414***	0.661***
Observations	72000	72000
Log likelihood	–5113	–5203
Chosen options with $u'_y < 0$	0%	0%
Chosen options with $u'_l < 0$ males	49%	0%
Chosen options with $u'_l < 0$ females	50%	0%

Table 13: Fit log quadratic model for couples with children (obs. frequencies in brackets)

	Hours males					
Hours females	0	8	16	24	32	40
0	5.6%	0.0%	0.2%	1.8%	9.4%	22.1%
	(6.9%)	(0.2%)	(0.5%)	(0.3%)	(10.4%)	(21.9%)
8	0.6%	0.0%	0.0%	0.5%	2.3%	4.8%
	(0.1%)	(0.0%)	(0.1%)	(0.1%)	(2.3%)	(3.7%)
16	0.7%	0.0%	0.2%	1.3%	5.4%	10.4%
	(0.8%)	(0.2%)	(0.1%)	(0.4%)	(8.0%)	(12.7%)
24	0.9%	0.0%	0.2%	1.7%	6.4%	11.5%
	(0.6%)	(0.2%)	(0.4%)	(0.7%)	(7.4%)	(8.5%)
32	0.7%	0.0%	0.2%	1.0%	3.5%	5.9%
	(0.8%)	(0.3%)	(0.4%)	(0.3%)	(4.2%)	(4.8%)
40	0.2%	0.0%	0.0%	0.2%	0.8%	1.3%
	(0.3%)	(0.1%)	(0.1%)	(0.1%)	(1.0%)	(2.1%)

Table 14: Fit Box-Cox 1 model for couples with children (obs. frequencies in brackets)

	Hours males					
Hours females	0	8	16	24	32	40
0	5.7%	0.1%	0.4%	2.0%	8.1%	22.9%
	(6.9%)	(0.2%)	(0.5%)	(0.3%)	(10.4%)	(21.9%)
8	0.7%	0.0%	0.1%	0.7%	2.6%	6.7%
	(0.1%)	(0.0%)	(0.1%)	(0.1%)	(2.3%)	(3.7%)
16	0.6%	0.0%	0.2%	1.3%	4.2%	10.0%
	(0.8%)	(0.2%)	(0.1%)	(0.4%)	(8.0%)	(12.7%)
24	0.7%	0.0%	0.3%	1.6%	4.9%	10.9%
	(0.6%)	(0.2%)	(0.4%)	(0.7%)	(7.4%)	(8.5%)
32	0.7%	0.0%	0.3%	1.2%	3.3%	7.0%
	(0.8%)	(0.3%)	(0.4%)	(0.3%)	(4.2%)	(4.8%)
40	0.2%	0.0%	0.1%	0.3%	0.7%	1.5%
	(0.3%)	(0.1%)	(0.1%)	(0.1%)	(1.0%)	(2.1%)

Table 15: Labour supply elasticities couples with children: log quadratic utility[a]

	Male own			Female cross			Female own			Male cross		
	Total	Ext.	Int.	Total	Ext.	Int.	Total	Ext.	Int.	Total	Ext.	Int.
Full sample	0.14	0.14	0.01	–0.16	–0.10	–0.06	0.50	0.38	0.12	–0.02	0.00	–0.02
By age of youngest child												
0–3	0.15	0.14	0.01	–0.16	–0.10	–0.07	0.51	0.38	0.12	–0.03	–0.01	–0.02
4–11	0.16	0.15	0.01	–0.15	–0.09	–0.06	0.54	0.41	0.12	–0.02	0.00	–0.02
12–18	0.11	0.10	0.01	–0.17	–0.11	–0.06	0.45	0.34	0.11	–0.03	0.00	–0.02
By characteristics of: males							females					
Age 20–28	0.14	0.14	0.01	–0.13	–0.07	–0.06	0.59	0.46	0.13	0.01	0.02	–0.02
Age 28–40	0.15	0.14	0.01	–0.15	–0.09	–0.06	0.51	0.38	0.12	–0.03	–0.01	–0.02
Age 40–57	0.14	0.13	0.01	–0.16	–0.10	–0.06	0.49	0.37	0.11	–0.03	0.00	–0.02
Lower educ.	0.24	0.23	0.01	–0.07	–0.02	–0.05	0.68	0.55	0.12	0.01	0.03	–0.01
Higher educ.	0.12	0.11	0.01	–0.18	–0.11	–0.06	0.47	0.34	0.12	–0.04	–0.01	–0.02

[a] Simulated labour supply elasticities following an impulse of 10% in gross hourly wages. Total is the elasticity of total working hours, ext. is the participation elasticity, int. is the hours per worker elasticity.

Table 16: Labour supply elasticities couples with children: Box-Cox 1 utility[a]

	Male own			Female cross			Female own			Male cross		
	Total	Ext.	Int.	Total	Ext.	Int.	Total	Ext.	Int.	Total	Ext.	Int.
Full sample	0.19	0.16	0.02	–0.29	–0.18	–0.11	0.52	0.40	0.12	0.00	0.02	–0.02
By age of youngest child												
0–3	0.20	0.17	0.02	–0.28	–0.17	–0.11	0.51	0.38	0.12	–0.01	0.01	–0.02
4–11	0.21	0.19	0.02	–0.26	–0.16	–0.10	0.53	0.41	0.12	0.00	0.02	–0.02
12–18	0.14	0.11	0.03	–0.33	–0.22	–0.11	0.52	0.40	0.12	–0.01	0.01	–0.02
By characteristics of: males							females					
Age 20–28	0.19	0.17	0.02	–0.25	–0.14	–0.11	0.60	0.46	0.14	0.03	0.05	–0.02
Age 28–40	0.21	0.19	0.02	–0.27	–0.17	–0.11	0.52	0.39	0.12	–0.01	0.01	–0.02
Age 40–57	0.17	0.15	0.02	–0.31	–0.20	–0.11	0.51	0.39	0.12	–0.01	0.01	–0.02
Lower educ.	0.31	0.28	0.03	–0.17	–0.08	–0.09	0.76	0.61	0.14	0.03	0.05	–0.01
Higher educ.	0.16	0.13	0.02	–0.32	–0.21	–0.11	0.47	0.35	0.12	–0.02	0.01	–0.02

[a] Simulated labour supply elasticities following an impulse of 10% in gross hourly wages. Total is the elasticity of total working hours, ext. is the participation elasticity, int. is the hours per worker elasticity.

Table 16 gives the results for the Box-Cox specification of preferences. The elasticities are somewhat higher for men and quite similar for women compared to the log quadratic specification. Also the relations with age, level of education and age of the youngest child are quite similar.

4.5 Summarizing

Our main findings on labour supply elasticities can be summarized as follows:

- The labour supply elasticity of single men and women is quite similar.
- The labour supply elasticity of single mothers and single fathers is somewhat higher than for singles.
- Men in couples have a much lower elasticity than women in couples, in particular when there are children present in the household.
- Cross-elasticities of men's wages on women's labour supply are sizeable, but not *vice versa.*
- Lower educated individuals have a higher labour supply elasticity than higher educated individuals, in particular for singles and single parents.
- Most of the response is on the extensive margin (participation), the response on the intensive margin (hours per week) is much more limited.
- Differences in labour supply elasticities are mostly driven by differences in the extensive margin response.
- For mothers the intensive margin is somewhat more responsive, but still less important than the extensive margin.
- Across household types we do not find a clear age pattern for labour supply elasticities for the young, middle aged and older workers (up to 57 years old, where our data ends).

Below we consider how our results compare to other studies, for the Netherlands and abroad.

5 Comparison with the findings of other studies

5.1 The Netherlands

Table 17 gives an overview of recent empirical labour supply studies using Dutch data, and our preferred estimates from above. We prefer the flexible log quadratic specification, provided it does not generate many individuals with a negative marginal utility of income. This is only a problem for single parents, for this group we prefer the Box-Cox 1 specification. We compare the results for the findings for the uncompensated wage elasticity of total working hours, participation and hours per worker.

Most studies focus on couples, we consider this group first. We find small elasticities for total hours worked for men in couples, in the order of .1. This is in line with the other studies. The response is on the extensive margin, not on the intenisve margin, in line with the other studies.

We find larger elasticities for women in couples. This is also in line with the other studies. Our results are in the range of the other studies. Studies find substantial extensive margin respones, whereas the results are more mixed for the intensive margin response, though they are on average smaller than the extensive margin.

The studies also report information on cross-elasticities in couples (not in the table). We find negligible cross-elasticities for men and women without children, but sizeable cross-elasticities of women with children (-.2). Van Soest and Das (2001) also find substantial cross-elasticities for women in couples (about half of their own wage elasticity), but not for men in couples. Van Soest *et al.* (2002) also report nonnegligible cross-wage elasticities for women in couples (-0.1). Vermeulen (2005) finds nonnegligible cross-wage elasticities on the intensive margin for both men (-0.1) and women (-0.1). Bloemen (2009) finds small cross-wage elasticities for men in couples without children, but somewhat larger cross-wage elasticiteis for women in couples without children (-.1 for unmarried couples and -.2 for married couples). Bloemen (2010) also finds small cross-elasticities for men and somewhat bigger cross-elasticities for women in some specifications.

A few studies also consider singles. Vermeulen (2005) estimates very small intensive margin elasticities for both single men and women, even smaller than our small estimates. Bargain *et al.* (2011) is the only other study that also considers singles. They present results for all variables. They also find very small intensive margin responses for this group, but also much smaller extensive margin responses than we do. However, negative marginal utilities might be a problem, and their analysis is based on only 313 observations for single men and 450 observations for single women.

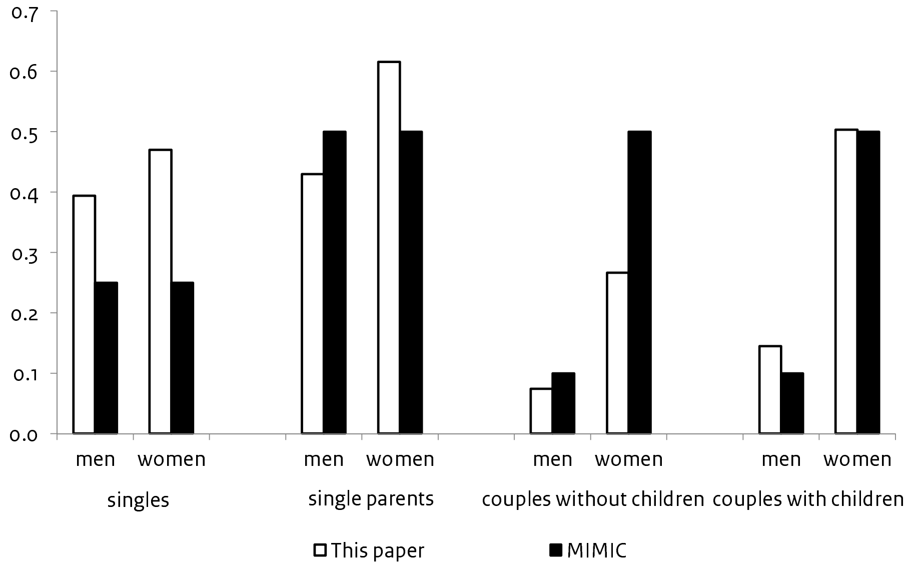
The relation with education is also of interest. Van Soest and Das (2001) also find

Table 17: Estimates of labour supply elasticities in the Netherlands

Study	Sample	Total hours		Participation		Hours per worker	
		Men	Women	Men	Women	Men	Women
This paper	Singles[a]	0.39	0.47	0.33	0.39	0.06	0.08
	Single parents[b]	0.43	0.62	0.31	0.43	0.11	0.18
	Couples w/o children[a]	0.07	0.27	0.07	0.22	0.00	0.05
	Couples with children[a]	0.14	0.50	0.14	0.38	0.01	0.12
Vlasblom et al. (2001)[c]	Couples		0.42		0.35		
Van Soest and Das (2001)	Couples	0.08	0.71				
Van Soest et al. (2002)[d]	Couples		1.04		0.44		
Vermeulen (2005)[e]	Singles					0.01	0.00
	Couples w/o children					–0.03	0.27
Bloemen and Kapteyn (2008)[f]	Couples		0.42		0.25		
Bosch and Van der Klaauw (2010)[g]	Couples						–0.13
Bloemen (2009)[h]	Unmarried couples w/o children	0.24	0.22				
	Married couples w/o children	–0.06	0.61				
Bloemen (2010)[i]	Couples w/o children			–0.02	0.31	0.00	0.26
Bargain et al. (2011)	Singles and single parents	0.08	0.16	0.08	0.11	0.01	0.02
	Couples	0.06	0.32	0.06	0.20	0.01	0.13

[a] Log quadratic utility function.
[b] Box-Cox 1 utility function.
[c] Elasticities are reported in Vlasblom (1998, Table 5.12).
[d] Van Soest et al. (2002, Table 2), estimates with second order polynomial for the utility function. The participation elasticity in Van Soest et al. (2002) is the change in percentage points in response to a 1% increase in the wage rate.
[e] Vermeulen (2005, Table 7), unitary model for couples (own wage elasticities).
[f] Average of the estimation results of the variant with simulated scores and the variant with discrete choices and a third order polynomial utility function, as reported in Bloemen (2010, p. 27).
[g] The parameter estimate is not significantly different from zero (on the 10% level).
[h] Bloemen (2009, Table 7), reduced form estimates.
[i] Bloemen (2010, Table 8), with unrestricted sharing rule and with fixed costs.

Figure 9: Comparison with assumptions in MIMIC



that low educated women in couples have somewhat higher labour supply elasticities (.93 compared to .71 for the whole sample of women in couples). With .46 the elasticity of low educated women in couples in Van Soest *et al.* (2002) is higher than the .37 for high educated women. Unfortunately, none of the other studies gives labour supply elasticities by age or by age of the youngest child.

Finally, CPB currently employs the CGE model MIMIC to study changes in taxes and benefits (see Graafland *et al.*, 2001, and De Mooij *et al.*, 2006). The labour supply elasiticities in MIMIC are based on the meta-analysis of labour supply elasticities in Evers *et al.* (2008). Filling in the values for the Netherlands, they calculate a meta value for the total hours elasticity of men and women of 0.12 and 0.49 respectively. Based on these findings the labour supply elasicity of primary earners (mostly men) and secondary earners (mostly women) in couples is set to 0.1 and 0.5 in MIMIC respectively. For single parents the elasticity is set to 0.5, whereas the elasticity of singles is set to an intermediate level of 0.25. Figure 9 shows how these values compare to the results in this paper. The labour supply elasticities for the different groups are quite comparable. However, there are some differences. The labour supply elasticity of women in couples without children is higher in MIMIC, whereas the labour supply elasticity of singles is lower in MIMIC. In MIMIC both the extensive and intensive margin are important. This study suggests that the extensive margin is more important than the intensive margin. Furthermore, the labour supply elasticity of lower educated individuals is almost the same as higher educated individuals in MIMIC. The results in this paper suggest that differences are bigger for singles and single parents.

5.2 Other countries

Excellent surveys of the labour supply elasticity in various countries can be found in Blundell and MaCurdy (1999) and Bargain *et al.* (2011). These studies indicate that women with children in couples and single mothers have relatively high labour supply elasticities. Men in couples have very low labour supply elasticities, and singles are somewhere in between. Most of the response is on the extensive margin. Finally the labour supply elasticity is higher for low educated individuals than for high educated individuals. Our results are in line with these 'stylized facts'.

As an illustration we can consider (unweighted) averages of the range of estimates from Bargain *et al.* (2011) for EU countries for men and women with and without partners (own calculations based on Table 8 to 11 in Bargain *et al.*, 2011). For women in couples they find on average across EU countries for total hours worked, participation and hours per worker a value of 0.27, 0.22 and 0.05 (with respective standard deviations 0.16, 0.14 and 0.03). For men in couples they find on average across EU countries for total hours worked, participation and hours per worker a value of 0.10, 0.08 and 0.01 (with respective standard deviations 0.05, 0.05 and 0.03). For single women they find on average across EU countries for total hours worked, participation and hours per worker a value of 0.25, 0.21 and 0.03 (with respective standard deviations 0.15, 0.12 and 0.02). For single men they find on average across EU countries for total hours worked, participation and hours per worker a value of 0.24, 0.23 and 0.02 (with respective standard deviations 0.15, 0.14 and 0.02). One interesting thing to note is that elasticities of singles are only somewhat lower than women in couples, which is also what we find.

6 Conclusion

Using a unique administrative panel dataset for the Netherlands we have been able to precisely estimate the labour supply elasticities of various subgroups, and the extensive and intensive margin response. The results are broadly in line with previous studies in the Netherlands, but we consider many more subgroups. The results are also broadly in line with findings of international studies.

However, the current analysis still has a number of limitations. Statistics Netherlands is currently expanding the dataset to 2009, and including information on search behaviour of the unemployed, and the use and parental fee of childcare. With this information we can study a number of additional issues.

With the new data we can track individuals and households over the period 1999-2009. With this longer horizon we can take a closer look at whether elasticities change systematically over time. A number of studies find that the extensive margin elasticity is lower when the participation rate of women is higher, over time (Heim, 2007) or across countries (Evers et al., 2008, Bargain et al., 2011).

With the current dataset we can not distinguish between chance and choice in labour participation. Specifically, we can not distinguish between individuals who are voluntarily unemployed and individuals who can not find a job. With the new dataset we will try to separate chance from choice using a double-hurdle model (see *e.g.* Bargain *et al.*, 2010).

With data on the parental fee and use of childcare we can further estimate preferences for formal and informal care, and study the impact of changes in the price of formal childcare on labour supply and the choice between formal and informal care (see *e.g.* Kornstad and Thoresen, 2006).

Finally, we also want to consider margins other than labour supply. People can respond to changes in taxes (and benefits) via labour supply, but also via their career choice, tax evasion *etc.* As argued by Feldstein (1995), all these effects are captured in the change in taxable income. Studies for the US suggest that this is particularly relevant for the top incomes (Gruber en Saez, 2002).

We will use all this information in a new microsimulation model to study changes in taxes and benefits, which is currently under construction, along the lines of the MITTS model for Australia (see Creedy *et al.*, 2002) and the IZAΨMOD model for Germany (see Peichl *et al.* 2010).

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A Overview discrete choice labour supply models

Table 18 gives an overview of microsimulation models for labour supply. In selecting the studies we have used two criteria: 1) structural analysis of policy reforms, and 2) published in or after 2000.

Table 18: An overview of microsimulation models for labour supply analysis[a]

Study	Country	Data type	Observations	Choice set	Utility function	Unitary/collective	Fixed costs
Aaberge *et al.* (2000)	Italy, Norway and Sweden	Cross-section	2,960	-	Box-Cox	Unitary	Yes
Blundell *et al.* (2000)	U.K.	Repeated cross-section	6,401	5x2	Quadratic	Unitary	Yes
Van Soest and Das (2001)	Netherlands	Cross-section	1,640	10x10	Log quadratic	Unitary	Yes
Creedy *et al.* (2002)	Australia	Repeated cross-section	8,624	11	Quadratic	Unitary	Yes
Flood *et al.* (2004)	Sweden	Repeated cross-section	3,297	7x7	Log quadratic	Unitary	Yes
Nelissen *et al.* (2005)	Netherlands	Repeated cross-section	56,709	11x11	Quadratic	Unitary	Yes
Brewer *et al.* (2005)	U.K.	Repeated cross-section	44,332	6x6	Quadratic	Unitary	Yes
Bargain and Moreau (2005)	France	Cross-section	-	5x4	Stone-Geary	Collective	Yes
Labeaga *et al.* (2005)	Spain	Cross-section	6,420	3x3	Quadratic	Unitary	Yes
Orsini (2006)	Belgium	Cross-section	1,151	3x4	Quadratic	Unitary	Yes
Fuest *et al.* (2006)	Germany	Cross-section	NA	3x5	Log quadratic	Unitary	No
Dearing *et al.* (2007)	Austria and West-Germany	Cross-section	67,348	3	Quadratic	Unitary	No
Gerfin and Leu (2007)	Switzerland	Cross-section	4,790	3x6	Quadratic	Unitary	No
Steiner and Wrohlich (2007)	Germany	Cross-section	6,928	3x5	Quadratic	Unitary	No
Arntz *et al.* (2008)	Germany	Cross-section	3,402	3x5	Quadratic	Unitary	Yes
Ericson *et al.* (2009)	Sweden	Cross-section	785,341	7x7	Log quadratic	Unitary	Yes
Bargain (2009)	France	Cross-section	3,397	5	Quadratic	Unitary	Yes
Pacifico (2009)	Italy, Norway and Sweden	Cross-section	2,002	3x5	Quadratic	Unitary	Yes
Ericson and Flood (2009)	Sweden	Repeated cross-section	-	7x7	Log quadratic	Unitary	Yes
Peichl *et al.* (2010)	Germany	Repeated cross-section	13,451	7x7	Log quadratic	Unitary	Yes
This study	Netherlands	Panel	≈1,000,000[b]	6x6	Various	Unitary	Yes

[a] Published in or after 2000.
[b] In the estimations we use a (random) subset of these observations.

Although not reported, the first thing to notice is that all studies use a discrete choice model. Probably there are some continuous labour supply models out there, but it seems fair to conclude that discrete choice models have become the dominant mode for simulating labour supply responses to policy changes.

Most studies use a (log) quadratic form for the utility function, and also include fixed costs of working. Furthermore, most models stick to the unitary model (as opposed to the collective model). The studies differ quite a bit in the number of discrete choice options. For couples the number of options ranges from 9 (3x3) to 121 (11x11).

B Descriptive statistics

Descriptive statistics are shown in Tables 19 to 22. 20% of the single men has no job and 7% of the men in couples has no job. 30% of the single women and 30% of the women in couples has no job. The average age is a bit higher for men and women in couples than for singles. The average hourly wage is the highest for men in couples (18.2 euros per hour) and the lowest for single women (9.7 euros per hour). For men in couples the fraction that is higher educated is the highest (0.79) and for single women it is the lowest (0.65).[9] Only 5% of single men has children, whereas 35% of the single women has children. 64% of the couples has children.

For the estimation further transformed and added some variables. We have made transformations for the year dummies as described in Deaton and Paxson (1994). The transformations are such that the time dummies add up to zero and are orthogonal to a time trend. The rationale is that time effects are due to macro shocks and average out over time. For age we have made a spline with knots at 30, 40, 50 and 60 years old. We have added cohorts of 5 birthyears and we also added GDP in the year of birth to check whether this would pick up cohorteffects. We run separate estimates for men and women, for singles and couples and for two education levels, so 8 groups in total.

C Estimating wages

C.1 Method

We use different estimators for the wage equation. First, we consider the pooled OLS estimator. This estimator only uses the panel element in our data to compute robust

[9] Lower educated refers to primary education or lower secondary education.

Table 19: Descriptive statistics: single men and single fathers[a]

	All	Employed	Unemployed
Age	38.7 (10.0)	38.6 (9.8)	39.1 (10.6)
Hourly wage	12.5 (9.0)	15.7 (7.1)	0
Hours worked per week	28.1 (15.7)	35.3 (7.4)	0
Ethnicity			
Native	0.80	0.68	0.13
Western immigrant	0.10	0.07	0.03
Non-western immigrant	0.10	0.05	0.05
Education levels			
Lower educated	0.28	0.18	0.10
Higher educated	0.72	0.61	0.11
Age of youngest child			
Below 4 years	0.00	0.00	0.00
Between 4 and 12	0.02	0.01	0.00
Between 12 and 18	0.03	0.02	0.00
Number of observations	134571	107238	27333
Number of individuals	51055	40953	10975

[a]Standard deviations in parentheses

Table 20: Descriptive statistics: single women and single mothers[a]

	All	Employed	Unemployed
Age	39.3 (10.1)	38.8 (10.0)	40.4 (10.1)
Hourly wage	9.7 (8.1)	14.3 (5.6)	0
Hours worked per week	21.1 (16.1)	31 (8.5)	0
Ethnicity			
Native	0.76	0.56	0.20
Western immigrant	0.10	0.06	0.04
Non-western immigrant	0.14	0.06	0.08
Education levels			
Lower educated	0.35	0.15	0.20
Higher educated	0.65	0.53	0.12
Age of youngest child			
Below 4 years	0.07	0.02	0.05
Between 4 and 12	0.17	0.08	0.09
Between 12 and 18	0.11	0.07	0.04
Number of observations	208897	142239	66658
Number of individuals	69001	50054	20972

[a]Standard deviations in parentheses.

Table 21: Descriptive statistics: men in couples[a]

	All	Employed	Unemployed
Age	44.1 (7.9)	44.1 (7.9)	43.6 (8.3)
Hourly wage	18.2 (9.7)	19.4 (8.7)	0
Hours worked per week	34.5 (10.3)	36.9 (4.8)	0
Married	0.88	0.88	0.86
Ethnicity			
Native	0.86	0.83	0.03
Western immigrant	0.08	0.07	0.01
Non-western immigrant	0.06	0.04	0.03
Education levels			
Lower educated	0.21	0.18	0.03
Higher educated	0.79	0.75	0.03
Age of youngest child			
Below 4 years	0.21	0.19	0.02
Between 4 and 12	0.27	0.25	0.02
Between 12 and 18	0.16	0.15	0.01
Number of observations	359719	335892	23827
Number of individuals	105226	96469	9279

[a]Standard deviations in parentheses.

Table 22: Descriptive statistics: women in couples[a]

	All	Employed	Unemployed
Age	41.8 (8.1)	41 (7.9)	43.4 (8.2)
Hourly wage	9.9 (8.6)	15 (5.9)	0
Hours worked per week	16 (13.6)	24.2 (9.1)	0
Married	0.88	0.84	0.95
Ethnicity			
Native	0.86	0.59	0.27
Western immigrant	0.08	0.05	0.03
Non-western immigrant	0.06	0.02	0.04
Education levels			
Lower educated	0.29	0.12	0.17
Higher educated	0.71	0.54	0.17
Age of youngest child			
Below 4 years	0.21	0.13	0.07
Between 4 and 12	0.27	0.17	0.09
Between 12 and 18	0.16	0.11	0.06
Number of observations	359719	237790	121929
Number of individuals	105249	68430	39578

[a]Standard deviations in parentheses.

standard errors. The equation is specified as:

$$w_{it} = x'_{it}\beta + \varepsilon_{it}, \tag{6}$$

where w_{it} denotes the log of the hourly wage of individual i in year t. The errorterm is assumed to be independent of the explanatory variables x_{it}, and $\varepsilon_{it} \sim IID(0, \sigma_\varepsilon^2)$.

Second, we estimate a Heckman two-step model, which allows for selection bias in observed wages. Employed workers may be a select subset in terms of wages of the whole group of employed and non-employed. The first step in the Heckman two-step model is to estimate a selection equation which determines participation:

$$p_{it} = x'_{it}\gamma + z'_{it}\psi + \nu_{it}. \tag{7}$$

The selection equation contains instrumental variables z_{it} (we will use the presence or absence of young children, and for couples also the marital status). We assume that these instrumental variables explain participation but do not explain the wage. The errorterm ν_{it} is assumed to be independent of the regressors x_{it} and z_{it} and $\nu_{it} \sim N(0, \sigma_\nu^2)$. Hence, (7) is estimated with a probit estimator. In the second step we add the inverse Mills' ratio, derived from the first step, to the wage equation (6):

$$invMills_{it} = \phi(\hat{p_{it}})/\Phi(\hat{p_{it}}), \tag{8}$$

$$w_{it} = x'_{it}\beta + invMills'_{it}\theta + \varepsilon_{it}. \tag{9}$$

The errorterm ε_{it} is assumed to be independent of x_{it} and the inverse Mills' ratio and $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$. Equation (9) is estimated using pooled OLS.

Third, we also use the Heckman two-step model in Stata. For robustness of the standard errors we use the clustering option.[10]

Fourth, we apply the fixed effects estimator. This estimator takes the panel element into account. The wage equation for panel data is:

$$w_{it} = x'_{it}\beta + \alpha_i + \varepsilon_{it}, \tag{10}$$

where α_i are fixed individual effects. The fixed effects estimator makes no assumptions on the distribution of fixed individual effects. The individual effects drop out of the equation by estimating in deviations from the mean. Indeed, all time invariant variables drop out. Thus we rewrite equation (10) to:

[10] The results for the Heckman two-step model in Stata and for the Heckman two-step model implemented with Equations 7 and 9 can be different due to the iterative estimation procedure for the Heckman two-step model in Stata and due to the use of the clustering option.

$$(w_{it} - \bar{w}_i) = (x_{it} - \bar{x}_i)'\beta + (\varepsilon_{it} - \bar{\varepsilon}_i), \tag{11}$$

where $\bar{w}_i$ is the average of the log of the wage over time and $\bar{x}_i$ is the average of x_{it}. The errorterm ε_{it} is independent of all x_{it} and $\varepsilon_{it} \sim IID(0, \sigma^2_\varepsilon)$.

Fifth, we apply the random effects estimator which assumes that the individual effects α_i are independent of x_{it} and ε_{it} and $\alpha_i \sim IID(0, \sigma^2_\alpha)$.

$$w_{it} = x'_{it}\beta + \alpha_i + \varepsilon_{it}, \tag{12}$$

where $\varepsilon_{it} \sim IID(0, \sigma^2_\varepsilon)$ and ε_{it} is independent of x_{it} and α_i. To determine whether the random effects estimator is consistent we apply a Hausman test (Hausman, 1978).

Sixth, we apply the quasi-fixed effects estimator (Mundlak, 1978). The fixed effects estimator makes no assumptions on α_i but then all time-invariant regressors drop out of the equation. The random effects estimator keeps the time-invariant regressors but assumes that the α_i are independent of the regressors x_{it}. The quasi-fixed effects estimator allows α_i to be correlated with regressors while maintaining the time-invariant regressors:

$$w_{it} = x'_{it}\beta + \bar{x}'_{1,i}\theta + \omega_i + \varepsilon_{it}, \tag{13}$$

where $\bar{x}_{1,i}$ is the average over time of the subset $x_{1,it}$ of regressors which are timevarying. The individual effect α_i is equal to $\bar{x}'_{1,i}\theta + \omega_i$ and ω_i is assumed to be independent of x_{it} and ε_{it} and $\omega_i \sim IID(0, \sigma^2_\omega)$. The errorterm ε_{it} is independent of x_{it} and ω_i and $\varepsilon_{it} \sim IID(0, \sigma^2_\varepsilon)$.

The Heckman two-step model is applied because a selection bias might arise from the fact that wages are only observed for individuals that are working. We can formally test whether there is a selection bias. We apply two tests for selection (see Wooldridge, 2002, pp. 581-582). The first test is to add a lagged selection indicator to the wage equation. The selection indicator s_{it-1} is one if an individual worked in the previous year and zero otherwise. The model is estimated with fixed effects. If the coefficient for the lagged selection indicator is significant then we reject that selection is not a problem. The second test starts with estimating

$$s_{it-1} = x'_{it}\psi + \bar{x}'_i\xi + \eta_{it}, \tag{14}$$

where s_{it-1} is the lagged selection indicator and $\eta_{it} \sim IID(0, \sigma^2_\eta)$. (14) is estimated with a probit model and the inverse Mills' ratio obtained from this regression is then added to the fixed effects model (11). When the inverse Mills' ratio is significant in the equation estimated by fixed effects we reject that selection is not a problem.

We work with a panel dataset, where not all individuals are present in all years. This is called an unbalanced panel dataset. There may be an attrition bias when attrition in the sample does not take place at random. We test for attrition bias by adding an attrition indicator which is one in the last year before attrition and zero otherwise. If this indicator is significant in the fixed effects model (11) we reject that attrition does not bias the estimated parameters.

C.2 Results

First we show the results for singles and then we show the results for couples. In the end we present the results of the selection and attrition tests.

C.3 Singles

For the higher educated men the results of the first five estimators are presented in Table 23. The coefficients are quite similar. We do not select these models for the following reasons. Pooled OLS is not selected because we want to correct for unobserved characteristics. With fixed effects we lose all information on time-invariant regressors. For the random effects model we reject the null hypothesis that the random effects model is consistent. Therefore we select the quasi-fixed effects model.

Table 24 shows the estimation results for singles assuming quasi-fixed effects. The coefficients for the age variables are always positive. For single men until 30 years of age with a higher education level the coefficient for the age effect is 0.0564. For the same group with a lower education level the coefficient is only 0.0394. Thus the age effect is stronger for the higher education level. Also the age effect becomes smaller with age, thus income rises more for younger employees, which is also in line with other studies (e.g. Vella and Verbeek, 1999, find that the coefficient for age is positive and the coefficient for age squared is negative).

The cohortvariables were added to capture cohort effects that are caused by specific conditions in the past. For example the GDP-level in the year of birth was added to pick up the effect of the economic situation in the year in which an individual is born. The coefficient for GDP is significant for women. The cohortvariables are jointly significant at the 1% level, except for lower educated women. For this group the cohortvariables are only significant at the 5% level.

We included age splines and cohort splines in the model and therefore we cannot include time dummies. To circumvent this problem we transformed the time dummies following Deaton and Paxson (1994). For 1999 and 2000 the coefficients have been calculated from the coefficients for the other years. Due to the Deaton and Paxson transformed time dummies there are no real time effects. All time effects are assumed to be transitory. The transformed time dummies are jointly significant at the 1% level.

Table 23: Outcomes: log hourly wages single men, higher educated

	Pooled OLS	Heckman 1	Heckman 2	Fixed Effects	Random Effects
Age effect					
20–30	0.0491***	0.0360***	0.0484***	0.0564***	0.0548***
31–40	0.0174***	0.0184***	0.0174***	0.0335***	0.0319***
41–50	0.0133***	0.0118***	0.0132***	0.0169***	0.0166***
51–57	0.00690***	0.00725***	0.00692***	0.0116***	0.0114***
Cohort effect					
1975–1985	0.0491	–0.0400	0.0446		0.281***
1970–1974	0.0322	–0.0420	0.0285		0.228***
1965–1969	0.0173	–0.0376	0.0145		0.151***
1960–1964	–0.00947	–0.0585	–0.0119		0.0624**
1955–1959	–0.0505	-0.0849***	-0.0522*		–0.00914
1950–1954	-0.0547*	-0.0738**	-0.0556*		–0.0308
1945–1949	-0.0511*	-0.0667**	-0.0519*		-0.0500*
GDP-level year of birth	–0.000526	–0.000569	–0.000528		0.000463
Time effect					
2001	0.0110***	0.00479*	0.0107***	0.0151***	0.0149***
2002	0.00319*	–0.00404	0.00283	0.0108***	0.0103***
2003	0.000286	-0.00356*	9.27e-05	0.00513***	0.00477***
2004	-0.00219*	–2.61e-07	–0.00208	-0.00398***	-0.00399***
2005	-0.00351**	0.00266	-0.00320**	-0.0105***	-0.00997***
1999[a]	0.0211	–0.00283	0.01988	0.01969	0.0352
2000[b]	–0.038	0.00146	–0.03597	–0.04559	–0.0602
Ethnicity					
Western immigrant	-0.158***	-0.0698**	-0.154***		-0.163***
Non-western immigrant	–0.00308	-0.0410***	–0.00499		0.00295
Inverse Mills' ratio		-0.264***			
Observations[c]	71752	71752	71752	71752	71752
Number of individuals				19766	19766

*** p<0.01, ** p<0.05, * p<0.1

[a] Calculated as –(t2000 + t2001 + t2002)

[b] Calculated as –2 x t2001 – 3 x t2002

[c] This is the number of uncensored observations, the number of censored observations is 12059

Table 24: Outcomes for quasi-fixed effect estimator: singles and single parents

	Lower educated		Higher educated	
	Men	Women	Men	Women
Age effect				
20–30	0.0394***	0.0574***	0.0564***	0.0533***
31–40	0.0152***	0.0193***	0.0334***	0.0292***
41–50	0.0112***	0.0191***	0.0168***	0.0208***
51–57	0.00759***	0.0151***	0.0116***	0.0164***
Cohort effect				
1975–1985	0.192***	0.149***	–0.0618	–0.0294
1970–1974	0.0996	–0.00894	–0.0576	-0.0723*
1965–1969	0.0579	–0.0432	–0.0377	-0.0704*
1960–1964	0.0181	–0.0622	–0.0308	-0.0718**
1955–1959	0.00888	-0.0800**	-0.0736*	-0.0713**
1950–1954	–0.0304	-0.0894***	-0.0800**	-0.0609**
1945–1949	–0.00252	-0.0535**	-0.0643**	-0.0472**
GDP-level year of birth	5.39e-05	-0.00159**	-0.00104*	-0.00100**
Time effect				
2001	0.00295	0.00606***	0.0149***	0.0107***
2002	0.00387**	0.0187***	0.0104***	0.0181***
2003	0.0118***	0.00780***	0.00496***	0.0101***
2004	-0.00313*	-0.00822***	-0.00385***	-0.00400***
2005	-0.00801***	-0.00937***	-0.0102***	-0.0156***
1999[a]	0.01069	0.04346	0.0357	0.0469
2000[b]	–0.01751	–0.06822	–0.061	–0.0757
Ethnicity				
Western immigrant	-0.0781***	-0.0660***	-0.164***	-0.102***
Non-western immigrant	0.0216*	0.0116	0.00352	0.0275***
Mundlak averages				
Age 20–30	-0.00688*	-0.0272***	-0.00995***	-0.00738***
Age 31–40	–0.00579	-0.0139***	-0.0242***	-0.0235***
Age 41–50	–0.00204	-0.0133***	–0.00212	-0.0176***
Age 51–57	-0.0127**	-0.0193***	-0.00949*	-0.0131***
Observations	20200	26261	71752	99422
Number of individuals	5894	7628	19766	25858

*** p<0.01, ** p<0.05, * p<0.1

[a] Calculated as –(t2000 + t2001 + t2002)

[b] Calculated as –2 x t2001 –3 x t2002

Table 25: Chi-squared tests: singles and single parents

	Lower educated		Higher educated	
	Men	Women	Men	Women
Joint significance				
Mundlak averages	10.55^{*}	160.66^{***}	110.08^{***}	283.67^{***}
Age dummies	382.77^{***}	4922.4^{***}	942.55^{***}	6729.15^{***}
Cohort dummies	42.17^{***}	17.85^{**}	112.44^{***}	54.58^{***}
Time dummies (Deaton-Paxson)	44.67^{***}	403.51^{***}	108.53^{***}	795.38^{***}
*** p<0.01, ** p<0.05, * p<0.1				

An individuals ethnicity sometimes has a significant influence on the wage. Western immigrants have a somewhat lower wage, whereas the reverse seems to be true for Non-western immigrants.

The Mundlak variables are not directly interpretable; they are included to correct for the correlation between the (unobserved) individual effects and the time-varying explanatory variables. They are jointly significant at the 1% level, except for lower educated men, which indicates that there are unobserved fixed effects that are correlated with the time-varying explanatory variables, which motivates our choice to use the quasi-fixed effects model.

C.4 Couples

Table 26 shows the estimation results for men and women in couples. The coefficients are quite similar to those for single men and women. There are three extra variables: the age of the partner, the marital status and the Mundlak variable of marital status. For lower educated men and women the coefficient for the age of the partner is significant but small. Higher educated married partners have a somewhat higher wage than higher educated partners that are not married.

C.5 Selection and attrition

For all 8 subgroups we test for selection and attrition. As described above, selection is not a problem when the lagged selection indicator is not significant. The same holds for the inverse Mills' ratio. The results for singles are shown in Table 28 and for couples in Table 29. In some specifications we can not reject that selection and/or attrition is present in the estimates for wages. This is particularly true for higher educated women.

Table 26: Outcomes for quasi-fixed effect estimator: couples

	Lower educated		Higher educated	
	Men	Women	Men	Women
Age effect				
20–30	0.0261***	0.0309***	0.0447***	0.0400***
31–40	0.0143***	0.0136***	0.0254***	0.0218***
41–50	0.00785***	0.0125***	0.0102***	0.0177***
51–57	0.00281***	0.00698***	0.00299***	0.0143***
Cohort effect				
1975–1985	-0.0989**	-0.111**	0.0846***	-0.151***
1970–1974	-0.0885***	-0.162***	0.0709***	-0.167***
1965–1969	-0.108***	-0.144***	0.0431**	-0.163***
1960–1964	-0.105***	-0.128***	0.0105	-0.169***
1955–1959	-0.0903***	-0.116***	0.00380	-0.142***
1950–1954	-0.0739***	-0.0662**	–0.00201	-0.108***
1945–1949	-0.0417***	–0.0443	–0.00643	-0.0690***
GDP-level year of birth	–7.27e-05	0.000163	0.000249	0.000651*
Time effect				
2001	0.00971***	0.0132***	0.0134***	0.0124***
2002	0.00605***	0.0177***	0.00952***	0.0215***
2003	0.00504***	0.00833***	0.00549***	0.0105***
2004	0.00148*	-0.0178***	-0.00253***	-0.00965***
2005	-0.0101***	-0.00358***	-0.0105***	-0.0133***
1999[a]	0.02181	0.0486	0.03244	0.0554
2000[b]	–0.03757	–0.0795	–0.05536	–0.0893
Ethnicity				
Western immigrant	-0.133***	-0.0785***	-0.213***	-0.0938***
Non-western immigrant	0.0193**	0.00425	0.000463	0.0227***
Partner				
Age partner	0.00381***	–0.000640	0.00707***	–0.000265
Married	0.00613	–0.00235	0.0104***	0.0159***
Mundlak averages				
Age 20–30	-0.0135*	–0.00352	–0.00276	0.00810***
Age 31–40	-0.00800***	-0.0118***	–0.00148	-0.0125***
Age 41–50	-0.00940***	-0.0155***	-0.00963***	-0.0231***
Age 51–57	-0.0156***	-0.0138***	–0.00112	-0.0136***
Married	0.0384***	-0.0208*	–0.00229	-0.0954***
Observations	59254	40768	255807	182785
Number of idnr	15055	10735	60574	43428

*** p<0.01, ** p<0.05, * p<0.1

[a] Calculated as –(t2000 + t2001 + t2002)

[b] Calculated as –2 x t2001 –3 x t2002

Table 27: Chi-squared tests: couples

	Lower educated		Higher educated	
	Men	Women	Men	Women
Joint significance				
Mundlak averages	84.51***	57.74***	99.26***	792.08***
Age dummies	249.07***	3009.36***	208.45***	2092.84***
Cohort dummies	20.88***	31.83***	35.47***	54.8***
Time dummies (Deaton Paxson)	199.19***	1876.85***	237.54***	1792.24***
*** p<0.01, ** p<0.05, * p<0.1				

Table 28: Tests for selection and attrition: singles and single parents

	Lower educated		Higher educated	
	Men	Women	Men	Women
Selection				
Lagged selection indicator	0.000632	0.0145*	0.00845	0.0274***
Inverse Mills' ratio	–0.160	-1.152***	0.210*	-0.393***
Attrition				
Attrition indicator	–0.00387	–0.00161	0.00201	0.00391**
*** p<0.01, ** p<0.05, * p<0.1				

Table 29: Tests for selection and attrition: couples

	Lower educated		Higher educated	
	Men	Women	Men	Women
Selection				
Lagged selection indicator	0.0148	0.0220***	0.0447***	0.0227***
Inverse Mills' ratio	–0.0833	–0.000864	-0.170***	0.138**
Attrition				
Attrition indicator	-0.00565***	–0.00235	-0.00290***	–0.000955
*** p<0.01, ** p<0.05, * p<0.1				